2025

EJEL Volume 23, Issue 4

Editors

Heinrich Söbke

Published by Academic Conferences & Publishing International Limited
Curtis Farm, Kidmore End, Nr Reading, RG4 9AY, United Kingdom
karen.harris@academic-publishing.org

eISSN: 1479-4403

The Role of Learning Motivation Factors in Deepseek Generative AI Adoption among Higher Education Students in India

Ravi Sankar Pasupuleti[1], Deevena Charitha Jangam[2], Anitha Bhimavarapu[3], Venkata Reddy Gunnam[4], Venkata Ramana Sikhakolli[5] and Deepthi Thiyyagura[6]

[1]Department of Applied Science & Humanities, Tirumala Engineering College, Jonnalagadda, Andhra Pradesh, India

[2]Department of Logistics and Retail Operations, Andhra Loyola College, Vijayawada, Andhra Pradesh, India

[3]Department of Business Administration, Kakaraparti Bhavanarayana College, Vijayawada, Andhra Pradesh, India

[4]School of Management Studies, Sreenidhi Institute of Science and Technology, Ghatkesar, Hyderabad, Telanagana, India

[5]KL Business School, Koneru Lakshmaiah Education Foundation (Deemed to be University), Vaddeswaram, Andhra Pradesh, India

[6]Department of Management Studies, A.M. Reddy Memorial College of Engineering & Technology, Narasaraopeta, Andhra Pradesh, India

pravisankar615@gmail.com (Corresponding Author)
deevenacharitha69@gmail.com
anitharesearch21@gmail.com
venkatreddygunnam@gmail.com
dr.venkataramana1@gmail.com
deepthi.t17@gmail.com

https://doi.org/10.34190/ejel.23.4.4245

Abstract: This research explores adoption of the Deepseek, an artificial intelligence (AI) platform among higher education students in India by integrating the Technology Acceptance Model (TAM) with learning motivation factors. Given the rapid rise of AI-based platforms in educational sector, understanding their adoption is not only timely but also essential for ensuring equitable and effective learning outcomes. Addressing a critical research gap in understanding of rapidly evolving EdTech sector, the research blends constructs such as learning interest, achievement goals, self-efficacy, and subjective norms in expanding the typical TAM model. This integrative approach allows for a more holistic framework that captures both technological perceptions and learner-driven motivational factors, making the model especially relevant in emerging economies where educational technology adoption varies widely. Data were gathered using an online survey via Google Forms, providing 346 valid responses from students. The sample consisted of students from diverse academic disciplines, ensures representativeness across different fields of study and thereby enhancing the generalizability of the results. The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS-3 software. The findings support the extended TAM model which indicated that learning interest and achievement goals have significant impact on perceived ease of use. Self-efficacy and subjective norms have significant impact on perceived usefulness and behavioral intention has significant impact on actual usage, demonstrating its pivotal role in technology adoption. These relationships suggest that motivation-related constructs are not peripheral but central in shaping how students interact with AI-powered platforms. This study advances the literature on educational technology by establishing a new TAM model as applied to AI-powered learning tools in emerging economies. The practical implications are that developers of Deepseek need to make the platform more user-centered in order to increase adoption. Future research avenues involve analyzing other contextual factors and longitudinal patterns of adoption over time. These findings provide useful insights for stakeholders who want to maximize AI learning tool integration in universities.

Keywords: Artificial Intelligence, DeepSeek, Higher education, Learning motivation, Learning interest, Education technology, PLS-SEM

1. Introduction

DeepSeek, a new artificial intelligence (AI) model, is transforming the process of seeking information by offering superior reasoning abilities, great computational efficiency, and ease of use (Kumar, 2025). In contrast to

Cite this article: Ravi Sankar Pasupuleti, R.S. et al. 2025. "The Role of Learning Motivation Factors in Deepseek Generative AI Adoption among Higher Education Students in India", *Electronic Journal of e-Learning*, 23(4), pp 01-14 https://doi.org/10.34190/ejel.23.4.4245

conventional search engines and generative AI models, DeepSeek combines several computational approaches, thus being especially useful in higher education environments, where students need precise, contextually appropriate, and well-organized answers (Jiang, Gao and Karniadakis, 2025). In contrast to popular models such as ChatGPT, DeepSeek has proven to outperform them in niche applications, such as mathematical computation, scientific computation, and code writing (Jahin et al., 2025). Its open-access status and flexibility render it a suitable instrument for augmenting online learning experiences at universities and colleges (Peng, Chen and Shih (2025).

DeepSeek has been applied to different industries with great success in healthcare (Egger et al., 2025; Faray de Paiva et al., 2025), accounting (Arabiat, 2025), and fintech (Krause, 2025). In the education field, DeepSeek has emerged as a disruptive innovation that can revolutionize digital learning. Its capacity to deliver customized tutoring, support scholarly research, and improve engagement with students has attracted educators and researchers (Allen, 2025). Chinese universities have significantly utilized DeepSeek in filling technological gaps within AI innovation to make students capable of creating sophisticated computational abilities (Allen, 2025). DeepSeek has also been promising in education testing, helping students solve difficult math problems with greater accuracy (Jahin et al., 2025).

Various research studies have compared the capabilities of DeepSeek and other AI models. Neha and Bhati (2025) compared DeepSeek models, where they emphasized the evolution of natural language processing and knowledge retrieval. Liao (2025) made a technical assessment of DeepSeek's large model, presenting its computational efficiency and real-time implementation across various fields. In addition, comparative analyses of DeepSeek and ChatGPT have highlighted its stronger mathematical reasoning and code generation abilities (Jiang, Gao and Karniadakis, (2025); Manik, 2025). Previous research has largely centered on the technical features of DeepSeek instead of the motivational and psychological aspects that shape its adoption (Kerimbayev et al., 2024). In addition, whereas research on educational generative AI has looked into usability, accessibility, and efficacy, there exists a gap in research to comprehend how motivation variables influence students' adoption of DeepSeek.

The main aim of this research was to analyze the behavioral intentions (BI) of Indian higher education students in adopting DeepSeek by combining the Technology Acceptance Model (TAM) with learning motivation variables. The research seeks to fill the current research gap by exploring how learning motivation variable affect students' intentions toward the ease of use and usefulness of DeepSeek. In addition, this study will examine the effect of these perceptions on BI and use behavior. Using a hypothesized research model (as shown in Figure 1), this study adds strength to the conventional TAM model by addressing important motivational factors. The interactions among these constructs will be empirically examined to shed light on the drivers of DeepSeek's adoption by students.

This research makes several contributions to the literature. First, it presents empirical findings on the determinants of DeepSeek adoption behavior among Indian students. Second, it extends the TAM model by adding learning motivation factors, providing a richer explanation of technology acceptance in learning environments. Third, the findings of this study will help educators, policymakers, and AI developers create more efficient AI-based learning tools that are responsive to students' learning requirements.

2. Literature Review

The Technology acceptance model (TAM) developed by Davis (1989) extends the Theory of Reasoned Action (TRA) to offer explanations of users' adoption of new technology (Fishbein & Ajzen, 1977). The original TAM developed by Davis (1989) identifies four constructs: perceived ease of use (PEU), perceived usefulness (PU), behavioral intention (BI), and actual use (AU). The TAM is very flexible in that it is possible to integrate external variables in order to extend its applicability. It has been widely applied and developed throughout the years through the integration of different external variables to study a range of settings.

In particular, TAM was successful in the prediction of students' motivation, behavior, and performance in using various technologies, such as evaluating college students' actual use of AI systems (Thummalapenta et al., 2025). It provides a solid theoretical basis for the comprehension of how users develop intentions to use and adopt new technologies based on PEU and usefulness. Various external variables have been incorporated into TAM since its creation to examine and study the acceptance and intention to use AI in higher education (Tummalapenta et al., 2024; Pasupuleti & Thiyyagura, 2024).

This research including factors of learning motivation as independent variables, such as learning interest (LI), achievement goals (AG), self-efficacy (SE) and subjective norms (SN). The above-mentioned factors are studied to check their influence on the acceptance and usage of DeepSeek by students in higher education. The expanded TAM model shown in Figure 1 seeks to present more sophisticated explanations of the roles played by students' desire to learn and motivation in creating perceptions, intention, and final adoption of DeepSeek.

Learning motivation is a crucial determinant of the education system, especially in the implementation of AI-based systems. It includes different sub-factors such as LI, AG, SN and SE (Riaz et al., 2010; Ngan & Law, 2015; Firdaus, 2019). Many studies have highlighted that these factors have a significant potential to affect students' behavioral intentions towards AI systems either positively or negatively (Bhavana & Vijayalakshmi, 2022; Liu et al., 2022; Wu, Liu and Huang (2022)). These are both predictive and motivational variables that impact students' adoption intention for AI tools such as DeepSeek (Dirzyte et al., 2021). Learning motivation is usually referred to as the process of decision-making that stimulates students to participate in certain learning activities and the amount of effort they put into them (Bandhu et al., 2024). Learning motivation can be explained as the sum of incentives that result in people choosing certain behaviors or goals (Jarvis, 2005).

This research takes into account four important dimensions of learning motivation: LI, AG, SE and SN. LI is a student's internal motivation and curiosity to learn content and work on tasks, which creates a stronger sense of attachment to the learning process (Harefa et al., 2023; Ariani, 2020). AG signifies the hope of reaching certain educational outcomes, usually inspired by the need to improve ability or prove expertise in a subject (Elliot & Thrash, 2001). SE is the belief by students in their capacity to effectively accomplish educational tasks with the aid of certain learning tools, affecting their motivation, persistence, and technology adoption (Compeau & Higgins, 1995). SN concern peer, educator, and general academic community pressures and expectations on students' adoption and use (Börger & Hattam, 2017).

Various studies have examined the effect of LI, AG, SE and SN on students' behavior regarding the use of AI systems, and consistently reported a strong effect on their adoption and usage behavior (Roy et al., 2022; Moon & Jung, 2016). All these factors have proven to be good predictors of students' intention to employ AI tools in education such as DeepSeek (Huang, 2020; Mudiarti & Harjanti, 2021; Shiang Tyng et al., 2023). Thus, in this research, hypotheses are developed that investigate the relationship of PU, PEU, and the various dimensions of learning motivation.

Students who are more interested in learning will find AI-based learning platforms such as DeepSeek easier to use. This is due to the fact that intrinsically motivated students are prone to exhibit exploratory behavior (Deci & Ryan, 2000), persevere in the face of initial usability issues, and achieve increased familiarity with features of a platform, ultimately making them feel more ease of use (Venkatesh et al., 2003). LI will have a positive impact on students' perceptions of DeepSeek's use. Based on self-determination theory (Deci & Ryan, 2000), intrinsically motivated learners are more likely to identify and value the degree to which the capabilities of the platform fit their curiosity-oriented learning objectives, and thus make more favorable use judgments. Hence we propose

***H1**: LI has significant positive impact on PEU*

***H2**: LI has significant positive impact on PU*

Students with more robust AG will find AI learning platforms more user-friendly. AG students proactively search for mastery strategies (Elliot & McGregor, 2001) and hence are more likely to systematically investigate platform features and overcome usability obstacles, thus reinforcing ease-of-use perceptions (Huet et al., 2011; Teo et al., 2024). AG learners will find DeepSeek's functions to be more useful. By the goal-setting theory (Locke & Latham, 2002), these students consciously assess instruments that facilitate the achievement of performance goals, rendering them more responsive to attributes that optimize learning effectiveness and quality (Miron-Spektor & Beenen, 2015). The connection could be especially robust for students with performance-approach goals. Hence, we hypothesize that,

***H3**: AG has significant positive impact on PEU*

***H4**: AG has significant positive impact on PU*

Higher SE students will find AI learning platforms more convenient to use. Social cognitive theory (Bandura, 1997) suggests that those with high confidence in their online skills are likely to exhibit exploratory behavior, overcome technical difficulties, and establish effective interaction strategies, resulting in increased ease-of-use perceptions (Compeau & Higgins, 1995). This might be less so for highly intuitive platforms where little skill is needed for simple usage. SE learners will find the functionalities in DeepSeek more useful. Those with high confidence in their ability to use technology (Seshadri & Pasupuleti, 2023; Rahmawati, 2019) are likely to learn complex features through consistent use, improvise platform tools to learning tasks creatively and identify performance gains - all factors that significantly influence usefulness assessments (Venkatesh & Davis, 2000). This should hold particularly true in situations where self-directed learning is required. Therefore we propose,

***H5**: SE has significant positive impact on PEU*

***H6**: SE has significant positive impact on PU*

Students who feel greater social pressure to employ AI learning platforms will indicate greater PEU. This is due to two mechanisms, one is informational social influence, whereby users gain from peer-shared information regarding platform navigation (Venkatesh & Davis, 2000), and second is normative conformity, whereby the need for social conformity lessens resistance to initial usability obstacles (Fishbein & Ajzen, 1977). SN will have a positive impact on PU of DeepSeek. When referent groups that are significant (peers, faculty) support use of the platform, students are likely to assign value to suggested features they may otherwise ignore (Tran, Nguyen and Tang, 2023), and reinterpret early experience with use through socially confirmed frameworks for interpretation (Binyamin, Rutter and Smith, 2018). This relationship is expected to strengthen when users have limited prior experience with similar technologies, making them more reliant on social cues for usefulness evaluation. Hence we hypothesize that,

***H7**: SN has significant positive impact on PEU*

***H8**: SN has significant positive impact on PU*

PEU is the level to which someone feels that making use of a particular AI system will not cause them much trouble and will only improve their performance (Davis et al., 1989). In education, this means it is the intention of students to accept or dismiss a technological use depending on whether they feel the use will do a good job of facilitating learning and academic progress (Tummalapenta et al., 2024). PU, however, refers to the degree to which a user feels that the use of a specific system will enhance their productivity without incurring undue physical or mental effort (Davis et al., 1989; Rosli & Saleh, 2023). Studies have uniformly shown that PEU and PU have a considerable influence on users' attitudes towards a specific technology, with both having a fundamental role in defining behavioral intention (Pasupuleti and Thiyyagura, 2025; Li et al., 2024).

Behavioral intention in TAM is the intentional choice to do or not do something with a technology in the future (Basaran & Aksoy, 2017). When applied to AI tools, it is the students' willingness to incorporate Deppseek into their studies and their resolve to do so repeatedly over a period of time (Kuleto et al., 2021). There is evidence in the existing literature that behavioral intention has a strong association with the usage of AI systems. Finally, AU is the dependent variable, symbolizing the use of the technology, which is highly driven by behavioral intention (Li, 2023). Guided by this explanation, the research establishes hypotheses regarding PEU, PU, and behavioral intention, as summarized below.

***H9**: PEU has significant positive impact on BI*

***H10**: PU has significant positive impact on BI*

***H11**: BI has significant positive impact on AU*

Figure.1 presents the theoretical model relating to the use of DeepSeek and identified motivational factors.

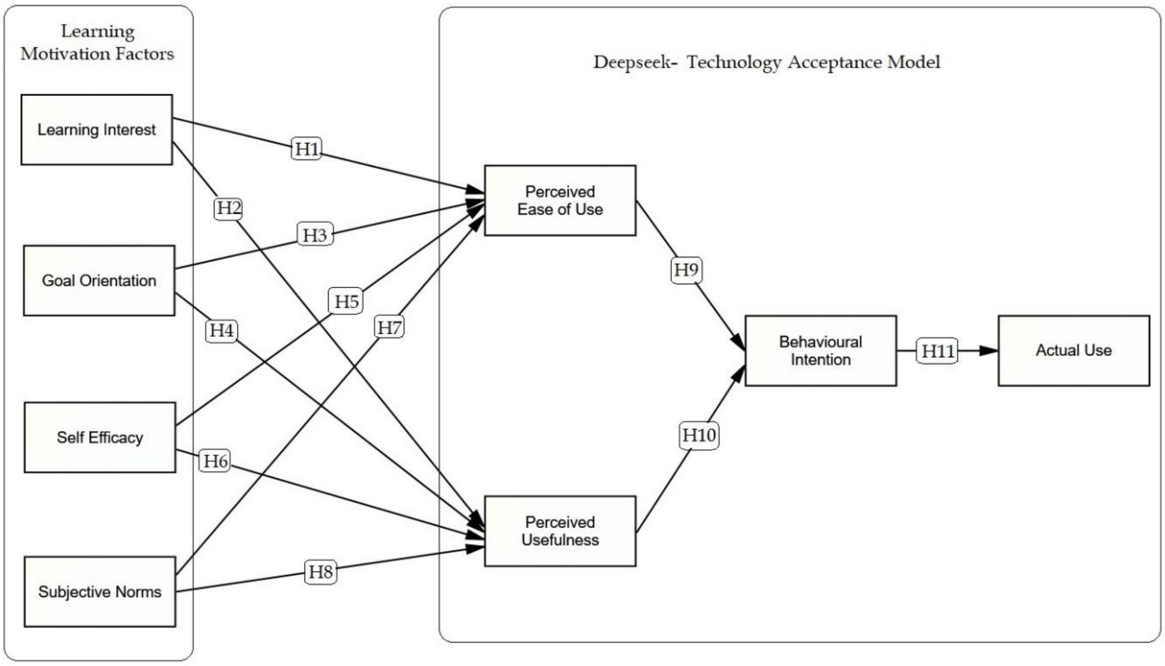


Figure.1: Proposed Research Model

3. Research Methodology

This research study used a quantitative research design to explore the determinants of DeepSeek use among Indian higher education students through the integration of the TAM and learning motivation factors. A systematic survey-based method was used for data collection, using an online Google Form that was disseminated through email and social networking sites. Participants were also asked to invite their friends and networks to take the survey, hence blending convenience sampling and partial snowball sampling.

The sample size was calculated using Partial Least Squares Structural Equation Modeling (PLS-SEM) recommendations. Since the research model has 8 variables and 31 measurement items, there should be at least 10 observations for every parameter estimate, resulting in a target sample size of 310 respondents. This agrees with guidelines from Hair et al. (2012) and Kline (2023), who state that SEM analysis must involve a minimum of 200 samples, and the bigger the sample the more elaborate the model. The questionnaire was kept brief and easy to use with inclusion of demographic items (gender, year of study, and course) and established scales from the literature. These constructs were assessed through a seven-point Likert scale (1 = strongly disagree and 7 = strongly agree). LI, AG, SE and SN measurement items were taken from Swarni (2024); Midgley et al. (1998); Chen, Gully and Eden (2001); and Van Acker et al. (2013), respectively. Four items each for PEU, PU and three items for AU were adopted from Davis (1989) and Tummalapenta et al. (2024), whereas BI was measured by scales developed by Park, Nam and Cha (2012). Prior to participation, participants were made aware of the study's aim, voluntary nature, confidentiality, and their right to withdraw at any time.

The study population was Indian higher education students who were aware about and using DeepSeek. Data collection occurred in February and March, 2025 and the survey was open until the second week day of March. Incomplete and inconsistent responses were excluded, and there remained 346 valid responses. Missing values and outliers were screened for in the dataset to maintain data quality. The final sample size was found to be adequate for further statistical analysis, such as measurement and structural equation modeling, to test the hypothesized relationships in the research model. By using a systematic data collection process and ensuring a representative sample, this research hopes to present meaningful findings into the factors driving DeepSeek adoption among Indian students.

4. Data Analysis and Results

The analysis used Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the postulated relationships between learning motivation factors, TAM constructs, and concrete usage behavior. Results of measurement model validation and structural path analysis are presented and provide insights into the determinants of students' DeepSeek BI and use.

Before performing the measurement model analysis, we initially explored the demographic profiles of our survey respondents to understand about the composition sample. The analysis provided significant information regarding the participants' background and DeepSeek usage patterns. As shown in the table.1, gender distribution indicated slightly greater participation among male students (56.9%, n=197) than female students (43.1%, n=149). Academic program distribution indicated undergraduate students constituting the largest student group among respondents at 41.6% (n=144), followed by postgraduate students at 33.8% (n=117). Professional and specialized course students contributed 16.5% (n=57) of respondents, with doctoral and research scholars making up the lowest student category at 8.1% (n=28). This division corresponds with the conventional student structure of higher education systems. The year-by-year breakdown of participants showed greater participation by advanced students, with the third-year students being the biggest group (35.8%, n=124). Fourth-year students were second at 29.5% (n=102), with second-year and first-year students making up 19.7% (n=68) and 15.0% (n=52) respectively. This trend implies that students in more advanced years of study might be more interested in academic support resources such as Deepseek.

In terms of awareness of Deepseek, most of the respondents (53.5%, n=185) were both aware of and regularly using the platform. A considerable number (32.4%, n=112) reported awareness but sporadic use, while merely 14.2% (n=49) reported not being familiar with the tool. This reflects quite high awareness and uptake of Deepseek among the student population under study. Frequency of use information showed that the most frequent users comprised the majority (41.9%, n=145) who used it on a weekly basis, and then those using it daily (29.8%, n=103). There were 28.3% (n=98) rare users. The split indicates multiple levels of engagement with the platform, with a high percentage including it in their everyday study practices and others less regularly.

Table.1: Demographic Profile of the Survey Participants

Demographic Variable	Category	Frequency	Percentage
Gender	Male	197	56.9
	Female	149	43.1
Course Studying	Undergraduate (UG) Courses	144	41.6
	Postgraduate (PG) Courses	117	33.8
	Professional & Specialized Courses	57	16.5
	Doctoral & Research Programs	28	8.1
Year of Study	I Year	52	15.0
	II Year	68	19.7
	III Year	124	35.8
	IV Year	102	29.5
Familiarity with DeepSeek	No, I am not familiar with it	49	14.2
	Yes, but I am not using regularly	112	32.4
	Yes, I am familiar and using it	185	53.5
Frequency of Deepseek Usage	Daily	103	29.8
	Weekly	145	41.9
	Rarely	98	28.3

4.1 Measurement Model

The measurement model fit test calculated the reliability, convergent validity, and discriminant validity of the constructs through factor loadings and variance inflation factor (VIF) values. All factor loadings were more than the advised value of 0.70, reflecting very high item reliability (See Table.2). The values of VIF varied between 1.244 and 2.719, far below the conservative value of 5 as recommended by Hair et al. (2021), which ensures there are no problems of multicollinearity within the measurement model.

Table.2: Measurement Model: Item Loadings and Variance Inflation Factors

Construct	Items	Factor Loadings	VIF
Learning Interest	LI1: DeepSeek makes my academic tasks more interesting to me.	0.876	2.409
	LI2: I enjoy using DeepSeek for studying and completing assignments.	0.868	2.417
	LI3: DeepSeek increases my interest in learning new concepts.	0.795	1.884
	LI4: I am motivated to learn more because of the innovative features of DeepSeek.	0.881	2.359
Achievement Goals	AG1: Using DeepSeek helps me achieve my academic learning goals.	0.862	2.194
	AG2: DeepSeek assists me in meeting the academic requirements of my courses.	0.886	2.713
	AG3: I am more likely to reach my academic goals with the help of DeepSeek.	0.840	2.183
	AG4: I feel that using DeepSeek supports my progress toward academic success.	0.871	2.550
Self-Efficacy	SE1: I believe I have the ability to use DeepSeek for my academic tasks.	0.856	2.285
	SE2: I am confident that I am able to generate well-structured answers using DeepSeek	0.878	2.347
	SE3: I am confident that I am able to find relevant study materials using DeepSeek	0.827	1.984
	SE4: I am confident that I am able to use DeepSeek to improve my learning experience.	0.788	1.736
Subjective Norms	SN1: My peers encourage me to use DeepSeek for academic tasks.	0.857	2.245
	SN2: My instructors expect me to use DeepSeek in my coursework.	0.866	2.313
	SN3: My classmates believe that using DeepSeek is considered socially acceptable among students.	0.871	2.408
	SN4: My classmates generally expect me to use DeepSeek for learning and studying.	0.844	2.195
Perceived Ease of Use	PEU1: Learning how to use DeepSeek is easy for me.	0.839	2.028
	PEU2: My interaction with DeepSeek is clear and understandable.	0.857	2.156
	PEU3: I find DeepSeek easy to use.	0.857	2.218
	PEU4: It is easy for me to become skillful at using DeepSeek.	0.867	2.382
Perceived Usefulness	PU1: I find DeepSeek is useful in my daily life.	0.765	1.613
	PU2: Using DeepSeek helps me accomplish things more quickly.	0.797	1.726
	PU3: Using DeepSeek increases my productivity.	0.814	1.856
	PU4: Using DeepSeek helps me perform many things more conveniently.	0.717	1.244
Behavioral Intention	BI1: I intend to use DeepSeek regularly for my academic tasks in the future.	0.868	2.348
	BI2: I will strongly recommend others to use DeepSeek for learning and studying.	0.884	2.719
	BI3: I expect my use of DeepSeek for academic support to continue in the future.	0.868	2.343
	BI4: I intend to use DeepSeek for quick and easy access to information and learning resources	0.865	2.408

Construct	Items	Factor Loadings	VIF
Actual Use	AU1: I frequently use DeepSeek for academic tasks.	0.884	2.093
	AU2: My usage of DeepSeek for learning has increased over time.	0.860	1.899
	AU3: I rely on DeepSeek to complete major academic assignments.	0.879	2.182

The reliability and validity of the measurement model were tested by several criteria such as Cronbach's alpha, rho_A, composite reliability (CR), and average variance extracted (AVE). As shown in Table.3, all the constructs reflected good levels of internal consistency with Cronbach's alpha values ranging from 0.777 to 0.895, well above the threshold of 0.7. The rho_A values, being a more conservative measure of reliability, also closely replicated the alpha values, ranging from 0.777 to 0.895, again supporting the reliability of the scales.

Table.3: Construct Reliability and Convergent Validity

Variable	Alpha	rho_A	CR	AVE
LI	0.879	0.894	0.916	0.733
AG	0.888	0.893	0.922	0.748
SE	0.878	0.878	0.916	0.731
SN	0.777	0.777	0.856	0.599
PEU	0.858	0.862	0.904	0.702
PU	0.882	0.884	0.919	0.739
BI	0.895	0.895	0.927	0.760
AU	0.846	0.848	0.907	0.765

Composite reliability coefficients, which estimate the internal consistency of the latent constructs, were 0.856 to 0.927, all higher than the desired measure of 0.7. AVE scores, which estimate the variance explained by the construct in comparison to measurement error, were 0.599 to 0.765. Whereas the majority of constructs passed the 0.5 threshold, SN had a slightly lower AVE of 0.599, yet one that is still deemed acceptable within social science studies when composite reliability is satisfactory. The findings provide strong evidence of convergent validity since all the constructs achieved the reliability criterion and most of them surpassed the AVE criterion. LI had exceptionally good psychometric qualities with an alpha of 0.879, CR of 0.916, and AVE of 0.733. Likewise, BI had very high reliability with an alpha of 0.895, CR of 0.927, and AVE of 0.760. PEU and AU also demonstrated high reliability and validity, with CR values of 0.904 and 0.907 respectively.

The measurement model showed high discriminant validity using two corroborative assessment techniques: Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. Both methods validated that all constructs in the model are empirically different and capture distinctive theoretical concepts. The Fornell-Larcker evaluation showed that square roots of AVEs (0.774 to 0.875) were larger than all corresponding inter-concept correlations in their respective columns and rows (See table.4). AG (AG) had particularly strong discriminant validity with a diagonal of 0.865 that over its highest correlation of 0.687 with AU (AU). Analogously, BI (BI) remained clear with a distinctiveness AVE root of 0.872 versus its strongest correlation of 0.566 with PEU (PEU).

Table.4: Discriminant Validity (Fornell-Larcker Criteria)

	AG	AU	BI	LI	PEU	PU	SE	SN
AG	**0.865**							
AU	0.687	**0.875**						
BI	0.529	0.482	**0.872**					
LI	0.468	0.502	0.485	**0.856**				
PEU	0.475	0.327	0.566	0.434	**0.838**			
PU	0.446	0.338	0.459	0.362	0.587	**0.859**		
SE	0.454	0.380	0.330	0.345	0.268	0.529	**0.855**	

	AG	AU	BI	LI	PEU	PU	SE	SN
SN	0.484	0.383	0.379	0.428	0.468	0.487	0.438	**0.774**

The HTMT analysis also supported these results, as all of the ratios were below the conservative mark of 0.85 (See table.5). These figures were safely below the discriminant validity threshold. SE was the least associated, as its highest HTMT ratio was 0.599 with PU, as expected, supporting its relative independence within the model. These results confirm the psychometric quality of the constructs and warrant their treatment as separate entities in further structural model analysis.

Table.5: Discriminant Validity (HTMT Ratio)

	AG	AU	BI	LI	PEU	PU	SE	SN
AG								
AU	0.792							
BI	0.593	0.551						
LI	0.521	0.579	0.549					
PEU	0.541	0.383	0.644	0.492				
PU	0.501	0.389	0.515	0.403	0.676			
SE	0.512	0.440	0.372	0.388	0.311	0.599		
SN	0.574	0.468	0.446	0.514	0.565	0.582	0.520	

4.2 Structural Model

After confirming reliability, convergent validity, and discriminant validity in the measurement model, we proceed to test the structural relationships between constructs (See Figure.2). The structural model analyzed the hypothesized paths between the proposed relationships. Using bootstrapping analysis (5,000 subsamples), we tested each relationship's significance and strength in order to assess their impact on students' adoption of DeepSeek. The results revealed that, nine out of the eleven hypothesized relationships were empirically supported, whereas two paths indicated non-significant effects (See Table.6).

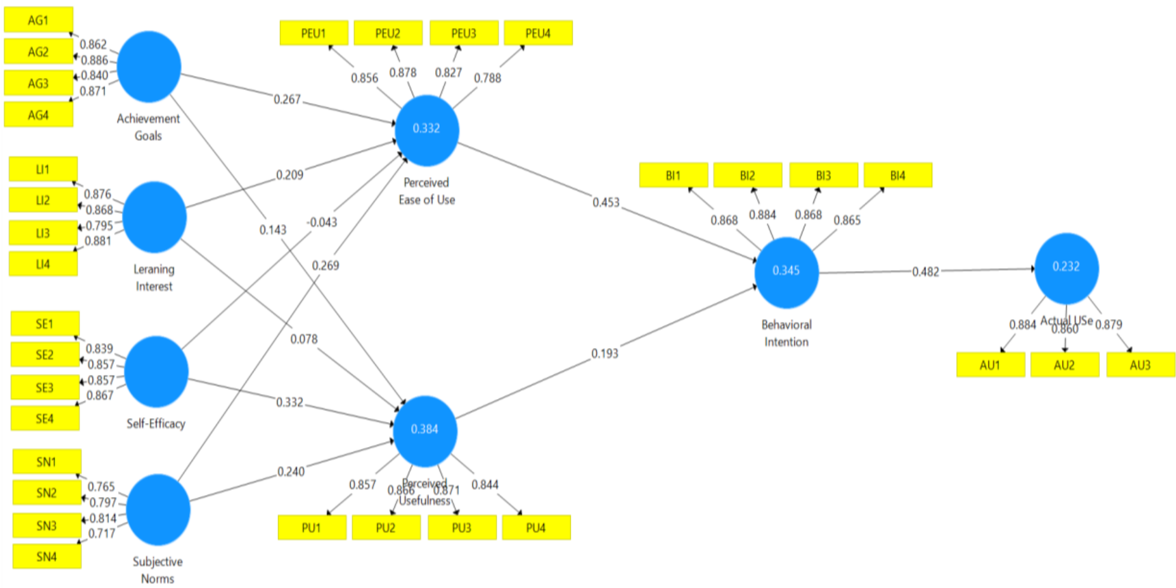


Figure.2: Structural Model

Table.6: Hypothesis Test Results

Hypothesis	Original Sample	Sample Mean	Std Dev	T Value	P Values	Result
LI → PEU	0.209	0.208	0.055	3.820	0.000	Significant
LI → PU	0.078	0.080	0.046	1.708	0.088	Not Significant

Hypothesis	Original Sample	Sample Mean	Std Dev	T Value	P Values	Result
AG → PEU	0.267	0.270	0.052	5.140	0.000	Significant
AG → PU	0.143	0.141	0.056	2.548	0.011	Significant
SE → PEU	-0.043	-0.044	0.055	0.785	0.433	Not Significant
SE → PU	0.332	0.332	0.052	6.401	0.000	Significant
SN → PEU	0.269	0.271	0.052	5.180	0.000	Significant
SN → PU	0.240	0.246	0.052	4.640	0.000	Significant
PEU → BI	0.453	0.453	0.052	8.657	0.000	Significant
PU → BI	0.193	0.193	0.055	3.535	0.000	Significant
BI → AU	0.482	0.483	0.052	9.290	0.000	Significant

LI had a strong positive impact on PEU ($\beta = 0.209$, $t = 3.820$, $p < 0.001$) but did not have a significant impact on PU ($\beta = 0.078$, $t = 1.708$, $p = 0.088$). AG revealed strong positive effects on both technology acceptance constructs, significantly predicting PEU ($\beta = 0.267$, $t = 5.140$, $p < 0.001$) and PU ($\beta = 0.143$, $t = 2.548$, $p < 0.01$). The analysis presented differing findings for SE. While it did not demonstrate a significant correlation with PEU ($\beta = -0.043$, $t = 0.785$, $p = 0.433$), it had a positive influence on PU ($\beta = 0.332$, $t = 6.401$, $p < 0.001$). SN proved to be a reliable predictor, having a significant impact on both PEU ($\beta = 0.269$, $t = 5.180$, $p < 0.001$) and PU ($\beta = 0.240$, $t = 4.640$, $p < 0.001$). The TAM relationships were fully supported. PEU had a strong influence upon BI ($\beta = 0.453$, $t = 8.657$, $p < 0.001$), as did PU ($\beta = 0.193$, $t = 3.535$, $p < 0.001$). The terminal path from BI to AU was especially significant ($\beta = 0.482$, $t = 9.290$, $p < 0.001$), accounting for a large level of usage variance. These findings are largely in line with the integrated theory framework, where LI, AG, and SN play significant roles as antecedents to technology acceptance constructs. The final strong path from BI to AU confirms the model's predictive validity in explaining DeepSeek adoption among Indian higher education students.

5. Discussion

The strong positive relationship between LI and PEU supports that intrinsically motivated learners perceive DeepSeek to be easier to use. This finding aligns with Venkatesh and Bala's (2008) extension of the TAM, which demonstrated that learning-focused individuals are more likely to develop adequate mental representations of new systems, thereby enhancing their PEU. In the present context, the results suggested that curiosity-oriented activity assists students in overcoming initial technology challenges through exploratory behavior. This interpretation is consistent with earlier studies in educational technology, such as Wu, Liu and Huang (2022), which emphasized the role of intrinsic interest in facilitating smoother adoption of digital tools. However, LI did not have a significant impact on PU. This outcome stands in contrast to some earlier research in educational technology, at the same time this result is consistent with Zhai and Shi (2020), who found that LI alone is insufficient to ensure PU unless its immediate connection with academic performance is established . This non-significant association suggests that while students find the platform enjoyable, they do not independently recognize its usefulness unless it explicitly demonstrates academic values. .

The robust positive influences of AG on both PEU and PU validate the well-established association between AG and technology judgment. These findings are consistent with Elliot and Thrash (2001) whose AG theory emphasized that goal-directed learners systematically evaluate functional characteristics of the tools. In this study the more significant influence on PEU specifically substantiates Teo et al. 2024, who argued that achievement-oriented users place greater value on interface efficiency when selecting learning tools. This suggested that for learners with strong AG, PEU becomes a decisive factor in adopting educational technologies.

In contrast, the non-significant relationship between SE and PEU is in conflict with standard TAM extensions but receives support from prior literature. This aligns with Wang and Tseng (2010), who reported that SE predicts PEU less accurately when intelligent systems are equipped with adaptive interfaces designed to accommodate varying skill levels. Yet, the strong SE to PU relationship reaffirms Bandura's (1997) social cognitive theory and also consistent with Rahmawati (2019) in e-learning context, where efficacy beliefs were shown to significantly impact use decisions. Thus, while SE may not directly determine perceptions of ease of use, it remains a critical driver of PU of AI- enabled learning systems.

The results also indicated that, SN significantly predicted technology acceptance variables, confirming Venkatesh and Davis' (2000) normative influence hypotheses. The stronger influence of SN on PEU compared to PU builds on findings from Bhimavarapu et al. (2024) and Banala et al. (2024). Specifically, these results suggested that word-of-mouth recommendations and peer influence may initially reduce perceived complexity before building use beliefs in educational AI scenarios. These results reiterate the dual social influence mechanism in technology adoption proposed by Morris and Venkatesh (2010). Furthermore, the relationships between PEU, PU and BI reaffirm Davis' (1989) original TAM hypotheses in the context of AI-based learning environments. Notable, the increased PEU effect confirms emerging evidence by Scherer, Siddiq and Tondeur (2019) in educational app adoption, which emphasizes that usability continues to be the key driver of adoption, particularly in voluntary usage environments. Lastly, the positive relationship between BI and AU is in consistent with Pasupuleti and Seshadri (2023) as well as Ajzen's (1991) theory of planned behavior under barrier-free conditions. In the context of AI in education this finding aligns with Wu, Liu and Huang (2022) further demonstrating that BI strongly translates into AU when contextual constraints are minimized.

6. Implications, Limitations, Future Research Directions and Conclusion

The findings of the study have significant implications across theoretical, practical, and methodological areas. From a theoretical point of view, the findings extend our knowledge on technology acceptance in learning contexts by illustrating how various motivational factors work through different routes. The results indicate that theories of educational technology adoption must explain these differential motivational processes. These results build on conventional technology acceptance models by integrating educational psychology perspectives, specifically how intrinsic and achievement-based motivations affect technology perceptions and use differently. The practical applications for teachers are significant and multi-faceted. Teachers need to prioritize initial training and support in order to help students overcome early usability hurdles. Establishing opportunities for peer sharing and modeling of good use can have a strong impact on adoption. Teachers can create guided activities in which students show and think about their application of the technology, thus reinforcing competence beliefs and social norms of proper use.

For designers and implementers of educational technology, the findings point to a number of design and implementation considerations. The priority of ease-of-use perceptions implies that interface design should reduce initial learning curves while offering transparent paths to uncover more sophisticated features. The high intention-behavior relationship implies that systems that make first-time use easy and rewarding will likely experience high rates of adoption. Developers could integrate smart onboarding mechanisms that respond to users' levels of demonstrated competence, with focused support building confidence through increasingly advanced functionalities. The social influence results imply that features facilitating peer sharing and exposure to others' usage patterns can strongly increase adoption.

At an institutional level, the research highlights the need for robust support structures for the integration of educational technology. The different motivational pathways that have been identified imply that homogeneous training schemes might prove less effective than differentiated programs targeting different user dispositions. Institutions may, therefore, want to establish multiple onboarding paths, e.g., different resources for students whose primary motivation is interest versus those whose goal is achievement outcomes. Strong social influence effects show that building communities of practice on educational technologies in which both teachers and students share experiences and best practices could potentially lead to improved adoption and usage.

These collective implications imply that successful educational technology integration demands consideration of several interrelated factors - individual motivation, social contexts, institutional supports, and technology design characteristics. The findings extend beyond simplistic "if you build it they will come" assumptions about educational technology, instead portraying a more realistic picture of the psychological and social processes involved in successful adoption. This insight can be used to develop more advanced technology implementation strategies for educational environments that can result in increased adoption and better utilization of these powerful learning tools.

6.1 Limitations and Future Research Directions

A number of avenues for future research open up on the basis of the present study's results. First, cross-cultural comparison studies would establish whether these results generalize across varied educational systems and national cultures, especially in the face of the observed social influence effects. Second, experimental research would be able to test interventions specifically aimed at reinforcing specific motivational routes, e.g., interest-evoking features versus achievement-focused functionalities. Third, the influence of individual differences outside those considered in this research, including learning styles or personality, should be explored to create more inclusive models of educational technology adoption. Fifth, qualitative methods might shed more light on the cognitive processes behind the found relationships, especially concerning how students subjectively assess ease of use versus usefulness in actual learning contexts. Sixth, studies focusing on how these psychological variables interact with varying technological designs might advise more sophisticated educational technology design. Finally, longitudinal studies can monitor how the found relationships change as users move from initial adoption to long-term use. Such research may indicate whether ease-of-use perceptions lose significance as users accumulate experience, whereas usefulness perceptions become more important.

6.2 Conclusion

This research offers useful insights into the factors that drive DeepSeek adoption by Indian higher education students using an integrated theoretical model that integrates TAM and learning motivation factors. The results confirm that various motivational factors work through different paths, with AG and SN having particularly robust effects on adoption-related perceptions. The strong intention-behavior relationship indicates that well-designed instructional technologies can indeed successfully translate favorable attitudes into real use when implementation obstacles are kept to a minimum. The findings emphasize the significance of taking both individual psychological aspects and social influences into account in the implementation of instructional technologies. Although the research was conducted specifically on DeepSeek within the Indian context of higher education, the theoretical findings and methodological strategies could potentially generalize to applying educational technology to multiple platforms and cultures. The results as a whole add to richer models of technology acceptance in educational settings and offer practical advice to educators, developers, and policymakers seeking to further the effective incorporation of learning technologies. Subsequent research based on these findings can further develop our knowledge of the intricate interrelationship between human factors and technological characteristics in learning environments.

AI Statement: The authors declare that AI tools were not used in this study for the paper's conception, revision, or the creation of figures and tables.

Ethics Statement: All participants provided informed consent by proceeding after reading a statement on the study's purpose, anonymity, and voluntary nature of participation.

References

Allen, R. (2025). DeepSeek and AI innovation: How Chinese universities broke through the glass ceiling of technological advancement. *American Journal of STEM Education*, *6*, 1–10. https://doi.org/10.32674/10bz2d04

Arabiat, O.(2025). DeepSeek AI in Accounting: Opportunities and Challenges in Intelligent Automation. *Accounting: Opportunities and Challenges in Intelligent Automation (January 29, 2025).*

Banala, T. V., Pasupuleti, R. S., Thiyyagura, D. and H, DArathi. P. (2024). Measuring the role of trust and information quality on intention to use ai chatbots in mobile shopping: A structured equation modeling approach. *2024 First International Conference on Data, Computation and Communication (ICDCC)*, . 284–292. https://doi.org/10.1109/ICDCC62744.2024.10961076.

Bandhu, D., Mohan, M. M., Nittala, N. A. P., Jadhav, P., Bhadauria, A. and Saxena, K. K.(2024). Theories of motivation: A comprehensive analysis of human behavior drivers. *Acta Psychologica*, *244*, 104177. https://doi.org/10.1016/j.actpsy.2024.104177

Bandura, A (1997). Self-efficacy: The exercise of control. W.H. Freeman.

Basaran, U., and Aksoy, R. (2017). The effect of perceived value on behavioural intentions. *Journal of Management Marketing and Logistics*, *4*(1), 1-16.

Bhavana, S. and Vijayalakshmi, V. (2022). AI-based metaverse technologies advancement impact on higher education learners. *WSEAS Transactions on Systems*, *21*, pp. 178-184.

Bhimavarapu, A., Thiyyagura, D., Pasupuleti, R. S. and Babu, P. V. (2024). Artificial intelligence in the pocket: Factors influencing generation z's intention to use ai-powered mobile banking applications. *2024 First International Conference on Data, Computation and Communication (ICDCC)*, 278–283. https://doi.org/10.1109/ICDCC62744.2024.10961558.

Binyamin, S. S., Rutter, M. J. and Smith, S. (2018). The influence of computer self-efficacy and subjective norms on the students' use of learning management systems at King Abdulaziz University. *International Journal of Information and Education Technology*, *8*(10).

Börger, T. and Hattam, C. (2017). Motivations matter: Behavioural determinants of preferences for remote and unfamiliar environmental goods. *Ecological Economics*, *131*, 64-74.

Chen, G., Gully, S. M. and Eden, D. (2001). Validation of a new general self-efficacy scale. *Organizational research methods*, *4*(1), 62-83.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly, 319-340. Deci, E. L. and Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227-268. https://doi.org/10.1207/S15327965PLI1104_01

Dirzyte, A., Vijaikis, A., Perminas, A. and Rimasiute-Knabikiene, R. (2021). Associations between depression, anxiety, fatigue, and learning motivating factors in e-learning-based computer programming education. *International journal of environmental research and public health*, *18*(17), 9158.

Egger, J., de Paiva, L. F., Luijten, G., Krittanawong, C., Keyl, J., Sallam, M. and Puladi, B. (2025). Is DeepSeek-R1 a Game Changer in Healthcare?–A Seed Review.

Elliot, A. J. (1999). Approach and avoidance motivation and achievement goals. Educational Psychologist, 34(3), 169-189. https://doi.org/10.1207/s15326985ep3403_3

Elliot, A. J. and Thrash, T. M. (2001). Achievement goals and the hierarchical model of achievement motivation. *Educational psychology review*, *13*, 139-156.

Faray de Paiva, L., Luijten, G., Puladi, B. and Egger, J.(2025). How does DeepSeek-R1 perform on USMLE?. *medRxiv*, pp.2025-02..

Firdaus, A. (2019). Factors affecting students motivation to learn in school: a qualitative study of school management. *International Journal of Scientific & Engineering Research*, *10*(12), 206-211.

Fishbein, M. and Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research.

Hair Jr, J.F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook (p. 197). Springer Nature

Hair, J. F., Sarstedt, M., Ringle, C. M. and Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the academy of marketing science*, *40*, 414-433.

Harefa, D., Sarumaha, M., Telaumbanua, K., Telaumbanua, T., Laia, B. and Hulu, F. (2023). Relationship student learning interest to the learning outcomes of natural sciences. *International Journal of Educational Research &Amp*, 240-246.

Huang, C.H. (2020). December. The influence of self-efficacy, perceived usefulness, perceived ease of use, and cognitive load on students' learning motivation, learning attitude, and learning satisfaction in blended learning methods. In *Proceedings of the 2020 3rd International Conference on Education Technology Management.* 29-35.

Huet, N., Escribe, C., Dupeyrat, C. and Sakdavong, J. C. (2011). The influence of achievement goals and perceptions of online help on its actual use in an interactive learning environment. *Computers in Human Behavior*, *27*(1), 413-420.

Jahin, A., Zidan, A. H., Bao, Y., Liang, S., Liu, T. and Zhang, W. (2025). Unveiling the Mathematical Reasoning in DeepSeek Models: A Comparative Study of Large Language Models. *arXiv preprint arXiv:2503.10573.*

Jarvis, M. (2005). *The psychology of effective learning and teaching*. Nelson Thornes.

Jiang, Q., Gao, Z. and Karniadakis, G.E. (2025). DeepSeek vs. ChatGPT vs. Claude: a comparative study for scientific computing and scientific machine learning tasks. *Theoretical and Applied Mechanics Letters*, *15*(3), 100583.

Kerimbayev, N., Menlibay, Z., Garvanova, M., Djaparova, S. and Jotsov, V. (2024).. A Comparative Analysis of Generative AI Models for Improving Learning Process in Higher Education. In *2024 International Conference Automatics and Informatics (ICAI),* 271-276. IEEE.

Kline, R.B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Krause, D. (2025). DeepSeek and FinTech: The Democratization of AI and Its Global Implications. *Available at SSRN 5116322*.

Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O.M., Păun, D. and Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability*, *13*(18), 10424.

Kumar, P.R.V. (2025). Revolutionizing the Search Game: How Deepseek is Transforming Information-Seeking Behavior in the Digital Age.

Li, K. (2023). Determinants of college students' actual use of AI-based systems: An extension of the technology acceptance model. *Sustainability*, *15*(6), 5221.

Li, W., Zhang, X., Li, J., Yang, X., Li, D. and Liu, Y. (2024). An explanatory study of factors influencing engagement in AI education at the K-12 Level: an extension of the classic TAM model. *Scientific Reports*, *14*(1), 13922.

Liao, H. (2025). DeepSeek large-scale model: Technical analysis and development prospect. *Journal of Computer Science and Electrical Engineering*, *7*(1), 33-37.

Liu, P. (2022). Influencing Factors of Negative Motivation in College Students' English Learning Relying on the Artificial Neural Network Algorithm. *Computational Intelligence and Neuroscience*, *2022*(1), 2323870.

Manik, M.M.H. (2025). ChatGPT vs. DeepSeek: A Comparative Study on AI-Based Code Generation. *arXiv preprint arXiv:2502.18467*.

Midgley, C., Kaplan, A., Middleton, M., Maehr, M.L., Urdan, T., Anderman, L.H., Anderman, E. and Roeser, R. (1998). The development and validation of scales assessing students' achievement goal orientations. *Contemporary educational psychology*, *23*(2), 113-131.

Miron-Spektor, E. and Beenen, G. (2015). Motivating creativity: The effects of sequential and simultaneous learning and performance achievement goals on product novelty and usefulness. *Organizational Behavior and Human Decision Processes*, *127*, 53-65.

Morris, M.G. and Venkatesh, V. (2010). Job characteristics and job satisfaction: Understanding the role of enterprise resource planning system implementation. *MIS quarterly*, 143-161.

Mudiarti, H. and Harjanti, A.E. (2021). The Impact of Online Lectures on Accounting Students' Interest in Learning. *Bongaya Journal of Research in Accounting (BJRA)*, *4*(1), 16-22.

Neha, F. and Bhati, D. (2025). A Survey of DeepSeek Models. *Authorea Preprints*.

Ngan, S.C. and Law, K.M. (2015). Exploratory network analysis of learning motivation factors in e-learning facilitated computer programming courses. *The Asia-Pacific Education Researcher*, *24*, 705-717.

Park, S.Y., Nam, M.W. and Cha, S.B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British journal of educational technology*, *43*(4), 592-605.

Pasupuleti, R.S. and Seshadri, U. (2023). Subdimensions of Smart Servicescape: Empirical Evidence Using Confirmatory Factor Analysis. *IUP Journal of Marketing Management*, *22*(2), 136-153.

Pasupuleti, R.S. and Thiyyagura, D. (2024). An empirical evidence on the continuance and recommendation intention of ChatGPT among higher education students in India: An extended technology continuance theory. *Education and Information Technologies*, *29*(14), 17965-17985. https://doi.org/10.1007/s10639-024-12573-7

Pasupuleti, R.S. and Thiyyagura, D. (2025). Customers' Continuance Intention Toward AI-Driven Mobile Banking Apps. *IUP Journal of Marketing Management*, *24*(1), 55-76. DOI:10.71329/IUPJMM/2025.24.1.55-76

Peng, Y., Chen, Q. and Shih, G. (2025). DeepSeek is open-access and the next AI disrupter for radiology. *Radiology Advances*, *2*(1), umaf009.

Rahmawati, R.N. (2019). Self-efficacy and use of e-learning: A theoretical review technology acceptance model (TAM). *American Journal of Humanities and Social Sciences Research*, *3*(5), 41-55.

Riaz, S., Rambli, D.R., Salleh, R. and Mushtaq, A. (2010). Study to investigate learning motivation factors within formal and informal learning environments and their influence upon web-based learning. *International Journal of Emerging Technologies in Learning (Online)*, *5*(4), 41.

Rosli, M.S. and Saleh, N.S. (2023). Technology enhanced learning acceptance among university students during Covid-19: Integrating the full spectrum of Self-Determination Theory and self-efficacy into the Technology Acceptance Model. *Current Psychology*, *42*(21), 18212-18231.

Scherer, R., Siddiq, F. and Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & education*, *128*, 13-35.

Seshadri, U. and Pasupuleti, R.S. (2023) "An empirical exploration of the continuance intention of m-shopping app users through the lens of smart experience co-creation," *International Journal of Business Excellence*, 1(1), 1. https://doi.org/10.1504/IJBEX.2023.10055330.

Shiang Tyng, K., Badioze Zaman, H., Hanan Mohamad, U. and Ahmad, A. (2023). Perceived ease of use on visual learning application for mathematics using holography display for the topic on shape and space. *F1000Research*, *12*, 636.

Swarni, A. (2024). Testing the Construct Validity and Reliability of the Student Learning Interest Scale Using Confirmatory Factor Analysis (CFA). *Jurnal Penelitian Pendidikan IPA*, *10*(9), 6322-6330.

Teo, T., Moses, P., Cheah, P.K., Huang, F. and Tey, T.C.Y. (2024). Influence of achievement goal on technology use among undergraduates in Malaysia. *Interactive Learning Environments*, *32*(8), 4314-4331.

Tran, H.T.T., Nguyen, N.T. and Tang, T.T. (2023). Influences of subjective norms on teachers' intention to use social media in working. *Contemporary Educational Technology*, *15*(1), ep400.

Tummalapenta, S.R., Pasupuleti, R.S., Chebolu, R.M., Banala, T.V. and Thiyyagura, D. (2024). Factors driving ChatGPT continuance intention among higher education students: integrating motivation, social dynamics, and technology adoption. *Journal of Computers in Education*, 1-24. https://doi.org/10.1007/s40692-024-00343-w

Van Acker, F., Van Buuren, H., Kreijns, K. and Vermeulen, M. (2013). Why teachers use digital learning materials: The role of self-efficacy, subjective norm and attitude. *Education and Information Technologies*, *18*,495-514.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478. . https://doi.org/10.2307/30036540

Venkatesh, V. and Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204. . https://doi.org/10.1287/mnsc.46.2.186.11926

Wang, T.L. and Tseng, Y.F. (2010). Developing and evaluating a game-based project management learning platform. In *IEEE EDUCON 2010 Conference,* 1391-1394. IEEE.

Wu, C.H., Liu, C.H. and Huang, Y.M. (2022). The exploration of continuous learning intention in STEAM education through attitude, motivation, and cognitive load. *International Journal of STEM Education*, *9*(1), 35.

Zhai, X. and Shi, L. (2020). Understanding how the perceived usefulness of mobile technology impacts physics learning achievement: A pedagogical perspective. *Journal of Science Education and Technology*, *29*(6), 743-757.

Developing Conscious Information Consumption Skills and Media Literacy in the Age of Digital Change and Media Technologies

Mariia Plotnikova[1], Nataliia Vovchasta[2], Vsevolod Zelenin[3], Natalia Hnedko[4] and Liudmyla Hetmanenko[5]

[1]Department of Economics, Entrepreneurship and Tourism, Faculty of Economics and Management, Polissia National University, Zhytomyr, Ukraine
[2]Department of Foreign Languages for Engineering, Lviv Polytechnic National University, Lviv, Ukraine
[3]Department of Psychology, Faculty of Psychology, Mykhailo Dragomanov State University of Ukraine, Kyiv, Ukraine
[4]Department of Digital Technologies and Computer Science Teaching Methods, Faculty of Mathematics and Informatics, Rivne State University of Humanities, Rivne, Ukraine
[5]Department of Natural Sciences and Mathematics Education and Technologies, Institute of In-Service Teachers' Training, Borys Grinchenko Kyiv Metropolitan University, Kyiv, Ukraine

mfplotnikova@gmail.com (corresponding author)
natvovchasta@gmail.com
sevacello@gmail.com
natalia.hnedko@rshu.edu.ua
hetmanenko@kubg.edu.ua

https://doi.org/10.34190/ejel.23.4.4268

Abstract: Relevance. The need to study media literacy is driven by the growing destructive influence of information, which is transforming public consciousness and increasing the risk of manipulation in the digital environment. Declining trust in the media, the spread of disinformation, and the growing role of social networks as the main source of news require an in-depth analysis of new communication threats and the search for effective means to overcome them, especially in the field of education. Therefore, the problem of critical thinking among young people, who are at the epicenter of digital interaction and most susceptible to information influence, is becoming increasingly relevant. **Aim.** The purpose of this scientific article is to empirically measure the levels of media literacy and critical thinking in a social sample, as well as to identify the statistically significant impact of variables such as age, level of education, and participation in media education programs on the formation of relevant cognitive competencies. **Methods.** During the study, a sociological survey was conducted among Ukrainian citizens in 2024-2025 using a structured online questionnaire, which allowed us to form the initial data for further analysis. Based on this data, the hypotheses were tested using the classic Student's t-test for independent samples with the JASP software package (in particular, the "Descriptives" and "Independent Samples T-Test" tools). **Results.** The results of the analysis revealed that taking media education courses has a statistically significant impact on the level of media literacy (M = 32.915 and 20.910) and critical thinking (M = 33.111 and 21.059) among respondents, as evidenced by a t-test with a high Cohen's effect (d ≈ -1.57, p < 0.001). The educational level of respondents has a significant impact on cognitive indicators, in particular, respondents with higher education had significantly higher mean values of media literacy (M = 30.023 and 18.473 at p < 0.001) and critical thinking (M = 30.556 and 18.871 at p < 0.001). In addition, a statistically significant age differentiation was found in the levels of media literacy (Group 0: M = 29.904, SD = 6.301; Group 1: M = 20.448, SD = 9.380) and critical thinking (Group 0: M = 30.201, SD = 6.530; Group 1: M = 20.510; SD = 9.209), as evidenced by high t-statistics (t = -13.244; p < .001) and a large Cohen's effect (d = -1.187), indicating a significant association of younger age with higher levels of cognitive competence. **Conclusions.** The study revealed a low level of media literacy and critical thinking among certain groups of respondents, which indicates the need to implement systematic educational programs aimed at developing cognitive and socio-communication skills. Importantly, the findings highlight the potential of e-learning as an effective environment for media literacy development, since online courses and digital learning platforms can flexibly adapt content for different age and educational groups. This supports the practical integration of media literacy modules into formal and informal e-learning formats, demonstrating how digital tools enhance accessibility and personalization of training. Furthermore, the results reveal a shift in e-learning theory, showing that the effectiveness of online learning in this domain depends not only on access to information but also on the design of interactive, competence-oriented educational interventions. Thus, the study contributes to both the practice and theory of e-learning by identifying critical factors for structuring digital courses that strengthen resilience against disinformation and manipulation. At the same time, the lack of a deeper analysis of socio-cultural factors is a limitation, which opens prospects for further interdisciplinary research in this area.

Cite this article: Plotnikova, M. et al. 2025. "Developing Conscious Information Consumption Skills and Media Literacy in the Age of Digital Change and Media Technologies", *Electronic Journal of e-Learning*, 23(4), pp 15-29
https://doi.org/10.34190/ejel.23.4.4268

Keywords: Media education, Search skills, Critical analysis of media materials, Cognitive components, Media literacy, Critical thinking, Cognitive competence, Information society, Digital environment

1. Introduction

In the current conditions of intensive development of the information environment, the formation of media literacy as a key component of citizens' information security is of particular importance. Rapid transformations in the field of digital technologies and the active penetration of social networks into everyday life are changing the mechanisms of communication, affecting not only the way information is disseminated but also the structure of public perception. It is in the online space that a new type of interaction between the user and media content is being formed, in which social platforms are the main source of news, opinions, and positions (Chen, Chen & Xia, 2022). At the same time, this media space is increasingly being used as a tool for information pressure, manipulation, and dissemination of false information (Truba *et al.*, 2024).

The decline in trust in traditional and digital media, recorded both in global and Ukrainian practice, is evidence of a crisis in the communication system caused by the spread of fake news, information polarization, and loss of public reflexivity (Parker, 2024). These challenges are particularly acute among young people, who are the most vulnerable to visually appealing, emotionally charged, and personalized messages. Therefore, the need to study the problem of media literacy is due to the growing destructive information influence that transforms public consciousness and increases the risks of manipulation in the digital environment. The decline in trust in the media, the spread of disinformation, and the growing role of social media as the main source of news require an in-depth analysis of new communication threats and the search for effective ways to overcome them. The problem of critical comprehension of information among young people, who are at the epicenter of digital interaction and are most exposed to information influence, is of particular relevance.

The purpose of this research article is to empirically substantiate the level of critical thinking and media literacy among the population through quantitative analysis to identify the links between these cognitive characteristics and such factors as the level of education, age of respondents, and experience in media education programs. The study aims to typologize the levels of cognitive competence, identify intra-group differences, and outline structural imbalances that necessitate systemic intervention in information culture policy.

2. Literature Review

In the scientific discourse, media literacy and critical thinking are seen as key cognitive components necessary for effective navigation in the context of information overload and digital polarization. Media literacy is interpreted as an integrative process of acquiring knowledge, skills, and attitudes that allow a person to identify, interpret, critically evaluate, and produce media content in various formats (Chen, Chen & Xia, 2022; Truba *et al.*, 2024). At the same time, critical thinking is understood as the ability to independently analyze, logically generalize, identify cause and effect relationships, and formulate informed judgments in the context of media consumption (Ekawati & Jannah, 2025; Hidayati *et al.*, 2024; Santamaría-Cárdaba *et al.*, 2024). Given the transformations of the educational environment, current research emphasizes the importance of implementing comprehensive educational initiatives focused on the development of digital and media literacy, in particular through the integration of artificial intelligence, innovative teaching methods and the creation of training modules that stimulate critical thinking and digital resilience (Oliveira *et al.*, 2024).

The relevance of developing these competencies is increasing in the context of the spread of fake news, disinformation and manipulative influence, which transforms the information environment in the context of cognitive confrontation (Shah *et al.*, 2024; Trixa & Kaspar, 2024; Zou *et al.*, 2024). In this context, numerous empirical studies have shown the positive impact of media education on information security awareness, increased cognitive reflection, and the development of critical source verification skills (Almulla & Al-Rahmi, 2023; Lee, Cho & Kim, 2023; Martin *et al.*, 2021; Tommasi *et al.*, 2023). In particular, the works of González-Pérez and Ramírez-Montoya (2022), Qi and Yang (2024), Tazhenova, Mikhaylova and Turgunbayeva (2024) emphasize the role of formal and informal educational initiatives that activate analytical thinking and promote digital resilience skills. At the same time, empirical studies show that young people are increasingly aware of the importance of critical thinking for navigating the media space, and confirm the need to institutionalize relevant educational programs that combine media education, technical awareness, and the ability to analyze information independently (A Bani Yassen & Al Danani, 2024; Kiss, 2024).

Much of the research also emphasizes the age, social, and educational variability in the level of critical thinking and media literacy (Akimova, Akimova & Akimova, 2022; Almulla & Al-Rahmi, 2023; Budnyk, 2023; Qi & Yang, 2024). The study by Qi and Yang (2024) shows that young people, despite their high level of digital activity, show insufficient ability to distinguish between authentic content and manipulation, which necessitates targeted educational interventions. At the same time, the results of the study by Alharbi, Elfeky and Sultan (2022) indicate that educational level and experience in media education programs are significant determinants of the development of relevant competencies.

However, a critical comparison of these studies reveals several research gaps. First, while many works confirm the positive influence of media education on resilience to disinformation, they often lack a longitudinal perspective that would allow assessing the sustainability of these effects. Second, the majority of studies focus either on youth or students, whereas older age groups and socially vulnerable categories remain underexplored, despite evidence of their lower levels of media literacy. Third, although there are findings on the role of online education, insufficient attention is paid to how different formats of e-learning (synchronous vs. asynchronous, formal vs. informal) affect the development of critical thinking. Finally, much of the current literature is descriptive in nature and does not provide a systematic theoretical framework that integrates media literacy with broader concepts of digital citizenship and societal resilience. These gaps justify the need for further empirical research aimed at identifying the determinants of media literacy across socio-demographic groups and developing models of effective educational interventions adapted to the digital environment. Thus, the generalization of scientific positions suggests that systemic support for media literacy and critical thinking requires the integration of educational, cultural, and information and communication strategies aimed at increasing the cognitive autonomy of the individual in a complex information ecosystem.

3. Methods

The empirical basis of this study was a sociological survey conducted during 2024–2025 using a structured online questionnaire (Appendix A). The total sample included 507 respondents selected using non-probability quota sampling, which ensured variability in age, education level, and previous participation in media literacy courses. The answers in the critical thinking (critical_score) and media literacy (media_score) blocks were evaluated using a Likert scale, where each statement in the questionnaire had a five-point rating scale: 1 – completely disagree, 2 – rather disagree, 3 – hard to say, 4 – rather agree, 5 – completely agree.

The respondents were citizens of Ukraine aged 18 to 46 who voluntarily agreed to participate in the study and provided informed consent to the processing of personal data in an anonymous form. The study included people who had basic skills in using digital technologies and were able to fill out the online questionnaire on their own. Those who were under the age of majority, had limitations in the perception of written content due to cognitive or psychological factors, or did not complete the survey were excluded from the analysis.

To generate the initial data for the t-test, respondents were divided into two consolidated age groups: those aged 20 to 25 years inclusive (Group 0) and those aged 26 years and older (Group 1). Similarly, the respondents were divided into two groups by education: those with secondary or incomplete higher education (Group 0) and those with complete higher education or a degree (Group 1). Participation in media literacy training was operationalized as a binary variable: "yes" (Group 1) and "no" (Group 0).

The aim of the study was to assess the impact of these three socio-demographic characteristics on two key dependent variables: critical_score (level of critical thinking skills) and media_score (level of media literacy). Each of these indicators was measured on a standardized continuous scale, with respondents classified into five ordinal categories: low (8-15 points), below average (16-23 points), average (24-31 points), above average (32-36 points), and high (37-40 points).

The methodology was structured into three consecutive analytical stages, each of which included hypothesis testing by applying the classical Student's t-test for independent samples. In the first stage, the mean values of critical_score were compared between the groups formed by the variable MediaCourses_Taken to test whether participation in educational initiatives significantly correlated with improved critical thinking. In the second stage, the same variable was analyzed in the dichotomous categories of Education_Level, which allowed us to identify statistically significant differences based on formal academic achievement. The third stage included comparisons based on Age_Group to identify age differences in cognitive resilience to manipulative content and disinformation. A similar three-stage approach was applied to the media_score analysis, which allows for a comprehensive assessment of the relationship between media literacy and the same socio-demographic parameters. All statistical procedures were conducted using the JASP software package (in particular, the Descriptives and Independent Samples T-Test tools).

The main hypotheses of the study are as follows:

Hypothesis (H1): Taking media education courses has a statistically significant positive impact on the level of media literacy and critical thinking.

Hypothesis (H2): The level of education is a factor of differentiation of media literacy and critical thinking.

Hypothesis (H3): Respondent's age correlates with the level of media literacy and critical thinking, with younger participants of the study having higher scores of both characteristics compared to representatives of the older age group.

To ensure methodological consistency and comparability of the results, both dependent variables (critical_score and media_score) were normalized, which eliminated scale-related distortions and increased the reliability of intergroup comparisons. This approach allowed us to statistically test the hypotheses about the differential impact of education, age, and targeted media training on the development of critical and media analytical competencies in the Ukrainian socio-cultural context.

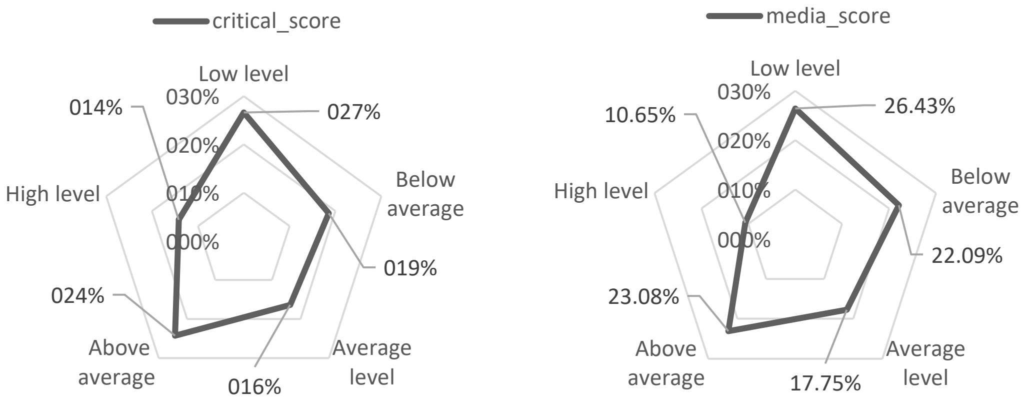
4. Results

Currently, media literacy and critical thinking are emerging as integrative cognitive and analytical abilities that provide a high level of objective comprehension of information flows, its relevant evaluation, reasoned analysis of reliability, and timely identification of risks of manipulative influence and disinformation strategies. Media literacy involves not only the ability to assess the reliability and legitimacy of information sources, but also the ability to identify cause-and-effect relationships between information messages, predict the social and cognitive effects of their impact, formulate logically sound conclusions and build hypothetical scenarios (Park *et al.*, 2021). These competencies are most effective in a structured educational environment, where the critical and analytical potential of the individual is systematically developed. In particular, structured e-learning platforms and online courses provide scalable and flexible frameworks for developing these skills, enabling interactive exercises, multimedia content, and scenario-based simulations. Examples include online modules that guide learners through fake news detection, social media content analysis, and interactive critical thinking challenges (Alharbi, Elfeky & Sultan, 2022; Martin et al., 2021).

In the pedagogical discourse, critical thinking is interpreted as a holistic process of independent, rational and at the same time socially oriented comprehension of problems, which involves the ability to deep conceptual analysis, generate innovative ideas, make non-standard decisions and formulate predictive strategies based on intellectual modeling. The development of critical thinking and media literacy requires the simultaneous activation of cognitive resources (i.e. analytical thinking, logical generalization, reflection) and socio-cultural resources (i.e. socialization, critical communication, countering destructive information influence). Therefore, the parallel development of both competencies within educational programs is of particular importance. The methodological foundations of this approach are the formation of digital skills, mastering the principles of information security, cyber hygiene, personal data protection, and the ability to recognize fake news and information provocations as key threats to the modern information environment.

The results of a quantitative study conducted among 507 respondents allowed us to typologize the levels of critical thinking (critical_score) and media literacy (media_score) based on a five-level scale. The obtained empirical data show significant intra-group fluctuations and reveal the structural features of both cognitive constructs in the study sample (Figure 1).

Despite the relatively large sample (N = 507), it should be emphasized that its representativeness is limited by several factors. First, the study relied on voluntary participation, which may have led to self-selection bias and overrepresentation of individuals already interested in the topic of media literacy. Second, the sample is geographically and socio-culturally concentrated, which reduces the possibility of extrapolating the findings to broader populations. These limitations may affect the generalizability of the results: for example, the identified structural disproportions in cognitive competencies could be even more pronounced in rural or socio-economically disadvantaged groups not represented in the study. Therefore, while the findings are robust within the studied cohort, caution should be exercised in applying them universally.



Source: Compiled by the author

Figure 1: Distribution of respondents by the level of critical thinking and media literacy

The empirical results based on the survey of 507 respondents allow us to identify the characteristic features of the levels of critical thinking and media literacy. The analysis of the critical_score criterion showed that the most common is the low level of development of the relevant cognitive skills, which was recorded in 135 people, which is more than a quarter of the entire sample. A similar figure is observed in the “below average” category, which included 94 respondents. Together, these two levels demonstrate that almost half of the survey participants do not have sufficient skills to critically evaluate information, which indicates the presence of significant cognitive deformities or a lack of appropriate information culture. At the same time, only 14.2% of respondents demonstrated a high level of critical thinking, while the average and above average levels were found in the aggregate in a little more than 40% of respondents. This structural unevenness in the distribution suggests that there is significant potential for the development of critical thinking, provided that there is systematic and targeted intervention at the level of educational policy.

In terms of the media_score indicator, which represents the level of media literacy, a similar trend is also observed. The largest groups were those with low (134 people) and below average (112 people) levels, which together make up almost half of the sample. This indicates that a significant part of the population is not ready to comprehend the information flow, recognize manipulations, fakes and other threats of destructive information influence. A high level of media literacy was found in only 10.7% of respondents, which indicates an extremely limited number of people capable of full participation in a critical information dialogue. The average and above-average scores indicate some positive trends, but their representativeness is not yet sufficient to confirm the systemic impact of media literacy education practices.

Comparison of both scales shows that some respondents' critical thinking skills exceed the level of media literacy, which suggests the presence of cognitive resources that are not yet integrated into information and communication competence. This imbalance is due to the lack of specialized training in media education, which increases the need to roll out programs to develop both critical thinking and media literacy at all levels of education and through non-formal educational initiatives. The findings allow us to conclude that systemic intervention in the field of information culture formation is relevant and that further analysis of the impact of age, educational and behavioral variables on the level of formation of relevant competencies is advisable. E-learning interventions can bridge this gap by providing targeted, adaptive modules focusing on the practical application of critical thinking in media analysis.

Overall, the inclusion of e-learning strategies, tools, and methods – ranging from collaborative virtual environments to AI-powered assessment platforms – could provide actionable pathways for practitioners to implement the study’s findings across diverse educational settings, thereby promoting systematic improvement in cognitive competencies.

Given the identified disproportions in the structure of respondents' cognitive skills, it is logical to conduct an in-depth analysis of the influential factors that potentially determine the level of media literacy and critical thinking. In this context, the following analysis focuses on three key variables: the level of awareness of media literacy and critical thinking, the level of education, and age characteristics.

4.1 The Impact of Media Education Courses on the Level of Media Literacy and Critical Thinking

One of the important determinants of cognitive competencies is participation in targeted training programs, so it is important to study how media education courses affect the level of critical thinking and media literacy, with a focus on identifying the effectiveness of educational interventions in increasing information resilience (Table 1).

Table 1: Indicators of media literacy and critical thinking depending on media education courses

Descriptives								
Group Descriptives								
	Group	N	Mean	SD	SE	Coefficient of variation	Mean Rank	Sum Rank
media_score	0	354	20.910	8.232	0.438	0.394	195.977	69376.000
	1	153	32.915	6.128	0.495	0.186	388.248	59402.000
critical_score	0	354	21.059	8.374	0.445	0.398	196.686	69627.000
	1	153	33.111	5.763	0.466	0.174	386.608	59151.000

Source: Compiled by the author

The results of the descriptive statistics showed that people who took media education courses (Group 0) had significantly higher mean values on media literacy (M = 32.915) and critical thinking (M = 33.111) compared to those who did not take the relevant courses (Group 1: M = 20.91 and M = 21.059, respectively). In addition, the group that received training shows lower variability, indicating more stable results. This distribution indicates the systemic effect of formalized learning on cognitive abilities: media education programs develop students' critical reading skills and ability to reflect. The results of a systematic review by Tommasi *et al.* (2023) also show that formalized media education courses demonstrate significant potential as an effective tool for developing metacognitive competencies in the context of initial vocational education and training. These findings also provide empirical support for the integration of e-learning methods, such as interactive online workshops, gamified learning platforms, and AI-assisted feedback systems, which can systematically enhance students' cognitive competencies in both media literacy and critical thinking.

In addition, structured online learning environments enable adaptive content delivery tailored to the learners' baseline skills, which can help reduce disparities observed across age and education levels. Implementing blended learning formats combining synchronous virtual discussions, asynchronous analytical exercises, and scenario-based simulations may further enhance the observed positive effects of formal training programs.

Instead, the lower standard deviation and coefficient of variation in the training group indicates the effectiveness of the course methodology. Taking specialized courses has a positive impact on the formation of media literacy and critical thinking, providing more stable and higher results for students. Almulla and Al-Rahmi (2023) study supports the conclusion that the methodology of specialized courses is effective, which is manifested in the lower standard deviation and coefficient of variation in the experimental group, as the results of SEM modeling show statistically significant positive relationships between socio-cognitive factors (social contact, influence, identity, support) and the development of reflective thinking and research style of learning; which, in turn, has a significant impact on the development of critical thinking and problem-solving skills, which leads to improved learning outcomes and educational sustainability.

In order to determine the impact of specialized training in media education, a t-test was conducted (Table 2), which revealed significant differences in the levels of media literacy and critical thinking depending on the courses taken.

Table 2: Results of the t-test for media literacy and critical thinking based on media education courses

Results						
Independent Samples T-Test						
	Test	**Statistic**	**df**	**p**	**Effect Size**	**SE Effect Size**
media_score	Student	-16.199	505.000	< .001	-1.567	0.113
	Welch	-18.163	381.623	< .001	-1.654	0.115
	Mann-Whitney	6541.000		< .001	-0.758	0.056
critical_score	Student	-16.215	505.000	< .001	-1.569	0.113
	Welch	-18.704	409.203	< .001	-1.677	0.115
	Mann-Whitney	6792.000		< .001	-0.749	0.056

*Source: Compiled by the author

Note. For the Student t-test and Welch t-test, the effect size is given by Cohen's d. For the Mann-Whitney test, the effect size is given by the rank biserial correlation

The independent Student's t-test revealed statistically significant differences between the groups for both indicators: t = -16.215 (p < 0.001) for media literacy and t = -16.199 (p < 0.001) for critical thinking. In addition, the difference in means is quite significant, and the effect is significant (Cohen's d = -1.567 and -1.569, respectively). In this context, Martin *et al.* (2021) emphasize the need for teacher-student interaction in the digital environment, emphasizing that structured learning involving interactive technologies is a factor in the development of higher cognitive skills. The obtained t-test values indicate the existence of a real, rather than random, effect of the influence of educational programs on cognitive performance. The high Cohen's effect confirms the power of the impact, which is consistent with the theory of cognitive constructivism, according to which the assimilation of information in a structured learning environment promotes deeper integration of knowledge. In addition, Jaboob, Hazaimeh and Al-Ansi (2025) found that the level of cognitive skills development is directly influenced by the use of new technologies, including artificial intelligence, which is mediated by students' behavioral factors (t = 4.963; β = 0.478). Such results strengthen the argumentation about the effectiveness of educational innovations that integrate modern technologies in accordance with the theoretical provisions of the constructivist approach to learning.

The results are also confirmed by the Mann-Whitney test, which demonstrates similar statistical significance with a large effect (biserial correlation rank: -0.758 and -0.749, respectively), which indicates the sustainability of the impact regardless of the type of statistical analysis used and indicates the consistent advantage of media literacy education programs in the context of critical thinking. In particular, the results of the study presented in Park *et al.* (2021) show that media literacy education significantly increases the level of cognitive characteristics such as critical thinking, recognition and response to media content, as well as media interpretation and creation skills. At the same time, Lee, Cho and Kim (2023) notes that media education practices have an indirect impact on youth involvement in social and political life by activating motivation for information consumption, reflection, and engagement in public discourse. Therefore, the data from the t-test indicate that taking media literacy courses is a powerful factor in improving the cognitive competence of citizens. The high degree of effectiveness of such courses proves the feasibility of their widespread implementation in educational and outreach programs, especially in the context of information threats and hybrid warfare; which confirms the hypothesis (H1), demonstrating that participation in media education programs serves as a catalyst for the development of critical thinking and media literacy, increasing the cognitive stability of individuals in a complex information environment.

4.2 Dependence of the Level of Media Literacy and Critical Thinking on the Level of Education

The intellectual and cognitive capital of a person is largely determined by the educational trajectory, so a comparative analysis of the levels of media literacy and critical thinking depending on formal education (Table

3) will help to establish whether there is a relationship between increasing educational level and better information handling.

Table 3: Indicators of media literacy and critical thinking depending on the level of education

Descriptives								
Group Descriptives								
	Group	N	Mean	SD	SE	Coefficient of variation	Mean Rank	Sum Rank
media_score	0	241	18.473	6.792	0.437	0.368	161.990	39039.500
	1	266	30.023	8.031	0.492	0.268	337.363	89738.500
critical_score	0	241	18.871	6.994	0.451	0.371	165.838	39967.000
	1	266	29.974	8.240	0.505	0.275	333.876	88811.000

Source: Compiled by the author

Based on the results of the analysis of descriptive statistics, a clear dependence of the level of development of media literacy and critical thinking skills on the level of education was found. Thus, respondents with higher education (Group 1) have significantly higher mean values (M = 30.023 and M = 29.974) compared to those without higher education (Group 0: M = 18.473 and M = 18.871). People with higher education are likely to have experience in research, critical reading and interpretation of information, which contributes to the development of their media competence. This is in line with the principles of education as a social elevator and cognitive catalyst. Higher education significantly contributes to the formation of cognitive resilience to manipulative practices in the media space. According to Tkacova *et al.* (2023), it reduces the risk of forming an illusory belief in personal "immunity" to media influences, which, according to current theoretical research, is one of the main factors of vulnerability to digital manipulation.

Thus, educational experience ensures the development of analytical skills and increases the ability to be critical and self-reflective about one's own susceptibility to information influences. However, to empirically test the assumption of the relationship between educational level and cognitive characteristics of respondents, a t-test was applied, the results of which are presented in Table 4.

Table 4: Results of the t-test for media literacy and critical thinking by level of education

Results						
Independent Samples T-Test						
	Test	Statistic	df	p	Effect Size	SE Effect Size
media_score	Student	-17.391	505.000	< .001	-1.547	0.113
	Welch	-17.534	502.654	< .001	-1.553	0.114
	Mann-Whitney	9878.500		< .001	-0.692	0.051
critical_score	Student	-16.270	505.000	< .001	-1.447	0.111
	Welch	-16.401	502.894	< .001	-1.453	0.111
	Mann-Whitney	10806.000		< .001	-0.663	0.051

Source: Compiled by the author

Note. For the Student t-test and Welch t-test, the effect size is given by Cohen's d. For the Mann-Whitney test, the effect size is given by the rank biserial correlation

The results of the Student's t-test show that there are statistically significant differences in the levels of media literacy and critical thinking depending on the educational status of the respondents. According to the data, people with higher education demonstrated significantly higher average scores in both media literacy and critical thinking than those without a complete higher education. For media literacy, the t-test value is -17.391 at $p < 0.001$, and the Cohen's effect size is -1.547, which corresponds to a very large effect. An alternative variant using the correction for unequal variances (Welch) gave a similar result: t = -17.534 at $p < 0.001$, with an identical effect size (d = -1.553), which further confirms the stability of the observed difference.

The results of the non-parametric Mann-Whitney test (U = 9878.5; $p < 0.001$) also show significant differences, with a rank-biserial correlation value of -0.692, which confirms a strong inverse relationship between the lack of higher education and lower levels of media literacy. A similar trend was found for the level of critical thinking: t = -16.270 at $p < 0.001$, Welch t = -16.401 at $p < 0.001$, accompanied by a significant effect (d = -1.447 and d = -1.453, respectively). The rank-biserial correlation of -0.663, according to the Mann-Whitney test (U = 10806.0 at $p < 0.001$), also indicates a significant association between the level of education and the level of critical thinking. These results suggest that higher education is a systemic catalyst for the formation of both media literacy and critical thinking. The high values of the effect size indicate a deep socio-cognitive differentiation that is formed in the context of academic learning. This allows us to consider formal education as a key prerequisite for a person's resistance to manipulative influences and disinformation, as well as a fundamental factor in the development of cognitive autonomy, logical thinking, and the ability to rationally analyze the information space.

The findings correlate with the results of an experimental study by Alharbi, Elfeky and Sultan (2022), according to which e-collaborative learning has a positive impact on the development of critical thinking and higher cognitive skills, in particular by stimulating hypothetical thinking, argumentation, and variable correction. A comparative analysis between the groups involved in collective and individual e-learning demonstrated a statistically significant advantage of the former in terms of the level of higher order thinking, which further confirms the importance of interactive educational practices in the cognitive development of the individual. Thus, the obtained empirical data of the t-test confirm the hypothesis (H2) about the positive impact of higher education on the cognitive characteristics of the individual, but also justify the expediency of integrating media education and critical thinking components into the curriculum at all levels of the educational system.

4.3 Age-Specific Features of Media Literacy and Critical Thinking

The age dynamics of cognitive development in the information society requires the formation of a comparative characterization of the levels of media literacy and critical thinking among respondents of different age categories in order to identify age asymmetries and determine educational risk groups (Table 5).

Table 5: Indicators of media literacy and critical thinking in different age groups

Descriptives								
Group Descriptives								
	Group	N	Mean	SD	SE	Coefficient of variation	Mean Rank	Sum Rank
media_score	0	288	20.448	9.380	0.553	0.459	193.075	55605.500
	1	219	29.904	6.301	0.426	0.211	334.121	73172.500
critical_score	0	288	20.510	9.209	0.543	0.449	190.620	54898.500
	1	219	30.201	6.530	0.441	0.216	337.349	73879.500

Source: Compiled by the author

The results of the independent sample t-test show that there are statistically significant age differences in the levels of media literacy and critical thinking. The table of descriptive statistics shows that in the older age group

(Group 0), which includes 219 people, the average value of the media literacy index was 29.904 (SD = 6.301), which is significantly higher than the corresponding value in the older group (Group 1; N = 288), where the average level was only 20.448 (SD = 9.38). A similar situation is observed with regard to critical thinking: Group 0 demonstrates an average score of 30.201 (SD = 6.53) compared to 20.510 (SD = 9.209) in Group 1. Taking into account these results, a t-test was used to identify age differentiation in the level of development of key cognitive competencies, the results of which reflect the specifics of information perception among different age groups (Table 6).

Table 6: Results of the t-test for media literacy and critical thinking by age group

Results						
Independent Samples T-Test						
	Test	**Statistic**	**df**	**p**	**Effect Size**	**SE Effect Size**
media_score	Student	-12.872	505.000	< .001	-1.154	0.102
	Welch	-13.554	497.876	< .001	-1.184	0.102
	Mann-Whitney	13989.500		< .001	-0.556	0.052
critical_score	Student	-13.244	505.000	< .001	-1.187	0.102
	Welch	-13.855	502.677	< .001	-1.214	0.103
	Mann-Whitney	13282.500		< .001	-0.579	0.052

Source: Compiled by the author

Notes. For the Student t-test and Welch t-test, the effect size is given by Cohen's d. For the Mann-Whitney test, the effect size is given by the rank biserial correlation

Inferential statistical tests confirm these differences as statistically significant. For media literacy, the value of the Student's t-test is -12.872 at $p < 0.001$, while the Welch's t-test is $t = -13.554$ at $p < 0.001$. The size of the Cohen's effect reaches -1.154 and -1.184, respectively, indicating an extremely strong difference between the age groups. The non-parametric Mann-Whitney test ($U = 13989.500$; $p < 0.001$) also demonstrates the significance of the differences, with a rank-biserial correlation of -0.556, reflecting a significant inverse association between age and media literacy. Similarly, for the critical thinking indicator, the Student's t-statistic is -13.244 at $p < 0.001$, and the Welch's test is -13.855 at $p < 0.001$. The Cohen's effect is -1.187 and -1.214, respectively, meaning that in both cases the effect is very large. The Mann-Whitney test confirms these differences ($U = 13282.5$ at $p < 0.001$, with a rank-biserial correlation of -0.579), which also indicates a statistically significant and substantial difference between the groups. The rationale for such results can be found in the peculiarities of cognitive adaptation to the information environment: younger respondents who have been immersed in the digital context since childhood have a more developed ability to critically analyze and navigate the media flow. Older participants, on the other hand, demonstrate a lower level of these skills, which is due to both insufficient media education and less involvement in digitalization processes.

Thus, the results of the t-test show a high degree of age differentiation in the levels of media literacy and critical thinking, and outline an important socio-pedagogical problem that needs to be addressed systematically. According to Budnyk (2023), in this context, it is important to take into account the principles of critical pedagogy, which emphasize the need to overcome educational and socio-cultural barriers that hinder the formation of critical thinking in older age groups. Therefore, increasing the cognitive activity of mature adults should be based on pedagogical strategies focused on problem-based, dialogic, and project-based learning, which contribute not only to the assimilation of information but also to the formation of the ability to reflect, argue, and think for oneself. The conclusion of the analysis is that younger age is associated with a significantly higher level of these cognitive competencies, which should be taken into account when developing targeted educational programs for older age groups, in particular in terms of digital inclusion and media education. Thus, the hypothesis (H3) about the association of younger age with higher levels of media literacy and critical thinking was empirically confirmed, which necessitates the development of inclusive educational interventions aimed at bridging the cognitive and informational gap between age groups.

5. Discussion

The results of the descriptive statistics of Tommasi *et al.* (2023) confirm the conclusions drawn in the systematic review: formalized media education courses demonstrate significant potential as an effective tool for developing metacognitive competencies in the context of initial vocational education and training. At the same time, several findings of this study require a more critical reflection. For instance, the imbalance between higher critical thinking scores and relatively lower media literacy in a subgroup of respondents is somewhat unexpected, as it contradicts the dominant assumption that these competencies develop in parallel. This suggests the existence of latent cognitive resources that are not fully converted into practical skills of media navigation, which may point to shortcomings in current educational programs. Similarly, the sharp age differentiation – where younger cohorts substantially outperform older groups – highlights structural inequalities in access to digital education, raising the question of whether existing interventions are sufficiently inclusive. Rather than treating these gaps as simple correlational outcomes, they should be interpreted as signals of systemic educational fragmentation that requires targeted policy responses.

The pronounced increase in the mean values of media literacy (M = 32.915) and critical thinking (M = 33.111), as well as the decrease in variability in the training group, indicates the consistency between targeted educational interventions and the stability of the results achieved. These dynamics confirm that properly designed educational interventions have a systemic effect and can be integrated into educational strategies as a means of increasing students' cognitive autonomy. In contrast, Almulla and Al-Rahmi (2023) emphasize that the lower standard deviation and coefficient of variation in the trained group indicates the effectiveness of the course methodology, as the results were higher and more stable. This is confirmed by highly significant direct and indirect relationships between factors such as social contact (H3: t = 2.140; β = 0.107) and critical reflection (H4: t = 2.504; β = 0.145), social influence (H5: t = 2.030; β = 0.103; H6: t = 4.318; β = 0.250), social identity (H7: t = 4.797; β = 0.200; H8: t = 4.669; β = 0.221), and between critical thinking and academic performance (H18: t = 3.159; β = 0.186). Thus, taking specialized courses has a positive impact on the formation of media literacy and critical thinking, providing more stable and higher results for students. The significance of the intergroup differences is also confirmed by the Mann-Whitney test, which, despite a different approach to calculations, showed a similar level of effect (biserial correlation rank: Group 0 = -0.758 and Group 1 = -0.749), indicating the reliability of the identified patterns regardless of the analysis methodology. This result confirms the observations of Park *et al.* (2021), who proved that media literacy training significantly affects the development of the ability to critically interpret information, in particular in the field of media content. It is also worth noting that the high values of the t-statistic (t = -16.215 (p < 0.001) for media literacy and t = -16.199 (p < 0.001) for critical thinking) and the Cohen effect are fully consistent with the provisions of cognitive constructivism, according to which deep learning occurs under the condition of structured educational influence. This approach is also confirmed by the model proposed by Martin *et al.* (2021), which emphasizes the role of teacher-student interaction in the digital environment as a factor in the development of cognitive flexibility.

From an international perspective, our findings are consistent with McDougall's (2019) study in the UK and the US, which shows that media literacy education increases youth's resilience to disinformation when media literacy is integrated as a dynamic and mandatory part of curricula. Moreover, in Malaysia, a recent systematic review of eHealth & social media literacy among older adults indicates that individual, interpersonal, institutional, and social factors influence digital and media literacy, suggesting similar multi-level influences as found in our study (Zhang et al., 2025). These international comparisons underscore that the structural disproportions we observe (by age, education, training) are not unique to Ukraine but part of a global challenge in ensuring inclusive media competence.

The existence of a clear and statistically significant relationship between the level of formal education and indicators of media literacy and critical thinking, in particular, the results of the t-test, which showed extremely large effect sizes (Cohen's d > 1.4 for both variables), confirm the deep cognitive differentiation between respondents with higher education and those with secondary and incomplete higher education. Comparing these results with the scientific findings of Tkacova *et al.* (2023) allows us to consider higher education as an institutionalized safeguard against the formation of the "illusion of invulnerability" to manipulative influences. Education, which includes the stages of analysis, criticism, argumentation, and verification of information, contributes to the formation of the so-called cognitive immunity, making a person less prone to automatic assimilation of disinformation and able to maintain a reflective distance from media messages. At the same time, according to the study by Alharbi, Elfeky and Sultan (2022), not only the availability of higher education as such, but also the nature of educational interaction (including online learning, e-collaborative learning, etc.) significantly affects the development of cognitive skills. The results of this experiment indicate the advantage of interactive educational approaches in developing a higher level of critical thinking, which correlates with our observations: education that includes active participation in discussions, case studies, and simulation models contributes not only to the accumulation of knowledge but also to the formation of the ability to perform complex cognitive operations. Our results thus both replicate and extend international findings by showing not only that education matters, but that the modality and stability of educational interventions (in-course structure, frequency, interactivity) are crucial – a nuance less emphasized in prior studies.

The empirical data authors have obtained indicate that there is a distinct age asymmetry in the formation of media literacy and critical thinking. In particular, the mean scores of the younger age group (29.904 with SD = 6.301 for media literacy; 30.201 with SD = 6.530 for critical thinking) significantly exceed the corresponding results of the older group (20.448 with SD = 9.380 and 20.510 with SD = 9.209, respectively). The statistical significance of these differences is confirmed by the results of t-tests and non-parametric methods, where the Cohen's effect exceeds the threshold of ±1.1, indicating a large effect strength. These results are consistent with the findings of Budnyk (2023), who notes that the development of critical thinking in older adults requires overcoming socio-cultural barriers, including limited access to digital resources and lack of prior experience with media. Its emphasis on critical pedagogy as a methodology that stimulates reflection and reasoned thinking is relevant in the context of our study, as it found a statistically significant correlation between age and media competence (-0.556 and -0.579 for both scales, respectively). However, other studies, such as Qi and Yang (2024), show ambivalent results: the authors point to an increase in the level of critical thinking among older people due to their life experience and a tendency to think analytically in an unstable information environment. However, such conclusions, according to our analysis, are not empirically confirmed in the digital information ecosystem, where not only life experience but also the ability to adapt to technology and digital navigation become decisive factors. In the context of the study by de Abreu Alecrim *et al.* (2025), which emphasizes the importance of integrating media education into adult continuing education programs, our results demonstrate the urgency of such educational interventions. The level of cognitive competencies in the older age group is critically insufficient, as evidenced by both average values and high coefficients of variation (0.459 for media literacy and 0.449 for critical thinking), which indicate uneven skills development in this category of respondents. Thus, the results of our study not only confirm but also deepen the ideas about the age determination of the development of media literacy and critical thinking available in the scientific literature.

The originality of this study lies in its simultaneous empirical assessment of both critical thinking and media literacy on large-scale data and the identification of their structural disproportions across age and education levels. While previous works (e.g., Park et al., 2021; Lee, Cho & Kim, 2023; Yermachenko et al., 2023) predominantly treated these constructs in isolation, our findings demonstrate the importance of analyzing them as interrelated but not fully overlapping domains. This contributes to the theoretical refinement of the cognitive-informational paradigm and provides empirical justification for integrated educational strategies. By situating our results within international literatures (McDougall, 2019; Zhang et al., 2025 etc.), we also contribute to the comparability of findings across contexts, providing evidence that patterns observed in Ukraine reflect broader global trends. This enhances the study's impact and potential citability in the wider scientific community.

6. Conclusions

The study allowed us to empirically confirm that in the context of the digital transformation of the information environment, media literacy and critical thinking function as complementary cognitive and analytical constructs that ensure the ability of an individual to adequately navigate complex information flows, critically evaluate sources, recognize destructive influences, and formulate informed judgments. These findings address a significant research gap in Ukrainian scholarship, where the interrelation of media literacy and critical thinking under conditions of digital transformation has been insufficiently explored.

The study revealed the existence of deep intra-group disproportions in the levels of these competencies: almost half of the respondents demonstrate low or below average levels of both critical thinking and media literacy, which indicates the existence of a systemic deficit of information culture in the study sample. At the same time, the identified cognitive potential of some respondents indicates the possibility of successfully compensating for this deficit under the condition of systemic educational influence. This highlights the original contribution of the study: it formalizes an integrated approach to developing critical thinking and media literacy while providing empirical evidence of the effectiveness of formalized media education in fostering information resilience.

In response to the identified problems, the authors propose the introduction of comprehensive educational strategies based on the methodology of integrated development of critical thinking and media literacy. The results of the comparative analysis show that taking formalized media education courses provides significantly higher levels of formation of relevant competencies and lower variability of results, which confirms the effectiveness of such programs in increasing information resilience. Such an approach should include mastering digital skills, learning the basics of information security, developing critical communication and reflection skills, and identifying cognitive distortions and manipulative strategies in the media space. This approach not only strengthens individual information literacy but also provides a model for policy-makers and educational institutions to design targeted interventions for different socio-demographic groups.

Among the limitations of this study is the limited representativeness of the sample in terms of the socio-demographic spectrum, which limits the ability to generalize the results to a wide audience. In addition, the study focused mainly on quantitative indicators of competence formation, without covering the deep qualitative aspects of the processes of reflection, interpretation and cognitive modeling. Addressing these limitations in future research could offer a more nuanced understanding of the mechanisms through which media literacy and critical thinking develop in diverse populations.

Promising areas for further research include studying the impact of age, socio-cultural and behavioral variables on the dynamics of media literacy and critical thinking, modeling effective educational interventions in different types of learning environments, and developing indicators for assessing a person's resistance to information threats. Particular attention should be paid to the study of the long-term effect of integrated curricula aimed at the synergistic development of metacognitive skills in the context of digitalization.

Ethical Statement: This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Use of artificial intelligence: The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

A Bani Yassen, S. O. and Al Danani, A., 2023. Media Education and Digital Media: Nurturing Digital Literacy and Critical Thinking. *Journal of Namibian Studies,* 33*,* p. 604. Available at https://openurl.ebsco.com/EPDB%3Agcd%3A10%3A5727546/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A172998542&crl=c&link_origin=scholar.google.com.ua [Accessed 30 June 2025].

Akimova, N., Akimova, A. and Akimova, A., 2022. Specificity of internet texts understanding in youth age. *Psycholinguistics,* 32(1), pp. 6–28. https://doi.org/10.31470/2309-1797-2022-32-1-6-28

Alharbi, S. M., Elfeky, A. and Sultan, E., 2022. The effect of e-collaborative learning environment on development of critical thinking and higher order thinking skills. *Journal of Positive School Psychology,* 6(6), pp. 6848–6854. Available at https://www.researchgate.net/publication/368237806_The_Effect_Of_E-Collaborative_Learning_Environment_On_Development_Of_Critical_Thinking_And_Higher_Order_Thinking_Skills[Accessed 30 June 2025].

Almulla, M. A. and Al-Rahmi, W. M., 2023. Integrated social cognitive theory with learning input factors: The effects of problem-solving skills and critical thinking skills on learning performance sustainability. *Sustainability,* 15(5), pp. 3978. https://doi.org/10.3390/su15053978

Budnyk, O., 2023. Critical Pedagogy: Current Priorities and Prospects of Development. *Journal of Vasyl Stefanyk Precarpathian National University,* 10(1), pp. 7–23. https://doi.org/10.15330/jpnu.10.1.7-23

Chen, L., Chen, J. and Xia, C., 2022. Social network behavior and public opinion manipulation. *Journal of Information Security and Applications,* 64*,* 103060. https://doi.org/10.1016/j.jisa.2021.103060

de Abreu Alecrim, T. C., de Albuquerque, E. D. S., de Lira Silva, M., de Santana, J. D. L. and de Quental, O. B., 2025. Importance of continuing education in urgency and emergency practices in emergency care units. *Health and Society,* 5(01), pp. 69–80. https://doi.org/10.51249/hs.v5i01.2389

Ekawati, W. and Jannah, M., 2025. Improving Students' Critical Thinking and Writing Skills: Implementation using Integrated Problem Based Learning JEMBER Model Development. *Journal of Posthumanism,* 5(5), pp. 3964–3974. https://doi.org/10.63332/joph.v5i5.1839

González-Pérez, L. I. and Ramírez-Montoya, M. S., 2022. Components of Education 4.0 in 21st century skills frameworks: systematic review. *Sustainability,* 14(3), p. 1493. https://doi.org/10.3390/su14031493

Hidayati, N., Suryanti, S., Rahmayumita, R. and Aisya, S., 2024. Development of Critical Thinking Skills Instruments: Cases for Essay Tests. *Jurnal Kependidikan: Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran,* 10(1), pp. 77–88. https://doi.org/10.33394/jk.v10i1.10052

Jaboob, M., Hazaimeh, M. and Al-Ansi, A. M., 2025. Integration of generative AI techniques and applications in student behavior and cognitive achievement in Arab higher education. *International Journal of Human–Computer Interaction,* 41(1), pp. 353–366. https://doi.org/10.1080/10447318.2023.2300016

Kiss, I., 2024. The Role of Media Literacy in the Development of Critical Thinking. *Sarajevo Social Science Review,* 13(1-2), pp. 15–37. https://www.ceeol.com/search/article-detail?id=1300143

Lee, S., Cho, J. and Kim, S., 2023. Pathways to youth political participation: Media literacy, parental intervention, and cognitive mediation. *Mass Communication and Society,* 26(1), pp. 99–121. https://doi.org/10.1080/15205436.2022.2122846

Martin, F., Sun, T., Turk, M. and Ritzhaupt, A. D., 2021. A meta-analysis on the effects of synchronous online learning on cognitive and affective educational outcomes. *International Review of Research in Open and Distributed Learning,* 22(3), pp. 205–242. https://doi.org/10.19173/irrodl.v22i3.5263

McDougall, J. (2019). Media literacy versus fake news: critical thinking, resilience and civic engagement. *Media studies*, *10*(19), 29-45. https://doi.org/10.20901/ms.10.19.2

Oliveira, A. B., Cardoso, F., Salaberri, M. and Salgado, S., 2024. AI and media literacy integration in education: supporting digital transformation with digital literate. In: *ICERI2024 Proceedings.* (pp. 5907–5912). IATED. https://doi.org/10.21125/iceri.2024.1428

Park, Y. M., Chae, J. H., Kim, S. K. and Kwon, H. S., 2021. The effects of media literacy education and its influence on digital citizenship: Focusing on CMF education programs in Korea. *The Journal of Information Systems,* 30(3), pp. 113–135. https://doi.org/10.5859/KAIS.2021.30.3.113

Parker, J., 2024. The Role of Higher Education in the Post-Truth Era. *Journal of Political Science Education,* 20(3), pp. 391–404. https://doi.org/10.1080/15512169.2024.2354972

Qi, C. and Yang, N., 2024. Digital resilience and technological stress in adolescents: A mixed-methods study of factors and interventions. *Education and Information Technologies,* 29(14), pp. 19067–19113. https://doi.org/10.1007/s10639-024-12595-1

Santamaría-Cárdaba, N., Gajardo, K., Iglesias, J. C. and Ortega-Quevedo, V., 2024. Global Education and Critical Thinking: A Necessary Symbiosis to Educate for Critical Global Citizenship. *Open Education Studies,* 6(1). https://doi.org/10.1515/edu-2024-0010

Shah, N. Z., Hamid, N. S., Mariadass, M. E. and Aziz, N. S. A., 2024. Fostering Critical Thinking Skills in Tertiary-Level Students for Media and Information Literacy. *International Journal of Advanced Research in Education and Society,* 6(3), pp. 107–123. https://myjms.mohe.gov.my/index.php/ijares/article/view/27535

Tazhenova, G., Mikhaylova, N. and Turgunbayeva, B., 2024. Digital media in informal learning activities. *Education and Information Technologies,* 29(16), pp. 21673–21690. https://doi.org/10.1007/s10639-024-12687-y

Tkacova, H., Pavlikova, M., Stranovska, E. and Kralik, R., 2023. Individual (non) resilience of university students to digital media manipulation after COVID-19 (case study of Slovak initiatives). *International Journal of Environmental Research and Public Health,* 20(2), pp. 1605. https://doi.org/10.3390/ijerph20021605

Tommasi, F., Ceschi, A., Sartori, R., Gostimir, M., Passaia, G., Genero, S. and Belotto, S., 2023. Enhancing critical thinking and media literacy in the context of IVET: A systematic scoping review. *European Journal of Training and Development,* 47(1/2), pp. 85–104. https://doi.org/10.1108/EJTD-06-2021-0074

Trixa, J. and Kaspar, K., 2024. Information literacy in the digital age: information sources, evaluation strategies, and perceived teaching competences of pre-service teachers. *Frontiers in Psychology,* 15*,* 1336436. https://doi.org/10.3389/fpsyg.2024.1336436

Truba, H., Khrapatyi, S., Harashchuk, K., Shvets, D. and Proskurnia, A., 2024. Psycholinguistic underpinnings of image formation: Suggestion and manipulation in the educational network discourse. *Thinking Skills and Creativity,* 52*,* 101496. https://doi.org/10.1016/j.tsc.2024.101496

Yermachenko, V., Bondarenko, D., Akimova, L., Karpa, M., Akimov, O., & Kalashnyk, N. (2023). Theory and practice of public management of smart infrastructure in the conditions of the digital society' development: Socio-economic aspects. *Economic Affairs (New Delhi), 68*(1), 617-633. https://doi.org/10.46852/0424-2513.1.2023.29

Zhang, C., Mohamad, E., Azlan, A. A., Wu, A., Ma, Y., & Qi, Y. (2025). Social media and eHealth literacy among older adults: systematic literature review. *Journal of medical Internet research*, *27*, e66058. https://doi.org/10.2196/66058

Zou, W., Drake, A. P., Masur, P. K., Whitlock, J. and Bazarova, N. N., 2024. Examining learners' engagement patterns and knowledge outcome in an experiential learning intervention for youth's social media literacy. *Computers & Education,* 216*,* 105046. https://doi.org/10.1016/j.compedu.2024.105046

Appendix A

Questionnaire

Level of critical thinking and media literacy

Block 1: Socio-demographic characteristics

1. Age: ___

up to 20 years old

21-25 years old

26-30 years old

31 and more

2. Gender:

Male

Female

3. Level of education:

Secondary

Higher incomplete

Higher

Academic degree

3. Have you taken any media literacy courses?

Yes

No

Block 2: Critical thinking

I analyze arguments before accepting a point of view.

I am able to find weaknesses in the logic of a message.

I often question commonly accepted statements.

I am able to make decisions based on analysis rather than emotions.

I can formulate several alternative views of a problem.

I evaluate possible consequences before making a decision.

I am able to structure information logically.

I am aware of biases in my own thinking.

Block 3: Media literacy

I check sources of information before trusting them.

I know how to check facts online.

I know how to distinguish between news, facts and value judgments.

I notice manipulative techniques in the media (emotions, headlines, etc.).

I know what disinformation is and how to recognize it.

I avoid sharing questionable information on social media.

I understand the principles of social media algorithms (what forms the feed).

I can explain why it is important to protect your personal data online.

Using Learner-Generated Videos to Foster Multimedia Communication Skills in Graduate Health Profession Education

Jennifer Hogg[1], Emily Thompson[2], Christopher Johnson[3] and Bengt Carlson[3]
[1]Department of Health and Human Performance, The University of Tennessee Chattanooga, TN, USA
[2]Library, The University of Tennessee Chattanooga, TN, USA
[3]Walker Center for Teaching and Learning, The University of Tennessee Chattanooga, TN, USA

Jennifer-hogg@utc.edu (corresponding author)

https://doi.org/10.34190/ejel.23.4.4279

Abstract: The advent of graduate level athletic training education programs, including those with online didactic curriculum, encourages instructors to incorporate higher level thinking strategies into their curricula. "Create" and "synthesize" are high-level verbs in Bloom's Taxonomy. Pathomechanics, the study of how musculoskeletal structure and function affect movement patterns, provides a prime opportunity to emphasize higher levels of critical thinking. Because degree programs in the health sciences are heavily "hands-on" and applied, creatively using technology in an online environment to develop transferable skills is critical for such health specialties as athletic training or physical therapy. The purpose of this experiential case study is to describe a method whereby graduate athletic training students are assessed in their ability to create and synthesize information pertaining to structural and gait anomalies. Doing so will allow for empirical work to determine the efficacy of this approach on student learning. Specifically, learner-generated videos may be used as an assessment tool, either in a traditional classroom or in an online classroom. Students report higher levels of active learning, engagement, and acquisition of competencies following creation of video content, which also fosters multimedia manipulation skills and development of 21st century communication ability. Approximately a month prior to the end of the term, the instructor provides students with the instructions for the assignment, each student's individual gait prompt, and the rubric. A collaborating multimedia librarian instructs the students in the use of technology for video creation and editing. The deliverable product is a video ~1 minute in length of a gait demonstration of the assigned gait prompt, complete with annotations and voice-over explanations of how the studied gait anomaly may influence kinematics and kinetics throughout the body. Learner-generated videos increase active learning, competency acquisition, and multimedia communication skills. Another primary advantage of this assessment is the potential for student-student and instructor-student collaboration and its ability to be a formative iterative assignment. Furthermore, mastery of pathomechanical content requires synthesis of information from anatomy, physiology, and orthopedic assessment courses. Learner-generated videos offer numerous advantages to student engagement and learning and require synthesis of information from across an athletic training curriculum, serving as a compact and comprehensive assessment.

Keywords: Gait, Synthesis, Library, Multimedia, Multimodal, Athletic training, Pathomechanics

1. Introduction

Professional athletic training (AT) education transitioned to an entry-level Master's degree relatively recently, with the final baccalaureate cohorts admitted in Fall 2022. Along with this change has come the ability for educators to employ more rigorous methods in the classroom. Although more rigorous accreditation standards did not formally accompany the higher degree requirement, graduate level education holds greater opportunity to engender more complex and nuanced thinking than is possible at the undergraduate level. In the Revised Bloom's Taxonomy of Educational Objectives (Anderson and Krathwohl, 2001), *create* is the highest level of learning. Appropriate verbs for this level of Bloom's Taxonomy include *synthesize*, *develop*, *make*, and *produce*, which offer greater opportunity for an instructor to instill critical thinking skills in graduate students. Especially in the age of artificial intelligence, proficiency in higher order reasoning skills is paramount, and it would behoove professors to creatively explore alternative pedagogical methods which challenge students to think holistically. Healthcare practitioners specifically must be able to think creatively to synthesize information and "tell a story." Human physiology is complex and movement disorders often present with nuance in unique ways. Assessing rote information and using the lower levels of Bloom's Taxonomy is inadequate for a healthcare practitioner tasked with practicing *individualized* care.

In athletic training, pathomechanics is considered foundational knowledge associated with observing a movement pattern and subsequently inferring its underlying causes (Commission on Accreditation of Athletic Training Education, 2020 Professional Standards). For instance, observing a limp in a walking gait and correctly determining the underlying musculoskeletal shortcoming could be an appropriate educational goal in a

Cite this article: Hogg, J. et al. 2025. "Using Learner-Generated Videos to Foster Multimedia Communication Skills in Graduate Health Profession Education", *Electronic Journal of e-Learning*, 23(4), pp 30-36, https://doi.org/10.34190/ejel.23.4.4279

pathomechanics course for future ATs. Inherent in high-quality pathomechanical evaluation is the ability to observe; inspecting another's movement patterns is a visual task at its core. Thus, creating visual content as a means to synthesize and communicate pathomechanical concepts is a fitting innovative pedagogical strategy. In a fast-paced clinical education program in which students are enrolled in multiple overlapping courses with related content (e.g., anatomy and physiology, orthopedic evaluation, biomechanics / pathomechanics), creating visual content is an innovative way to encourage students to synthesize information from across courses.

The reported advantages of learner-generated videos are vast, to include greater motivation, multimodal literacy, ability to problem-solve, and content mastery (Morgan, 2013). Compared with standard classroom learning materials (e.g., assigned readings, slide deck review), the creation of an original video increased student understanding in a repeated-measures design (Cohen's $d = .45$, $p = .02$) (Marley, 2014), indicating that students learn more when they are required to teach the content to others rather than in a passive learning paradigm. Others have corroborated these findings, demonstrating that active learning via learner-generated videos increased perceived acquisition of competencies and academic performance across various disciplines (Orús et al., 2016, Ariza, 2023, Pereira et al., 2014, Thomas and Marks, 2014). Development of technical skills and multimedia literacy supports post-graduation employment potential and communication competence, readying students for 21st century industry (Thomas and Marks, 2014, Sullivan, 2001, Genereux and Mangione, 2009). Further increasing the impact of learner-generated visual content, some have reported improvements in metacognition upon generation of visual video content (Schuck and Kearney, 2006). Creating videos as short as 1 minute has been shown to increase STEM students' perceptions of self-efficacy and engagement (Campbell, Heller, and Pulse, 2020), in addition to general improvements in content retention (Khalid, 2014) and critical thinking (Baclay, 2020).

Despite these purported advantages, descriptions of this pedagogical technique among medicine and health disciplines are lacking (BalikÇI and KarataŞ, 2024). A scoping review (Snelson, 2018) investigated the prevalence of student-generated videos in a content-area course. Healthy science courses accounted for ~20% of the total included studies, but none in sports medicine or athletic training. Therefore, the purpose of this experiential report is to present implementation of learner-generated videos as a means for assessing pathomechanical knowledge and application in a Graduate Athletic Training curriculum. Presenting this technique will allow graduate faculty to further their instruction of multimedia communication skills for 21st century healthcare professionals. Moreover, shedding light on the potential for collaboration between healthcare instructors and multimedia librarians will encourage future empirical data and analyses of the effectiveness of multimedia instructional modalities on student learning.

2. Description of Educational Technique

The specific learning outcomes in the syllabus addressed by this assignment are: 1) Communicate using basic biomechanical terminology, 2) Describe how anatomy and anatomical variations inform biomechanics, 3) Describe pathomechanics associated with musculoskeletal injuries frequently encountered during athletic activity, and 4) Evaluate an individual's gait pattern and identify problematic movement strategies. The programmatic curriculum is such that pathomechanics is taught concurrent with gross anatomy and orthopedic evaluation courses; therefore, the student learning objectives leverage this overlap to create reinforcement between courses. The pathomechanics course serves as a 'bridge' between anatomy and orthopedic evaluation. The present assignment is administered at the end of the term in lieu of a final exam.

Approximately a month prior to the end of the term, the instructor provides students with the instructions for the assignment (**Table 1**) as well as each student's individual prompt (**Table 2**). The rubric is also provided for student guidance (**Table 3**). Each student is required to record a short (~30 seconds) video of someone walking on a treadmill and displaying the respective gait pattern. The deliverable product is a video ~1 minute in length complete with annotations and voice-over explanations of how the studied gait anomaly may influence kinematics and kinetics throughout the body (still photo example in **Figure 1**). Because each student has a unique prompt, students are encouraged to discuss their assignments with each other and with the professor.

Figure 1: Example of student-submitted work with gait and annotations depicting the given prompt of "genu varum"

Since its inception, this assignment has been collaborative with the University Library's Studio, a multimedia lab that provides access to equipment, software, and expertise. In the weeks leading up to the assignment, classroom time is allocated to go over capturing the video on the students' phones, editing, adding a voice-over, and submitting the final project. For editing, the librarian teaches TechSmith Camtasia, a video editor used primarily for educational videos and screencasts. At this institution, it is available to students in the Studio Lab. The software is simple enough for students to gain competence in an hour, and comes with "Annotations," including text, arrows, and animated circles that help students bring attention to specific aspects of their video. The librarian also shows them how to export their video to the .mp4 format, which is compatible with most Learning Management Systems.

If the assignment occurs in a strictly online modality in which students may not have access to a University Library, lower-end technological solutions may be needed. Most smartphones have excellent cameras, although students may need guidance in recording in the proper format. For instance, iPhones default to a "high-efficiency" format that will need to be converted using a website like freefileconvert.com. As for software, iMovie comes free with Mac computers. Recently, there has been a boom in free or "freemium" software that makes video assignments more accessible to students using Windows. These include Shotcut and CapCut. However, instructors should familiarize themselves with free online softwares prior to mandating its use in an assignment. When working in an online-only modality, the University Library Studio adds help pages within the course's site in the Learning Management System, in the form of videos, screenshots, or repeating .gif images that walk the students through the process.

Modifications. This assignment lends itself to collaboration and peer review. For the student, completing the assignment is a visual task, and for the instructor, grading is also a visual task. Moving the assignment earlier in the semester would allow for structured peer review, in which classmates review and provide feedback on one another's projects. The current audience for the videos is internal to the class. If the instructor wanted to encourage more professional videos, they could be posted to YouTube or other social media forum.

Table 1: Instructions to the student for completion of the video assignment

For this final assignment, each of you will receive a unique pathomechanical movement pattern. Your assigned pattern will be delivered via the learning management system by the date specified in the syllabus. If you do not see or cannot find your prompt after that date, email me immediately. Your prompt will be randomly assigned to you. The deliverable will be an annotated and voiced-over video recording, approximately 1 minute in length. You will upload the video to a cloud service and submit the video link on our learning management system to fulfill the assignment.

Nuts & bolts of assignment:

1) Demonstrate the movement during a walking gait. Ideally you would be the person demonstrating. Also demonstrate what would be considered WNL/"normal" for your particular deviation. Be sure to capture the movement from the best plane and video angle. Your voiceover should provide explanation throughout.

2) State in which of the three cardinal planes this movement deviation lies.

3) Explain how this movement deviation will affect kinematics.

a. Briefly explain how it will affect joint-specific kinematics.

b. Explain how it will affect kinematics either up the chain or down the chain.

4) Explain how this movement deviation will affect kinetics. Keep in mind there are several different types of kinetics. You are free to discuss GRF, joint moments, center of pressure, center of mass, or any other kinetics. If you can explain the kinetics from a multi-joint perspective or a global body perspective, that would be best. (For instance, "for this movement pattern, the GRF will pass posterior to the X joint, creating a Y joint moment here and a Z joint moment there." or, "The center of pressure will be moved laterally, which will...")

5) State 1 musculoskeletal condition that could be caused by your abnormal movement pattern. Describe in detail how this movement could result in the injury/condition you give.

Ideas for Annotating

Don't be afraid to get creative with this assignment. If you think something will help you explain your point better, then go with it. In my mind, I'm picturing paused video at key moments, with angles drawn on joints that change when the deviation becomes abnormal. Imaginary joint moments and GRFs. The ideas are endless. Make sure to get good video, at the height and angle you need, which may change when looking up and down the chain. You will probably need more than 1 view of your movement pattern. Make sure to annotate/draw where/how the musculoskeletal condition can occur.

Voice-over

I expect proper terminology. Use anatomically appropriate and biomechanically sound terminology. You need to be specific in your wording and precise. You should be able to continuously explain and elaborate for a full 60 seconds. Don't assume that the video explains everything fully--make sure to state the needed components.

References

References are not required for this assignment. However, if you are struggling to put this in perspective and don't feel that you have a grasp of the material you need, then you need to read. The textbook can be helpful, but I recommend the Library website to search for some good literature. After going through those steps and coming up empty, I can likely direct you to some good reading material.

Table 2: List of potential musculoskeletal prompts for a video-based assignment

Frog-eyed patella	Anterior pelvic tilt
Hallux valgus	Hip adduction during mid and late stance
Lordosis	Limited hip flexion
Kyphosis	Coxa vara
Quad extension lag	Wide step width
Limited dorsiflexion	Pes planus
Rounded shoulders + forward head posture	Rearfoot valgus
Limited femoral internal rotation	Tibial torsion

Table 3: Rubric provided to the students for this assignment

	Excellent	Mediocre	Poor
Video and Voiceover **(20 points available)**	Contains appropriate and thorough viewing angles, annotations are helpful and clear, and voiceover supplements and clarifies the video (18-20 points)	Viewing angle is not ideal or annotations are not helpful or voiceover does not clarify the video (11-17 points)	The joint(s) or interest are difficult to see or the voiceover is difficult to understand or interpret (0-10 points)
Correct demonstration of movement anomaly **(10 points available)**	Correctly and clearly demonstrates the movement anomaly (8-10 points)	Demonstrates the movement anomaly, but not clearly or too subtle (5-7 points)	Does not demonstrate the movement pattern correctly (0-4 points)
Correct ID of plane of movement anomaly **(10 points available)**	Correctly IDs the plane of movement (8-10 points)	NA	Does not correctly ID the plane of movement (0-4 points)
Description of joint-specific kinematic implications **(10 points available)**	Accurately IDs how movement anomaly will influence joint-specific kinematics (8-10 points)	IDs generally how joint-specific kinematics will be impacted, but minor details are wrong (5-7 points)	Unable to describe how kinematics will be influenced. (0-4 points)
Description of kinematic implications throughout the chain (10 points available)	Accurately IDs how movement anomaly will influence global kinematics, with near exhaustive discussion of salient kinetic chain segments (8-10 points)	IDs generally how kinematics will be impacted, but minor details are wrong or omitted salient kinetic chain segments (5-7 points)	Unable to describe how kinematics will be influenced. (0-4 points)
Description of kinetic implications **(20 points available)**	Accurately and thoroughly describes 1 kinetic variable and how it influences multiple joints (18-20 points)	Accurately describes 1 kinetic variable, but key points are missed or the description is limited to 1 joint (11-17 points)	Does not ID any kinetic implications (0-10 points)
Accurate ID and description of possible MSK condition **(20 points available)**	Presents common and plausible MSK injury/condition and sound supporting rationale (18-20 points)	Presents feasible MSK injury/condition, but supporting rationale is incomplete or is based on unsound biomechanical principles (11-17 points)	Presents an MSK injury/condition that does not follow from the movement pattern given (0-10 points)

3. Discussion

The purpose of this paper was to present a pedagogical strategy as a method for improving not only content mastery of pathomechanical movement disorders (Greene, 2014), but also the “softer” skills associated with communication and presentation (Seiber, Schweikhart, and Bogacz, 2018). While there is evidence that student-generated videos improve myriad aspects of student engagement and learning, concrete strategies for use in professional education for healthcare providers is lacking. This brief experiential report provides considerations for further work to assess empirically the efficacy of student-created videos to improve learning outcomes in future healthcare professionals.

4. Advantages

There are several advantages to using learner-generated videos as an assessment of pathomechanical knowledge in athletic training. Namely, this technique encourages collaboration among class members. Because each student is assigned their own distinct prompt, they are free to brainstorm, communicate, and work collaboratively, helping each other through thought processes and presentation of the video content. In the same vein, academic integrity is not a concern for the instructor. The students are given their individual prompts weeks in advance and encouraged to communicate with the instructor and other classmates to work out their thinking processes, rending a truly collaborative assignment between the instructor and students (Gelman and Tosone, 2006) which can be used for face-to-face or remote learning paradigms, which has been demonstrated as an effective asynchronous tool for basic science courses (Graul et al., 2022). Additionally, the present pedagogical technique encourages students to synthesize information across a variety of related courses, which further emphasizes higher-order critical thinking. Finally, the resulting video products are a mere 1-2 minutes each. With the accompanying rubric, these are simple assignments to grade on a short timeline.

5. Disadvantages

The primary disadvantage associated with this technique is the necessity of advanced technology. As such, it is easiest to replicate in a collegiate or university setting in which myriad resources are available. However, with the advent of social media-related online editors such as CapCut or Adobe Premiere Rush, there are free and low-cost options. It is recommended to encourage students to use institutional resources as able, to render the highest-quality end-product. However, this can lead to accessibility concerns, in that access to institutional technology may be limited to library working hours. If you are not working with a library, the professor will have to invest time in learning the software in order to support the project. Additionally, the time required to compile and create videos has been reported as a barrier to students (Speed, Lucarelli, and Macaulay, 2018, Greene and Crespi, 2012). Thus, it is highly recommended to enlist a technology consultant to provide instruction and expertise for students.

Furthermore, one potential pitfall of the pedagogical strategy presented herein is related to grading of the assignment. Some report that assessment criteria often do not focus on content learned, but instead on visual quality of the end product (Schuck and Kearney, 2006). While technical quality is necessary for superior communication, learning of the content should still be retained as the primary goal. The rubric provided in the present paper appropriately reflects this concept.

6. Future Directions and Conclusion

While beyond the scope of the current paper, future work can expand empirically upon instructional benefits of collaborating with multimedia librarians and incorporation of audiovisual technology into course assignments. For instance, pre-post surveys administered to students over different iterations of a multimedia assignment could yield valuable information as instructors continually hone their craft. Additionally, it would be valuable to inspect strategies such as creating video banks for lay education, or instituting peer review of student-generated videos (Graul et al., 2022). Presented herein is an assessment technique geared to engage students in synthesizing and communicating pathomechanical concepts in an audio-visual format. Graduate AT education affords opportunity for such high-level assessments; additionally, learner-generated videos offer numerous advantages to student engagement and learning. Advantages of this strategy are greater student-student and instructor-student collaboration and brainstorming, active learning, and development of 21st century multimedia communication skills.

The authors declare that the preceding report was conducted in the absence of any commercial or financial relationship that could be construed as a conflict of interest.

Ethics Declaration: Ethics approval was not required for this study.

Use of Artificial Intelligence Statement: No artificial intelligence was used in the development of this paper.

References

Anderson, L. W. & Krathwohl, D. 2001. *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives*, Addison Wesley Longman.

Ariza, J. Á. 2023. Bringing active learning, experimentation, and student-created videos in engineering: A study about teaching electronics and physical computing integrating online and mobile learning. *Computer Applications in Engineering Education*, 31**,** 1723-1749.

Baclay, L. J. 2020. Student-created videos as a performance task in science. *International Journal of Research Studies in Education*, 10.

Balikçi, H. C. & Karataş, S. 2024. Student-Generated Videos: A Bibliometric Analysis and Systematic Review. *Bartın Üniversitesi Eğitim Fakültesi Dergisi*, 13**,** 147-161.

Campbell, L. O., Heller, S. & Pulse, L. 2020. Student-created video: an active learning approach in online environments. *Interactive Learning Environments*, 30**,** 1145-1154.

Gelman, C. R. & Tosone, C. 2006. Making It Real: Enhancing Curriculum Delivery Through the Use of Student-Generated Training Videos. *Journal of Technology in Human Services*, 24**,** 37-52.

Genereux, B. & Mangione, E. 2009. Enhancing Student Learning with Video Projects. *2009 Annual Conference & Exposition*. Austin, Texas.

Graul, B., Rollins, M., Powers, N. & Della Corte, D. 2022. Student created video content for assessment, experiential learning, and service. *The Physics Teacher*, 60**,** 491-495.

Greene, H. 2014. Learning through student created, content videos. *International Journal of Arts & Sciences*, 7**,** 469-478.

Greene, H. & Crespi, C. 2012. The Value of Student Created Videos in the College Classroom - An Exploratory Study in Marketing and Accounting. *International Journal of Arts & Sciences*, 5**,** 273-283.

Khalid, A. 2014. Use of student-generated videos to enhance teaching quality in aerospace engineering classes. *ASEE Southeast Section Conference*. American Society for Engineering Education.

Marley, K. A. 2014. Eye on the Gemba: Using Student-Created Videos and the Revised Bloom's Taxonomy to Teach Lean Management. *Journal of Education for Business*, 89**,** 310-316.

Morgan, H. 2013. Technology in the Classroom: Creating Videos Can Lead Students to Many Academic Benefits. *Childhood Education*, 89**,** 51-53.

Orús, C., Barlés, M. J., Belanche, D., Casaló, L., Fraj, E. & Gurrea, R. 2016. The effects of learner-generated videos for YouTube on learning outcomes and satisfaction. *Computers & Education*, 95**,** 254-269.

Pereira, J., Echeazarra, L., Sanz-Santamaría, S. & Gutiérrez, J. 2014. Student-generated online videos to develop cross-curricular and curricular competencies in Nursing Studies. *Computers in Human Behavior*, 31**,** 580-590.

Schuck, S. & Kearney, M. 2006. Capturing Learning through Student-Generated Digital Video. *Australian Educational Computing*, 21**,** 15-20.

Seiber, E., Schweikhart, S. & Bogacz, A. 2018. Comparing student perceptions of two pre-class engagement methods: online quizzes & student-created videos. *The Journal of Health Administration Education***,** 107-114.

Snelson, C. 2018. Video production in content-area pedagogy: a scoping study of the research literature. *Learning, Media and Technology*, 43**,** 294-306.

Speed, C. J., Lucarelli, G. A. & Macaulay, J. O. 2018. Student Produced Videos - An Innovative and Creative Approach to Assessment. *International Journal of Higher Education*, 7.

Sullivan, B. 2001. Developing 21st Century Skills with Student-Created Videos. *Ubiquitous Learning: An International Journal*, 5**,** 49-55.

Thomas, K. A. & Marks, L. 2014. Action!: Student-Generated Videos in Social Work Education. *Journal of Technology in Human Services*, 32**,** 254-274

Toward a Unified Framework for Evaluating Online Education Quality

Ibrahim Tanko Gampine[1], Bassirou Niang[1,2] and Kossi Kawedia Yakoubou[3]
[1]Université Paul Valéry (UFR4), laboratoire CORHIS, Route de Mendes, Montpellier France
[2]Université de Thiès, Sénégal
[3]Université de Kara, laboratoire LaRSEG, Kara, Togo

ibrahim.gampine@univ-montp3.fr
bassirou.niang@univ-thies.sn
kawekos@yahoo.fr

https://doi.org/10.34190/ejel.23.4.4280

Abstract: E-Learning has become a global phenomenon. It makes learning more accessible and acquisition of new skills and knowledge easier. In sub-Saharan Africa, however, online qualifications are often the subject of controversy regarding their recognition. This is clear evidence of unsuitable e-Learning systems, as well as the limited relevance of the programs they offered in addressing the Africans' context-specific needs. Despite the multitude of studies on the quality of online education, inconsistencies in findings make not only comparisons between studies difficult but also complicate the assessment of quality online education. To address this issue, this study integrated the Kirkpatrick with DeLone & McLean models to identify core quality dimensions. Furthermore, this study clarified the context-specific requirements of the identified dimensions. Ten hypotheses were tested using online survey questionnaires administered to four higher education institutions via Qualtrics. The findings supported eight hypotheses and rejected two. This model highlights the critical role played by system quality, the quality of course content, faculty and institutional support in enhancing learning. Furthermore, the model establishes a clear cause-and-effect pathway useful in addressing poor learning outcomes. We discussed the implications of the findings in the context of sub-Saharan Africa. The model is simple, theoretically sound, and comprehensive for real-life applications. Specifically, this study highlighted the importance of both formative and summative evaluations. Further qualitative studies on the context-specific requirements of the dimensions would be desirable.

Keywords: Quality education, e-Learning, Online learning, Kirk Patrick model, DeLone & McLean model, Quality assessment, Developing country

1. Introduction

Following the outbreak of the COVID-19 pandemic, e-Learning has become more important than ever. Online education plays an important role in developing human resources. In Africa, the e-Learning market is growing faster due to the rapid adoption of mobile devices, digital technologies, and internet services. In 2024, the market was valued at USD 3,411.38 million and it is projected to grow at a compound annual growth rate of 19.20% between 2025 and 2034. It is expected to reach an impressive USD 19,755.71 million by 2034, (e-Learning Africa, 2025). Revenue is expected to grow at an annual rate, resulting in a projected market volume of US$1.49 billion by 2029 (Statista, 2025). This growth highlights the immense potential of e-Learning to meet the diverse educational needs of Africa's population. However, ensuring quality remains a critical obstacle to the continued growth of e-Learning . Kotler (2019) defines quality as the provision of a distinctive product or service that satisfies the user's needs. According to the United Nations International Children's Emergency Fund (UNICEF, 2024), quality education means providing learners with access to basic literacy and numeracy without fear of exclusion.

By contrast, Green (1994) defines quality in education as producing graduates who meet the demands of private and public sector organisations. Lee-Post (2009) defines online learning as technology-mediated education dependent on quality of design and delivery. The increasing shift from traditional to online higher education (Hafeez, Naureen, & Sultan, 2022) makes discourse on quality assurance crucial. Barbour and Clark (2016) reported low performance among students in online education. One needs to determine the antecedents of quality online education and their contextual relevance in addressing the problems of quality online learning. While some existing studies have used subjective measures, others have adopted existing models (Barteit et al., 2020; Esfijani, 2018) to identify the antecedents of quality e-Learning . However, each study has a distinct framework with different quality dimensions (Khan et al., 2023; Tan, Chan, & Mohd Said, 2021). This makes assessment and comparison between studies challenging. Therefore, this calls for the need of a standardized

Cite this article: Gampine, I.T, Niang, B. and Kawedia Yakoubou, K. 2025. "Toward a Unified Framework for Evaluating Online Education Quality", *Electronic Journal of e-Learning* , 23(4), pp 37-52, https://doi.org/10.34190/ejel.23.4.4280

assessment framework for online education. To address this problem, we asked the following research questions:

RQ1: What are the critical dimensions of quality e-Learning education in Sub-Saharan Africa?

RQ2: How do these dimensions interact to influence perceived quality education?

RQ3: Can integrating Kirkpatrick and DeLone & McLean into an input–process–output framework provides a more consistent and comprehensive assessment model?

The effect of Western education remains apparent, despite the efforts made to contextualise the African educational curricula. This creates the need for an educational curriculum that addresses Africa context-specific needs (Masenya, 2021). Based on this assumption, we conceptualize quality education as an education that is accessible, relevant, and satisfactory to the needs of stakeholders. We approach this problem by anchoring on a theoretical framework that integrates the Kirkpatrick with the DeLone and McLean model. The Kirkpatrick model has gained popularity as a framework for measuring the effectiveness of teaching and learning in higher education (Cohen, Nørgård, & Mor, 2020). Likewise, DeLone and McLean (2003) model is useful in assessing the quality of information systems. Further, we draw insight into the input-process-output framework (Galais et al., 2021) to classify the dimensions of the two models; this is because of the interdependencies between the identified constructs (Tamkin et al., 2002). This study equally discussed the relevance of the identified dimensions with respect to the African context.

This study is significant, as it is the first to integrate the Kirkpatrick model with the DeLone and McLean model. Specifically, this integrated model links the technical system to other learning interventions such as course content, faculty, and institutional support. This model highlights the critical role of both formative and summative evaluations. Learners' satisfaction with system quality, quality of course content, faculty, and institutional support enhance the acquisition of knowledge. Besides, viewing quality education as a system emphasizes the need to classify quality dimensions based on the input, process, and output levels when addressing quality-related problems. This study lays the foundation for future studies to explore the potential of this integrated model in the assessment of quality online education. Unlike previous studies, this integrated framework supports both formative and summative evaluations. This implies that poor-quality education can be attributed to inadequate system quality, information quality, faculty or institutional support.

According to Statista, over 130 million children and youth in Sub-Saharan Africa were out of school as of 2022. This study highlights the importance of system quality, information quality, faculty or institutional support and their contextual relevance in the design and delivery of e-Learning in sub-Saharan Africa. Therefore, this study contributes to the achievement of the Sustainable Development Goal n°4, which is the commitment to promoting inclusive quality education and learning opportunities. This model is simple, theoretically based, and comprehensive for real-life applications. It provides clarity and consistency in how the various dimensions interact to produce quality education. The framework is a useful tool for instructional designers and quality assessment professionals. They can draw insights from the core quality dimensions with the three different levels of assessment when addressing quality-related challenges. We organized this study into three sections. The first section presents the theoretical background of the study. The second section outlines the methodological approach, data collection procedure, and analysis techniques. The final section presents the discussion, implications, and perspectives for future research.

2. Theoretical Background

2.1 Inconsistencies in Online Quality Education Assessment

We found inconsistencies in the studies of online quality education assessment. While some studies anchored on the Kirkpatrick model to assess quality online education (Quinton et al., 2022; Cahapay, 2021), others relied on the D&M model (Çelik & Ayaz, 2021; Lee-Post, 2009). Besides, some authors used other theoretical models (Almaiah et al., 2022; Tan, Chan, & Mohd Said, 2021) or subjectively selected dimensions (Altun & Johnson (2023; Safdar et al., 2020). In a meta-analysis of the literature, Isfijani (2018) revealed the lack of consensus on online education assessment. Besides, Tan, Chan, & Mohd Said (2021) found quality instruction, online interaction, and instructional and technical support as the factors that enhance the quality of online higher education. In a quantitative study of 273 university students in Pakistan, Safdar et al. (2020) found comfortability in computer usage, self-motivation, confidence and time spent on learning as important to quality online education. Though their study contributes to research by outlining employee-level antecedents, it failed to anchor on a theoretical framework. This implies that the choice of their antecedents was subjective.

Moreover, Marciniak (2018) draws insights from existing models to administer a questionnaire to 23 Spanish online education experts. She found training objectives, student profiles, training contents, learning activities, online teacher profiles, didactic materials, learning strategies, learning assessments, and tutorials as critical online dimensions. This study outlined the importance of institutional-level antecedents, but it provides no evidence of causal relationships. Conversely, in a qualitative study of 8 online education programme directors in the USA, Altun and Johnson (2023) found that students' needs, changes in education, the educational system, leadership, continuous improvement, the integration of learning and teaching theories, research on online education, and the quality of instructors contribute to achieving quality education. Similarly, in a thematic content analysis Wright et al. (2023) found course design, instructor facilitation, quality online infrastructure, and student engagement as key to achieving quality education. Despite the inclined bias and subjectivity, these studies contribute to literature by suggesting dimensions that are not evident in the existing models.

On the other hand, a systematic review of literature by Hafeez, Naureen & Sultan (2022) highlighted the importance of learner-teacher interaction, learner's prompt feedback, support service, and appropriate technology. In a study inspired by the D&M model, Çelik and Ayaz (2021) collected data from 882 university students in Turkey to assess the effectiveness of online learning using system quality, information quality, and service quality through the mediating role of system use and user satisfaction. These studies contribute to existing literature by emphasising the importance of technical and non-technical dimensions in enhancing quality education. The Online Learning Consortium (OLC, 2024) developed a balanced scorecard that outlines institutional support and technology support, course development or instructional design, course structure, teaching & learning, social and student engagement, faculty support, student support, and evaluations and assessment as dimensions to quality online education. Though the above review contributes to our understanding of dimensions that contribute to quality education, the inconsistencies in quality dimensions make quality assessment difficult for professionals and complicate comparison between studies. Furthermore, there is limited evidence of their applicability in the context of sub-Saharan Africa.

2.2 Quality Education Assessment Using the Kirkpatrick Evaluation Model

According to Smidt et al. (2009), a training evaluation model assesses whether a training intervention meets the needs of organising institutions and the training participants. There exist many learning evaluation models but the best known and the most widely used is the Kirkpatrick model (Alsalamah & Callinan, 2022; Cahapay, 2021). The overview of publications of the Kirkpatrick model shows that research in the area is still active and growing (Alsalamah & Callinan, 2022). It provides a holistic understanding of the key dimensions required to ensure high-quality training outcomes (Alsalamah & Callinan, 2021). Recent studies have explored training evaluation using the Kirkpatrick model (Mosquera et al., 2023; Peters & Gohlich, 2023; Quinton et al., 2022; Alsalamah & Callinan, 2021). Inspired by this model, Quinton et al. (2022) evaluated young people's reactions to learning in the context of community-based development learning in the United Kingdom. The findings of data collected from 301 young people living in housing services showed that higher-level engagement leads to positive reactions, whilst enjoyment positively predicted learning outcomes through the mediating effect of transfer intention. Whilst this study contributes to highlighting the role of programme enjoyment and the students' level of engagement in enhancing learning, the choice of its dimensions remains rather subjective and outside the control of the learning institution.

Furthermore, Alsalamah and Callinan (2021) evaluated reaction to learning, learning, behaviour and training outcomes of training programmes for 250 female head teachers and 12 supervisors in Saudi Arabia. Their approach helps determine the strengths and weaknesses of a training evaluation process, but it failed in examining the relationships between the learning antecedents (training content, training method, trainer skills, and training environment) and the organisational bottom line. Moreover, Peters and Gohlich (2023) adapted the Kirkpatrick's evaluation model to examine reaction, learning, transfer and transformative learning outcomes using 29 postgraduate students at a German university. The findings suggest that the group coaching was effective on all levels and fostered transformative learning. On the other hand, Rahmawati and Lukito (2020) evaluated the effectiveness of employee training in a hospital. The results of data collected from 55 employees found that the four-level hypothesis has a significant impact on the training programme effectiveness. Mosquera, Suarez, & Guerrero (2023) assessed learning efficiency using an experimental design of 82 programming students divided into an experimental and control groups. The findings showed no differences in the submission time between the experimental and control groups. However, the results revealed differences in the values of grades. This study contributes to assessing learning by using pre-tests and post-tests, but it failed to outline learning antecedents and any causal links between them and grades. In addition, the sample size of these studies is inadequate to warrant any generalisability.

Studies based on the Kirkpatrick model have helped us to understand how to measure learning by emphasising the importance of evaluating learning at upper and lower levels. However, their main limitation is that they failed to consider learning antecedents and their causal relationships. This limits their ability to probe the critical factors that impede on learning effectiveness (Aluko & Shonubi, 2014). The studies inspired by the Kirkpatrick model focus more on the levels of measurement. They ignore the role of the learning antecedents (training content, trainer skills, training environment and training methods, etc.) and their effect at each level. The trainee's or learner's feelings toward the course content, instructor ability, training environment, material, and learning activities are assessed at the reaction level (Abdulghani et al., 2014). Cahapay (2021) criticizes the Kirkpatrick model for its rigidity and focus on the lower-level criteria but also the paucity of evidence on the causal chains among the levels. The consideration of context in the design and delivery of learning effectiveness in higher education is critical (Cahapay, 2021). Few studies tested the Kirkpatrick model in an African context using university students as their target population. The Kirkpatrick model is simple and pragmatic (Tamkin, Yarnall, & Kerrin, 2002); it offers the opportunity for adaptation (Capahay, 2021). We present the Kirkpatrick model and their corresponding objectives in Table 1 below.

Table 1: The four levels of the Kirkpatrick training model

Levels	Objectives
Level 1 (reaction)	To assess the participants thoughts of the programme content, teaching material, learning environment, instructor, etc. It is normally measured using questionnaires.
Level 2 (learning)	To assess changes in knowledge, skills, or attitude concerning the training objectives; it is objectively measured using performance tests.
Level 3 (behaviour)	To assess changes in job behaviour resulting from the program, to identify whether the learning is being applied. Assessment methods include observation and productivity data.
Level 4 (Outcomes)	To assess the bottom-line contribution of the training program. Methods include measuring costs, quality, and return on investment (ROI).

Source: Adapted from Tamkin et al. (2002).

2.3 Quality Education Assessment Using the DeLone & McLean Model

Information systems have become pervasive and critical for the survival of today's organizations. Laudon and Laudon (2009) define an information system as a combination of hardware and software technologies that collect, store, and process data into useful information for decision-making purposes. DeLone and McLean (2003) models have six different dimensions. They were system quality, information quality, use, user satisfaction, individual impact, and organizational outcome. A later study refined the model to integrate service quality and replaced organizational impact with net benefits. The key information systems success factors are organized at three levels (Lee-Post, 2009). The first level addresses design quality, the second level measures delivery quality, and the final level assesses the outcome. We present the dimensions of the D&M model in Table 2 below.

Table 2: The dimensions of D&M model

S#	Construct	Measurement
1.	System quality	To evaluate ease of use, system flexibility, system reliability, and ease of learning, as well as system features of intuitiveness, sophistication, flexibility, and response times.
2.	Information quality	To assess relevance, understandability, accuracy, conciseness, completeness, understandability, timeliness, and usability.
3.	Service quality	To analyse the responsiveness, accuracy, reliability, technical competence, and empathy of the IT personnel staff.
4.	Use	To evaluate the amount of use, frequency of use, nature of use, appropriateness of use, extent of use, and purpose of use.
5.	User satisfaction	To evaluate user feelings or satisfaction
6.	Net benefit	To analyse improved decision-making, improved productivity, increased sales, cost reductions, improved profits, market efficiency, consumer welfare, creation of jobs, and economic development.

Source: Adapted from D&M model (2016).

2.4 Integrating Kirkpatrick to DeLone & McLean Models

DeLone and McLean's model was used in measuring system effectiveness (Çelik & Ayaz, 2022), while the Kirkpatrick model assesses learning effectiveness (Smidt et al., 2009). The Kirkpatrick and DeLone & McLean models were exclusively used to measure learning effectiveness in higher education (Mosquera et al., 2023; Çelik and Ayaz, 2022; Mkinga & Mandari, 2020). As D&M model, the key dimensions of the Kirkpatrick model are also interdependent (Tamkin, Yarnall, & Kerrin, 2002). This implies that each model is a system in its own with a structured organism composed of interdependent components. Luhmann, Baecker, & Gilgen, (2013) defines a system as a set of interconnected things forming a complete whole with input, process, and output feedback. The objective of this study was to identify the critical dimensions of online quality education assessment using the D&M and Kirkpatrick models. As a result, we classified the components of each model based on the input-process-output model (Galais et al., 2021).

Inputs are the primary means used to create value (Lannelongue, Gonzalez-Benito, & Gonzalez-Benito, 2015). At the input level, Kirkpatrick's reaction level represents the system quality, information, and service quality. A reaction is the learner's perception of the effectiveness of interventions in delivering a training program (Rahmawati & Lukito, 2020). Based on the context of this study, we operationalized the service quality to "faculty and institutional support" and the information quality to "quality of course content." Recent studies have highlighted the impact of system quality on information system effectiveness (Lufti, 2023; Almaiah et al., 2022). Other studies have reported a positive and significant relationship between technical and institutional support (Hafeez, Naureen, & Sultan, 2022); Tan, et al., 2021). Besides, some components of the integrated model are classified at the process level. For instance, Dennis and Meredith (2000) described the process as a value-addition mechanism. The dimensions of the two models that illustrate value addition are use, user satisfaction, learning, and behavioural change.

Based on the context of this study, we adopted learner satisfaction and acquisition of knowledge as the process dimensions. We adapted the user's satisfaction to learner satisfaction and learning and behavioural change to acquisition of knowledge. Studies have examined learning as a mediating variable (Quinton, et al., 2022), while others use user satisfaction (Almaiah, et al., 2022; Çelik and Ayaz, 2022; Ali & Jaafrey, 2017). Finally, an outcome is expressed either qualitatively or quantitatively (Lannelongue, Gonzalez-Benito, & Gonzalez-Benito, 2015). The most widely used e-Learning outcomes are information system success, organizational performance, quality education, and net benefits (Alsalamah & Callinan, 2022; Delone & Mclean, 2003). For the context of this study, we adopted quality education as the dependent variable. We present the dimensions of the integrated model in Table 3 below.

Table 3: The proposed integrated model

Characteristics	D&M Model	Kirkpatrick Model	Integrated Model
inputs	system quality, information quality, and service quality	Reaction	Reaction; satisfaction with system quality, course content, teacher and institutional support.
Process	Use, user satisfaction	Learning and Behavioural Change	Acquisition of knowledge, and learner's satisfaction,
outputs	net benefits	Organizational Outcome	Quality education

Source: Literature review

Based on the above taxonomy and the review of literature, this study proposes six ideal online learning dimensions. They are system quality, quality of course content, faculty and institutional support, acquisition of knowledge, learner satisfaction, and quality education. The proposed theoretical model is shown in Figure 1:

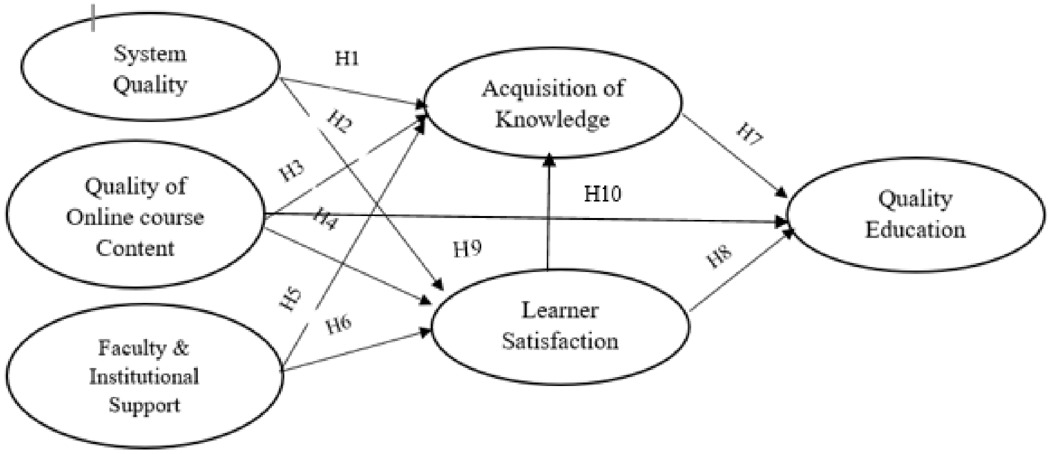


Figure 1: Theoretical model

Based on the above model, we formulate the following hypotheses:

H1: System quality positively relates to quality education.

H2: Quality of course content positively relates to quality education.

H3: Faculty and institutional support positively relate to quality education.

H4: Acquisition of knowledge mediates the relationship between system quality and quality education.

H5: Acquisition of knowledge mediates the relationship between quality of course content and quality education.

H6: Acquisition of knowledge mediates the relationship between faculty and institutional support and quality education.

H7: Learner satisfaction mediates the relationship between system quality and quality education.

H8: Learner satisfaction mediates the relationship between quality of course content and quality education.

H9: Learner satisfaction mediates the relationship between faculty and institutional support and quality education.

H10: Learner satisfaction positively affects acquisition of knowledge.

3. Research Methodology

3.1 Population and Sampling

This study adopted a quantitative approach. We conveniently administered questionnaires to four (4) higher educational institutions in Africa. These institutions are from Ghana, Burkina Faso, and Senegal. We opted for this sampling technique, as we were unable to randomly select participants. Because the selected institutions only agree to administer the questionnaire on their online platforms, this limits randomization. Easterby-Smith, Thorpe & Jackson (2018) describe convenience sampling as the use of an accessible sample in a population. They note that its sample characteristics limit its generalisability to a study population but can still be useful depending on the purpose of the study. This aligns with the objective of this study, which is to examine the relations between the identified constructs in the study context but not to generalize the findings. The choice of institutions is based on their strong online educational experience and blended teaching and learning delivery at the graduate and undergraduate levels.

The ethical guidelines for data collection and processing were strictly adhered to. Students were asked to voluntarily take part in the survey. They were also assured of the confidentiality of their responses. An online survey instrument was pilot tested before being administered to students via Qualtrics. The results of the pilot study showed Cronbach Alpha values for all studied constructs higher than 0.70. The link to the questionnaire was then published on the universities' online platforms upon approval from the various administrations. Regular reminders were sent, and the data collection lasted two months, from February to April 2024. 369 responses were received, and 36 were not useful to be part of the analysis, so they were discarded. Only 333 valid responses were included for analysis. The greater number of respondents are undergraduates (n = 175), representing 52.55% of the population. Most participants are from public institutions (n = 268), representing 55.85%. The respondents' demographic data are presented in Table 4 below.

Table 4: The respondents' demographic data

Variables	Classification	Frequency	Percentage %
Education level	Bachelor	175	52,55
	Master	158	47,45
	Total	333	100,00
Sex	Male	195	58,56
	Female	137	41,44
	Total	333	100,00
Age	20 to 25 years	245	73,57
	25 and above	88	26,43
	Total	333	100,00
Country	Ghana (2)	183	54,95
	Senegal (1)	85	25,53
	Burkina Faso (1)	65	19,52
	Total	333	100,00
Education sub-sector	Public	268	80,48
	Private	65	53,15
	Total	333	100,00

Source: Field data

3.2 Study Instrument

The six constructs were measured using previously validated scales. The first variable, system quality (SQ), was developed by Lee-Post (2009) and measured using five items. The items assessed the user's friendliness, reliability, and security of the information system. The second variable, the quality of course content (QOCC), was developed by Lee-Post (2009) and measured using four items, which assess the relevance and usefulness of course content. The third variable, faculty and institutional support (FIS) is developed by Hafeez, Naureen, & Sultan, (2022) and measured using four items that assess the availability and consistency of support from faculty and administration staff. The fourth variable, acquisition of knowledge (AK), is measured using four items identified from the literature; they assess completion of learning activities and ability to transfer learning. The fifth variable, learner satisfaction (LS), was developed by Lee-Post (2009) and measured using four items, which assess time spent learning, joy, and satisfaction in learning. The sixth variable, quality education (QE), is developed from Aledo-Ruiz, Martínez-Caro, & Santos-Jaén (2022) is measured using five items, which assess the quality of faculty members and infrastructure, the image, and pride for being associated with these institutions. Respondents were asked to rate the extent to which they agree with the questionnaire items on a five-point Likert scale, ranging from 1 = 'totally disagree' to 5 = 'totally agree.' Microsoft Excel was used to enter the coded data.

3.3 Data Analysis Techniques

Before performing the descriptive statistics, we used the Statistical Package for Social Sciences (SPSS) version 22 to look for outliers and missing data. This process ensures that the data to be analysed is clean and of high quality. Finally, SMARTPLS version 4 was used to evaluate the measurement and structural models. SMARTPLS does not require data to be normally distributed. Besides, Smart PLS has a user-friendly interface and supports small sample sizes (Adam, 2015). Compared to the covariance-based SEM, PLS-SEM provides a more consistent item loading that boost the reliability and validity of factors. However, in a path analysis, the two approaches produce similar results (Dash & Paul, 2021). Therefore, we proceeded to assess the measurement model for validity and reliability of the studied constructs. Finally, the structural models were used to estimate the formulated hypotheses. We controlled for the other demographic variables, such as country, sub-sector, and type of institution, because they are not of interest to the study's objectives (Frost, 2019).

4. Results of this Study

4.1 Measurement Model Analysis

We conducted confirmatory factor analyses (CFA) to test the psychometric properties of all the variables. The aim was to examine whether there was sufficient convergent and discriminant validity among all constructs. According to Hair et al. (2021), factor loading, average variance extracted (AVE), and composite reliability (CR) are critical tests to use to assess convergent validity. Apart from the faculty and institutional support, the composite reliability values for all the other constructs exceeded the minimum threshold of 0.70. The average variance extracted for all constructs was also higher than .50. Based on the values of the AVE, which were all greater than 0, it is concluded that the reliability of the measurement model is established. Results of the goodness of measures are presented in Table 5 below.

Table 5: The results of goodness of measures

Construct	Items	Loading	CR	AVE	VIF
Acquisition of knowledge	AK1	0,808	0,764	0,574	1.856
	AK2	0,719			1.849
	AK4	0,72			1.288
	AK5	0,656			1.266
Quality education	AR1	0,846	0,723		1.491
	AR2	0,821		0,53	1.402
	AR4	0,667			1.256
	AR5	0,678			1.260
Faculty and institutional support	FIS1	0,663	0,59	0,546	1.107
	FIS3	0,736			1.245
	FIS4	0,81			1.300
Learner satisfaction	LS1	0,666	0,743	0,565	1.546
	LS2	0,722			1.420
	LS3	0,74			1.407
	LS4	765			1.519
Quality of course content	QOCC1	0,759	0,741	0,552	1.434
	QOCC2	0,724			1.445
	QOCC3	0,793			1.463
	QOCC4	0,686			1.311
System quality	SQ2	0,739	0,743	0,565	1.524
	SQ3	0,706			1.413
	SQ4	0,815			1.704
	SQ5	0,742			1.480

Source: Statistical output

4.2 Discriminant Validity

Discriminant validity assesses how distinct a construct is from other constructs. It assesses how indicators represent only a single construct. The Heterotrait Monotrait (HTMT) ratios and the Fornell-Larcker criterion are the measurement criteria for discriminant validity. The decision rule for HTMT is that its ratio must be lower than a cut-off value of 0.85 (Henseler, et al., 2015). The Fornell–Larcker criterion decision rule is that the square root of the AVEs should be greater than the correlations of the constructs (Henseler, et al., 2015). For the HTMT, constructs that are conceptually more distinct have lower and more conservative threshold values of less than 0.85 (Henseler et al., 2015). The observed values in Table 6 below indicate that this study has acceptable convergent and discriminant validity.

Table 6: The results of discriminant validity

	Heterotrait monotrait						Fornell-Larcker criterion					
	AK	QE	FIS	LS	QOCC	SQ	AK	QE	FIS	LS	QOCC	SQ
AK							0.757					
QE	0.738						0.395	0.728				
FIS	1.035	0.721					0.689	0.406	0.739			
LS	0.520	0.871	0.660				0.384	0.720	0.367	0.752		
QOCC	0.826	0.616	0.816	0.644			0.621	0.456	0.601	0.483	0.743	
SQ	0.767	0.669	0.774	0.695	0.745		0.578	0.488	0.516	0.517	0.662	0.752

Source: Statistical output

4.3 The Goodness of Fit Model Test

The goodness-of-fit model was tested using R^2, F^2, and Q^2 values. The R^2 represents the variance explained in each of the endogenous variables, and it is a measure of the explanatory power (Shmueli & Koppius, 2011); it is also referred to as in-sample predictive power (Rigdon, 2012). The threshold values for endogenous constructs are 0.26 = substantial, 0.13 = moderate, and 0.02 = weak (Cohen, 1988). F^2 complements the R^2 test by assessing a change in R^2 when an exogenous variable is removed from the model. It is also referred to as effect size. According to Cohen (1988), the effect size is small at 0.02, medium at 0.15, and high at 0.35. Q^2 is a predictive relevance test that uses in-samples and holdout samples to measure whether a model has predictive relevance. A Q^2 value above 0 shows the model has predictive relevance. Table 7 below shows that all the endogenous latent variables had an R^2 value ranging from 0.304–0.563; therefore, the developed model is at a higher level for predicting endogenous variables. Table 7 below also shows that all endogenous latent variables had an F^2 value in the range of 0.003–0.089; therefore, the developed model has a high predictive relevance. Finally, Table 7 below shows that all endogenous latent variables had a Q^2 value ranging from 0.185 to 0.0563. Therefore, we can conclude that this model has predictive relevance. The results of the fit measures are presented in Table 7 below:

Table 7: The results of fit measures

Exogenous construct	Endogenous Construct	R-square	F-square	Q-square
SQ	AK	0,563	0,051	0.563
QOCC	LS	0,304	0,089	0.185
FIS			0,048	
			0.293	
			0.003	
			0,034	
AK	QE	0,535	0,036	0.180
LS			0,083	

Source: Statistical output

4.4 Testing of Hypotheses

Our study used bootstrapping of 5000 samples to test the relationship among latent variables. Significance is assessed through the p-value, T statistics, and coefficient of relationship. After confirming the goodness of the measurement model, we proceeded to examine the studied structural model. A relationship is significant if its p-value is < 0.05 and T statistics are > 1.96 (t-value two-tail, α 5%), whilst a p-value > 0.05 and T statistics < 1.96 (t-value two-tail, α 5%) mean that, the correlation is not significant (Hair, et al., 2021). Out of the ten formulated hypotheses, eight were validated against two rejected. The direct association between system quality and quality education is supported (β=0.254; p ≤ 0.000). Similarly, the direct association between quality of course content and quality education was accepted (β= 0.179; p ≤ 0.000). Likewise, the relationship between learner's satisfaction and acquisition of knowledge was confirmed (β=0.384, p ≤ .000). In contrast, the direct relationship between faculty and institutional support and quality education was rejected (β= 0.102; p = 0.051). Besides, this study has examined the mediating roles of acquisition of knowledge and learner satisfaction in the relationships between the independent variables and the dependent variable.

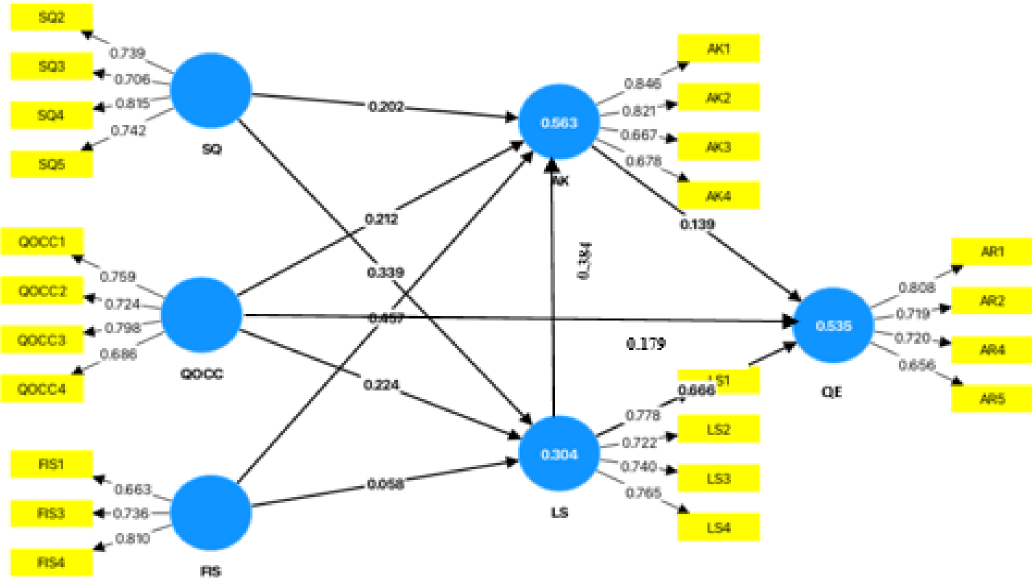
The first mediating hypothesis that acquisition of knowledge mediates the relationship between system quality and quality education is supported (β = 0.028, t = t=2.103 p ≤ 0.036). The second mediating hypothesis that learner satisfaction mediates the relationship between system quality and quality education is also supported (β = 0.226, t = t=4.702, p ≤ 0.000). The third mediating hypothesis is that acquisition of knowledge mediates the relationship between quality of course content and quality education is supported (β = 0.030, t = t=2.098, p ≤ 0.036). The fourth mediating hypothesis that learner satisfaction mediates the relationship between quality of course content and quality education is supported (β = 0.149, t = t=2.953, p ≤ 0.003). The fifth mediating hypothesis, that acquisition of knowledge mediates the relationship between faculty and institutional support and quality education, is supported (β = 0.064, t = t=2.215, p ≤ 0.027). However, the final mediating hypothesis that learner satisfaction mediates the relationship between faculty and institutional support and quality education is found not to be significant (β = 0.039, t = t=2.215, p ≤ 0.337); hence, this hypothesis is rejected. We present the results of the formulated hypothesized in Table 8 below.

Table 8: The results of formulated hypotheses

Hypotheses	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV)	P values	Decision
SQ->QE	0.254	0.200	0.060	3.381	0.000	Accepted
QOCC->QE	0.179	0.179	0.051	3.511	0.000	Accepted
FIS->QE	0.102	0.102	0.052	1.954	0.051	Rejected
LS->AK	0.384	0.030	0.068	4.999	0.000	Accepted
SQ->AK->QE	0.028	0.027	0.013	2.103	0.036	Accepted
QOCC->AK->QE	0.030	0.029	0.014	2.098	0.036	Accepted
FIS ->AK->QE	0.064	0.064	0.029	2.215	0.027	Accepted
SQ ->LS->QE	0.226	0.229	0.048	4.702	0.000	Accepted
QOCC->LS->QE	0.149	0.151	0.050	2.953	0.003	Accepted
FIS->LS->QE	0.039	0.039	0.044	0.883	0.377	Rejected

Source: Statistical output

The structural model of this study is presented in figure 2:



Source: Statistical output

Figure 2: Statistical model

5. Discussion

First, the objective of this study was to identify critical dimensions of quality in online education and then discuss their contextual relevance. To this end, the study integrated the Kirkpatrick with DeLone and McLean models to identify core quality dimensions. The integrated model shows the importance of system quality, quality of course content, faculty and institutional support, acquisition of knowledge, learner satisfaction, and quality education. Previous studies highlighted the role of system quality, information quality, and instructional and technical support (Wright, et al, 2023; Almaiah, et al, 2022; DeLone & Maclean, 2016). The design and implementation requirements of quality education are not universal but need to take account of the context-specific realities. In line with the sub-Saharan Africa context, we argue that learning systems should be optimized for mobile phones, since these are more accessible in Africa than computers. Furthermore, the technical system design must integrate lightweight materials such as compressed videos and downloadable PDF files or offer offline access to content due to the high cost of internet bandwidth in this region. Africa is a multicultural context with different ethnic groups and dialects, so instructional design must account for the local languages and dialects or offer translation subtitles. Africa needs a homegrown educational system that addresses the local challenges (Masenya, 2021; Cahapay, 2021).

In addition, the high level of illiteracy in this region requires an instructional design that accounts for varying literacy levels, using visuals and videos for low-level literacy users. Besides, the content design must also reflect the local realities, practices, and values, with more focus on collaborative learning than individualized learning. For instance, community-learning opportunities could be provided through group discussion and local mentorship. The course content must be free from bias and be inclusive of norms and cultural practices. It can be interactive and engaging, present real-life local scenarios. This indigenization of learning content will enhance learning outcomes by making it accessible and relevant (Cahapay, 2021; Masenya, 2021). The second objective of this study was to examine how the identified dimensions interact to influence perceived quality education. The dimensions of this study were classified into input, process, and output levels and operationalized as independent, mediating, and dependent variables (Galais et al., 2021). The relationships at each level are tested. Our findings show the direct effects of information systems on quality education (β=0.254; $p \leq 0.000$) and that of course content on quality education (β= 0.179; $p \leq 0.000$). This implied that students perceived quality digital infrastructure and relevant course content as catalysts to quality education. Previous studies corroborated these findings (Khan et al., 2023; Lufti, 2017; Delone & Maclean, 2016) but without emphasis on its critical role.

However, the direct effect of faculty and institutional support on quality education was not supported ($\beta=0.254$; $p \leq 0.051$). This finding contradicts the assumption of the existing literature that quality service as well as administrative and faculty support enhance organizational bottom lines (Altun & Johnson, 2023; Tan, Chan, & Mohd Said, 2021). The influence of both system quality and quality of course content might have overshadowed the support factors. Sometimes, the administrative staff are overburden with the day-to-day duties. This affects the quality of service they provide to students. In sub-Saharan Africa, often constrained by financial resources, educational service providers employ personnel who lack the requisite skills and competencies to perform faculty and administrative roles. These low-paid staff do not only lack the knowledge but also the motivation and commitment to support learners. There is a need for the top management of the concerned institutions to consistently examine their faculty and administrative support policies and strategies. This will ensure that they provide the support that meets the needs of their students. They need to motivate and provide training and development opportunities for their personnel. Studies have rather tested use, intention to use, and user satisfaction as the mediating variables (Lufti, 2023; Ali & Jaafrey, 2017). We contribute to the existing literature by testing the mediating roles of acquisition of knowledge and learner's satisfaction. Except for the mediating role of learner satisfaction in the relationship between faculty and institutional support, all the other mediating hypotheses were confirmed. The insignificant mediating effect of learner satisfaction in the relationship between faculty and institutional support and quality education implies the negative perceived role of administrative and faculty support by the students. This contradicts findings from existing literature (Lufti, 2023; Ali & Jaafrey, 2017). The context specific needs might explain these differences. Considering the contextual realities, students might have no clue of the support in question or merely such services are not up to the student's expectation. Therefore, it is important to motivate, train and develop the academic support staff.

Moreover, this study aims to investigate whether integrating the dimensions of Kirkpatrick and DeLone & McLean into an input–process–output framework would provide a more consistent and comprehensive assessment model for sub-Saharan Africa. This assumption is confirmed as most of the relationships were confirmed and supported by the study model (R^2, F^2, and Q values in table 7). Lufti (2023) argues that the D&M model has consistently proved to be unsuccessful in predicting behaviour. Besides, Aluko and Shonubi (2014) have criticized the Kirkpatrick model for failing to propose factors that impede learning transfer. This implies that none of the models can sufficiently explain the quality of e-Learning education. Kirkpatrick focuses on learning outcomes whilst D&M focuses on information system success. Thus, integrating these models reinforces their capacity in assessing quality online education. The combination of these models offers a holistic view to assessing both technical and non-technical interventions. Besides, the integration of the models highlights the importance of both formative and summative evaluations when assessing quality education. This establishes a clear cause-and-effect pathway. Moreover, it provides insights on how these critical dimensions interact together to produce a desirable outcome. This integrated model outlines the dimensions at the organizational level that are subject to institutional reconfiguration to enhance quality learning.

5.1 Implications and Limitations

Existing studies have used subjective measures to identify quality dimensions (Safdar et al., 2020; Marciniak, 2018). Others have borrowed dimensions from existing models (Lufti, 2023; Alsalamah & Callinan, 2022;). To the best of our knowledge, however, no study has examined the integration of the Kirkpatrick model to the D&M model. This study therefore extends existing literature by integrating complementary models: one that assesses learning evaluation and one that evaluates information system quality. This integrated model remedies inconsistencies in the existing literature by providing a unified and structured model that addresses gaps, overlaps, and misalignment in previous studies (Cahapay, 2021; Esfijani, 2018). In addition, using the input-process-output framework to classify quality dimensions enhances comparability among studies. Theoretically, this study highlighted the importance of contextual relevance in the formulation of e-Learning strategy. In practice, this model supports both formative and summative evaluations, as poor learning outcomes can be traced back to inadequate system quality. Similarly, quality technical infrastructure can lead to better learning outcomes.

The practical implication of this study is that policy and decision-makers at e-Learning institutions in Africa should advocate for online learning solutions that address a mix of technological, cultural, linguistic, pedagogical, and socio-economic realities of the region. As fully online qualifications are often subject to controversies for recognition in Africa, policy and decision makers must ensure that their course content conforms to local and regional standards. Adopting a technical system that is optimized for mobile phones and is energy and bandwidth efficient will enhance access to education. These outlined elements, coupled with context-specific instructional design that integrates local languages, can enhance access and the relevance of the online programmes. Quality assessment professionals could approach quality improvement from a system point of view with input-process-output analysis. Malfunctions at the process level, such as student dissatisfaction or poor performance, can result to bigger reputational problems. Finally, by recommending a context-specific design and delivery of e-Learning in a developing context, this study contributes to the achievement of the Sustainable Development Goal n°4, which is the commitment to promoting the delivery of inclusive but quality education and development opportunities. This model is simple, theoretically based, and comprehensive for real-life applications.

Despite the valuable insights gained from this study, several limitations warrant consideration. First, the use of self-reported questionnaires may introduce potential bias and inaccuracy. However, we have used cross-country data and controlled for this problem using Harman's single factor test to assess the total variance of the items. Common method variance remains a potential concern for studies that collect data using a self-reported questionnaire (Podsakoff, MacKenzie, & Podsakoff, 2012). The result reveals a value of 32.45% of total variance, which is less than the 50% threshold. This indicated that this study was free from common method bias. Future studies could use this integrated model with objective measures or collect data from multiple sources. They could also collect time series data. Additionally, the cross- sectional design may limit our ability to establish causality between the identified variables. Future studies could employ longitudinal methods with objective measures to provide a more nuanced understanding of these relationships in different contexts. Besides, the use of a convenient sampling technique limits the generalizability of the findings (Easterby-Smith, Thorpe, & Jackson, 2018). Future studies could adopt a simple random sampling technique using a larger sample size to test this model. Furthermore, our classification of dimensions using the input-process-output framework (Galais et al., 2021) may be somewhat subjective. Therefore, other studies could use different methods to categorize the dimensions of the Kirkpatrick and Delone & McLean models. Finally, as most of the respondents were undergraduates, our findings may not be generalizable to the graduate level.

5.2 Conclusion

Stakeholders are greatly concerned about the quality of online higher education assessment. Considering the growth of online education and its strategic importance for human resource development, it is critical to understand the critical dimensions that contribute to quality education. However, this has not been the case, given that we have a multitude of quality dimensions and assessment models. This makes quality assessment challenging and comparability between studies difficult. As a result, this study's objective was to identify the critical quality dimensions of online learning through the integration of the Kirkpatrick to DeLone & McLean models. Six dimensions, namely information quality, quality of course content, faculty and institutional support, acquisition of knowledge, learner satisfaction, and quality education were identified. Furthermore, the objective of this study was to propose a theoretically based quality assessment model based on the input-process-output framework. The findings of this study implied the appropriateness and suitability of the model in supporting both formative and summative evaluations. The integrated model offers a comprehensive lens to assess both technical and non-technical interventions of learning outcomes. This study emphasizes the critical role of the institutional-level dimensions, as learner-level dimensions such as time taken to study, learner's motivation are beyond the control of the training institutions. The thesis of this study is that certain dimensions are essential and should be consistent across studies. The integration of Kirkpatrick to D&M models revealed that these dimensions are course content, quality system, faculty, and institutional support. Adapting these dimensions to the region's specific needs, will enhance learning outcomes, bring economic and societal benefits to the region, and improve the recognition of online learning. The identified dimensions do not constitute an exhaustive list of institutional-level factors. Other factors, such as the learning environment, vision and mission statements, and ethical considerations, can be considered as moderating variables.

Acknowledgements

We would like to acknowledge the support of the concerned institutions for making this research project possible.

Ethics statement: Ethical review and approval were not required for this study in accordance with the local legislation and institutional requirements. Participation in the questionnaire was entirely voluntary, and all respondents provided informed consent before participating. No personal identifying information was collected, and data were analyzed anonymously to ensure participants' confidentiality.

AI statement: No AI was used at any point in the research, writing, or creating of this paper.

References

Abdulghani, H. M., Shaik, S. A., Khamis, N., Al-Drees, A. A., Irshad, M., Khalil, M. S., & Isnani, A. (2014). Research methodology workshops evaluation using Kirkpatrick's model: translating theory into practice. *Medical Teacher*, 36(sup1), S24-S29.

Adam, A., M. (2015). Statistics for business research: A Guide for non-statisticians. First Edition, ISBN-13: 978-1505358391. Global Research Publishers.

Aledo-Ruiz, M. D., Martínez-Caro, E., & Santos-Jaén, J. M. (2022). The influence of corporate social responsibility on students' emotional appeal in the HEIs: The mediating effect of reputation and corporate image. *Corporate Social Responsibility and Environmental Management*, *29*(3), 578-592.

Ali, B., & Jaafreh, A. (2017). Evaluation of information system success: applied delone and MClean information system success model in context banking system in KSA. *Assurance in Education*, 32(1), 1–16. Avaialble at https://doi.org/10.1108/QAE-05-2023-00836. [Accessed: 07 February 2024].

Almaiah, M. A., Al-Rahmi, A. M., Alturise, F., Alrawad, M., Alkhalaf, S., Lutfi, A., Al-Rahmi, W. M., & Awad, A. B. (2022). Factors influencing the adoption of Internet banking: An integration of ISSM and UTAUT with price value and perceived risk. *Frontiers in Psychology*, 13. Available at https://doi.org/10.3389/fpsyg.2022.919198. [Accessed: 01 September 2022]

Alsalamah, A., & Callinan, C. (2022). The Kirkpatrick model for training evaluation: Bibliometric analysis after 60 years (1959–2020). *Industrial and Commercial Training*, 54(1), 36–63. Available at https://doi.org/10.1108/ICT-12-2020-0115. [Accessed: 03 May 2024]

Altun, S. A., & Johnson, T. (2023). Online education directors' perceptions of leadership, management and administrative roles. *In Global Perspectives on the Internationalization of Higher Education* (pp. 300-314). IGI Global.

Aluko, F. R., & Shonubi, O. K. (2014). Going beyond Kirkpatrick's training evaluation model: The role of workplace factors in distance learning transfer. *Africa Education Review*, 11(4), 638–657. Available at https://doi.org/10.1080/18146627.2014.935007. [Accessed: 05 May 2022]

Barbour, M., & Clark, T. (2016). Cases of quality: Case studies of the approval and evaluation of K-12 online and blended providers. *In Society for Information Technology & Teacher Education International Conference* (pp. 809-815). Association for the Advancement of Computing in Education (AACE).

Barteit, S., Guzek, D., Jahn, A., Bärnighausen, T., Jorge, M. M., & Neuhann, F. (2020). Evaluation of e-Learning for medical education in low and middle-income countries: A systematic review. *Computers & Education*, 145, 103726.

Cahapay, M. (2021). Kirkpatrick Model: Its limitations as used in higher education evaluation. *International Journal of Assessment Tools in Education*, 8(1), 135–144. Available at https://doi.org/10.21449/ijate.856143. [Accessed: 20 February 2024]

Çelik, K., & Ayaz, A. (2022). Validation of the Delone and McLean information systems success model: A study on student information system. *Education and Information Technologies*, 27(4), 4709–4727. Available at https://doi.org/10.1007/s10639-021-10798-4. [Accessed: 07 May 2024]

Cohen, A., Nørgård, R. T., & Mor, Y. (2020). Hybrid learning spaces—Design, data, didactics. *British Journal of Educational Technology*, 51(4).

Cohen, J. (1988). Statistical Power analysis for the behavioural sciences (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*, 121092

Delone, W. H., & Mclean, E. R. (2016). Information systems success measurement. *Foundations and Trends® in Information Systems,* 2(1), 1–116. Available at https://doi.org/10.1561/2900000005. [Accessed: 09 May 2024]

Delone, W., & Mclean, E. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Journal. of Management Information Systems*, 19, 9–30. Available at https://doi.org/10.1080/07421222.2003.11045748. [Accessed: 11 May 2024]

Dennis, D. R., & Meredith, J. R. (2000). An analysis of process industry production and inventory management systems. *Journal of operations management*, *18*(6), 683-699.

Easterby-Smith, M., Thorpe, R., & Jackson, P. R. (2018). Management research. Sage. CA, Sage, 2018, 440 pp., ISBN 978-1-5264-2479-2, ISBN 978-1-5264-2479-8

Learning Africa (2025). Growth of Africa's e-Learning market. Published on January 29, 2025, 12:00 pm. Available at https://ela-newsportal.com/africa-e-Learning -market-transforming-education-across-the continent/#:~: text=Africa %20is%20experiencing. [Accessed: 03 May 2024]

Esfijani, A. (2018). Measuring quality in online education: A Meta-synthesis. *American Journal of Distance Education,* 32(1), 57–73. Available at https://doi.org/10.1080/08923647. 2018.1417658. [Accessed: 02 May 2024]

Frost, J. (2019). Introduction to statistics. *Statistics* Pennsylvania, State College, PA 16801. *Jim Publishing ISBN 978-1-7354311-0-9.*

Galais, C., Fernández-Martínez, J. L., Font, J., & Smith, G. (2021). Testing the input-process-output model of public participation. *European Journal of Political Research*, 60(4), 807-828.

Green, D. (1994). What is quality in higher education? Taylor & Francis, 1900 Frost Road, Bristol, PA 19007-1598. Available at https://eric.ed.gov/?id=ED415723. [Accessed: 11 May 2024]

Hafeez, M., Naureen, S., & Sultan, S. (2022). Quality indicators and models for online learning quality assurance in higher education. *Electronic Journal of E-Learning* , 20(4), Article 4. Available at https://doi.org/10.34190/ejel.20.4.2553. [Accessed: 21 May 2024]

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modelling (PLS-SEM) using R: A workbook* (p. 197). Springer Nature.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the academy of marketing science*, 43, 115-135.

Khan, E. A., Cram, A., Wang, X., Tran, K., Cavaleri, M., & Rahman, M. J. (2023). Modelling the impact of online learning quality on students' satisfaction, trust and loyalty. *International Journal of Educational Management,* 37(2), 281-299.

Kotler, P. (2019). The market for transformation. *Journal of Marketing Management*, 35(5-6), 407-409.

Lannelongue, G., Gonzalez-Benito, J., & Gonzalez-Benito, O. (2015). Input, output, and environmental management productivity: effects on firm performance. *Business Strategy and the Environment*, 24(3), 145-158.

Laudon, K., & Laudon, J. (2009). Management information systems: International Edition, 11/E. London, Uk: Pearson Higher Education.

Lee-Post, A. (2009). E-Learning success model: An information systems Perspective. *Electronic Journal* of E-Learning , 7(1), 61-70.

Luhmann, N., Baecker, D., & Gilgen, P. (2013). Introduction to systems theory (p. 63). Cambridge: Polity.

Lutfi, A. (2023). Factors affecting the success of accounting information systems from the lens of DeLone and McLean IS model. *International Journal of Information Management Data Insights*, 3(2), 100202. Available at https://doi.org/10.1016/j.jjimei. [Accessed: 07 May 2024]

Marciniak, R. (2018). Quality assurance for online higher education programs: Design and validation of an integrative assessment model applicable to Spanish universities. *International Review of Research in Open and Distributed Learning*, 19(2).

Martin, F., & Bolliger, D. U. (2022). Developing an online learner satisfaction framework in higher education through a systematic review of research. *International Journal of Educational Technology in Higher Education*, 19(1), 50. Available at https://doi.org/10.1186/ s41239-022-00355-5. [Accessed: 03 May 2024]

Masenya, M. J. (2021). Toward a relevant de-colonized curriculum in South Africa: suggestions for a way forward. *SAGE Open*, 11(4). Available at https://doi.org/10.1177/21582440211052559 (Original work published 2021) [Accessed: 07 May 2024]

Mkinga, M., & Mandari, H. (2020). Evaluating student's information system success using DeLone and McLean’s Model: Student’s Perspective. *Journal of International Technology and Information Management*, 29(2), 24–42. Available at https://doi.org/10.58729/ 1941-6679.1447. [Accessed: 07 May 2024]

Mosquera, J. M. L., Suarez, C. G. H., & Guerrero, V. A. B. (2023). Effect of flipped classroom and automatic source code evaluation in a CS1 programming course according to the Kirkpatrick evaluation model. Education and Information Technologies, 28(10), 13235–13252. Available at https://doi.org/10.1007/s10639-023-11678-9. [Accessed: 05 May 2024]

Online Learning Consortium (2024). Administration of online programs. Available at https://onlinelearningconsortium.org/consulting/quality-scorecards/administration-of-online-programs/. [Accessed: 07 May 2024]

Peters, B., & Göhlich, M. (2024). Transformative learning through group coaching. Journal of Transformative Education, 22(2), 157–179. Available at https://doi.org/10.1177/ 15413446231178897. [Accessed: 05 May 2024]

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual review of psychology*, 63(1), 539-569.

Praslova, L. (2010). Adaptation of Kirkpatrick’s four-level training criteria to assessment of learning outcomes and program evaluation in Higher Education. *Educational Assessment, Evaluation and Accountability,* 22(3), 215–225. Available at https://doi.org/10.1007/s11092-010-9098-7. [Accessed: 05 May 2024]

Quinton, M. L., Tidmarsh, G., Parry, B. J., & Cumming, J. (2022). A Kirkpatrick model process evaluation of reactions and learning from my strengths training for life™. *International Journal of Environmental Research and Public Health*, 19(18). Available at https://doi.org/10.3390/ijerph191811320. [Accessed: 22 May 2024]

Rahmawati, W. (2020). Evaluating the effectiveness of training with the Kirkpatrick method (study of Semen Padang Hospital employees). *Economica,* 8(2), 117–129. Available at https://doi.org/ 10.22202/economica. 2020.v8.i2.3649. v8.i2.3649. [Accessed: 20 May 2024]

Rigdon, E. E. (2012). Rethinking partial least squares path modelling: In praise of simple methods. *Long range planning, 45*(5-6), 341-358.

Safdar, G., Rauf, A., Ullah, R., & Rehman, A. (2020). Exploring Factors Leading to Quality Online Learning in the Era of Covid-19: A Correlation Model Study. *Universal Journal of Educational Research*, 8, 7324–7329. Available at https://doi.org/10.13189/. [Accessed: 03 May 2024]

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS quarterly*, 553-572.

Smidt, A., Balandin, S., Sigafoos, J., & Reed, V. A. (2009). The Kirkpatrick model: A useful tool for evaluating training outcomes. *Journal of Intellectual & Developmental Disability*, 34(3), 266–274. Available at https://doi.org/10.1080/13668250903093125. [Accessed: 06 May 2024]

Statista (2025). Online education Africa. Available at https://www.statista.com/outlook/emo/online-education/africa?srsltid=AfmBOorOWN-W0EMxtXOvF3iCR-5xJgMaDx3D8CiXOV2zojaq1aIF689. [Accessed: 10 September 2025]

Tamkin, P., Yarnall, J., & Kerrin, M. (2002). Kirkpatrick and Beyond: A Review of Models of Training Evaluation. Brighton, England: Institute for Employment Studies. Available at https://www.employment-studies.co.uk/system/files/resources/files/392.pdf. [Accessed: 20 February 2024]

Tan, K. H., Chan, P. P., & Mohd Said, N.-E. (2021). Higher education students' online instruction perceptions: A quality virtual learning environment. *Sustainability*, 13(19), Article 19. https://doi.org/10.3390/su131910840. [Accessed: 20 February 2024]

United Nation International Children Education Fund Unicef South Asia (2024). Quality of education. Available at https://www.unicef.org/ rosa/what-we-do/quality-education. [Accessed: 02 May 2024]

Wright, A. C., Carley, C., Alarakyia-Jivani, R., & Nizamuddin, S. (2023). Features of high-quality online courses in higher education: A Scoping Review. *Online Learning*, 27(1), 46-70.

Professional Development in Digital Competence for Special Education Teachers: A Systematic Review

Iga Setia Utami[1,2], Anik Ghufron[1] and Ishartiwi[1]
[1]Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[2]Universitas Negeri Padang, Padang, Indonesia

igasetiautami@fip.unp.ac.id (Corresponding author)
anikghufron@uny.ac.id
ishartiwi@uny.ac.id

https://doi.org/10.34190/ejel.23.4.4273

Abstract: Digital competence is increasingly being recognised as a crucial factor in transforming education in the technological era. Various studies have been conducted to identify and develop digital competence improvement programs for teachers. However, there has been a lack of comprehensive synthesis regarding their impact, particularly for special education teachers. This problem is important to explore, given that special education teachers face unique pedagogical challenges when serving students with disabilities. This systematic review aims to address this gap by exploring the implementation of digital competence programs for teachers in special education settings. In particular, this study analysed the characteristics of related publications, the effectiveness of training programs, the training materials expected by teachers, and the instruments used to assess digital competence. This study followed PRISMA guidelines, and a comprehensive search was conducted of the Scopus, ScienceDirect, and ERIC databases. This review synthesised 17 studies from 127 screened articles published between 2014 and 2024. The Inclusion and exclusion criteria were based on language, document type, publication year, research type, and full-text availability. The results indicated that while the interest in teacher digital competence is growing, research specifically targeting special education contexts remains limited. Most program initiatives adopt a one-size-fits-all approach, focusing on general digital tools rather than assistive or adaptive technologies suited to learners with disabilities. Training materials tend to emphasise technical rather than pedagogical and accessibility-related aspects. These findings indicate that there is a misalignment between the content of teacher training and the realities of inclusive digital classrooms. The results of this study provide valuable insights for developing digital competence development programs tailored to the needs of special education teachers. This research contributes to digital learning practice by providing a framework for designing practical digital training customised to special education contexts. It advances the scope of virtual and digital learning by highlighting the specific needs and conditions required for inclusive digital education to thrive.

Keywords: Digital competence, Professional development, Special education, Student with disabilities, Teacher training, Technology-Enhanced education

1. Introduction

The COVID-19 pandemic had a profound impact on the global education system. Many schools were closed to control the spread of the Coronavirus (Tadesse and Muluye, 2020; Meinck, Sabine, Fraillon, Julian and Strietholt, Rolf, 2022). Traditional classroom-based instruction shifted to distance learning facilitated by digital technology (Mali and Lim, 2021; Afikah et al., 2023; Fisher et al., 2024). Online education emerged as a solution for sustaining the teaching and learning process during the pandemic (Betancourt-Odio et al., 2021; Silletti et al., 2021; Starks and Starks, 2022; Bastian, Liza and Efastri, 2023). Technology integration in the online education system also ensured that learning is not confined to a specific space and time (Murphy, Malenczak and Ghajar, 2019; Podsiadlik, 2021). The crisis accelerated digital transformation in education, establishing new norms for integrating technology into teaching and learning environments.

The increased reliance on technology brought about a shift in the perception of digital tools from optional enhancements to essential components of educational delivery. Awareness of the importance of digital technology in the learning process has increased significantly following the COVID-19 pandemic. This shift is not limited to general education but also extends to special education contexts. The integration of technology in educational activities has provided new approaches and experiences (Kaplarević-Mališić et al., 2022; Liao et al., 2022). In special education specifically, this integration promotes inclusivity for students with disabilities (Olakanmi et al., 2020; Montenegro-Rueda and Fernández-Batanero, 2022). Various digital tools, such as screen readers, augmentative and alternative communication applications, and adaptive learning platforms, are increasingly being employed to support learning activities (Moreno-Rodriguez et al., 2021; Basnayaka et al.,

Cite this article: Utami, I.S, Ghufron, A. and Ishartiwi. 2025. "Professional Development in Digital Competence for Special Education Teachers: A Systematic Review", *Electronic Journal of e-Learning* , 23(4), pp 53-68, https://doi.org/10.34190/ejel.23.4.4273

2023; Reyes, Meneses and Xavier, 2023; Nino et al., 2024). These technologies bring with them opportunities for adaptive, flexible, and personalised learning for students with disabilities (Pearson et al., 2019; Thompson and Copeland, 2020; Ohalezim, Edwards and Aderemi, 2021). Technology devices thus serve both as an instructional media and as an empowering tool that enables differentiated instruction for students with disabilities.

Digital technology supplements traditional instruction and simultaneously transforms how teaching and learning occur. These changes require teachers to have adequate digital competence to utilise digital technology-based learning effectively (Claro et al., 2024; Gómez-Puerta et al., 2024; Kiryakova and Kozhuharova, 2024; Arif, Aziz and Ma'arif, 2025). Digital competence refers to the set of skills and abilities that enable the effective use of digital tools and technologies. In the teaching context, digital competence is a professional competence practice applied by the educator in their profession to use digital technology effectively in order to improve and innovate education (Redecker, 2017; Santoianni and Ciasullo, 2023). It generally includes technological proficiency, pedagogical awareness, content knowledge, attitude toward technology adoption, cultural insights, critical approaches, and professional engagement (Skantz-Åberg et al., 2022). Teachers' digital competencies influence their self-efficacy in relation to digital teaching (Börnert-Ringleb, Casale and Hillenbrand, 2021; Peng, Razak and Halili, 2024). The level of digital competence among teachers directly influences their confidence to teach effectively in a digital environment, which in turn impacts the students' learning outcomes (Pinto-Llorente et al., 2018; Tonks, Kimmons and Mason, 2021; Obesso, Nú˜nez-Canal and P´erez-Rivero, 2023).

The growing demand for digital integration in education emphasises the need for educators to adapt and improve their skills. Strengthening digital competence has become a significant area of study in educational practice and a primary goal of teachers' professional development (Alarcón, Jiménez and Vicente-Yagüe, 2020). Improving teachers' digital competence through professional development programs is critical for transforming education and preparing students for the future (Assainova et al., 2023; Baxter and Reeves, 2023). Such program opportunities include workshops, mentoring, online courses, and collaborative communities. The effectiveness of these programs is characterised by their relevance to the teachers' needs, sustained duration, active learning approaches, and opportunities for feedback and reflection.

Various studies have explored the topic of improving teachers' digital competence, highlighting both successes and challenges (Börnert-Ringleb, Casale and Hillenbrand, 2021; Tonks, Kimmons and Mason, 2021; Obesso, Nú˜nez-Canal and P´erez-Rivero, 2023; Peng, Razak and Halili, 2024). However, most of the existing research has focused on teachers in general education settings, with limited attention given to special education teachers (Carter and Rice, 2016; Almenara et al., 2023). This imbalance is concerning because teaching students with disabilities involves distinct pedagogical, technological, and contextual considerations (Hsieh, 2024). Students with disabilities may require tailored technological solutions such as assistive software, adaptive input devices, and accessible learning management systems that go beyond standard educational tools. For this reason, teachers in special education settings require digital skills that encompass understanding technological aspects and how technology can be effectively applied to teach students with disabilities (Gonçalves and Ferreira, 2021; Acuña-Gamboa, Mérida-Martínez and Pons-Bonals, 2023; Acuña-Gamboa and Pons-Bonals, 2024).

Despite the increasing recognition of the importance of digital competence in inclusive education, a systematic synthesis that evaluates the nature, design, and effectiveness of professional development programs tailored to special education contexts remains lacking. Previous studies have primarily examined general education teachers and focused on broader technology integration, leaving the specific professional learning needs of special education teachers underexplored. To address this gap, the present study conducts a systematic review of empirical research on the development of digital competence among special education teachers. Specifically, it analyses how professional development initiatives have contributed to enhancing the digital competence of special education teachers and identifies the instruments, content, and outcomes reported in previous studies. To achieve the objective, this study examines four research questions:

RQ1. What are the characteristics of publications in the field of digital competence among special education teachers?

RQ2. How effective is digital competence training on the abilities of special education teachers regarding technology-based learning for students with disabilities?

RQ3. What material do special education teachers expect from training related to technology-based learning for students with disabilities?

RQ4. What instruments are used to measure the digital competence of special education teachers?

Understanding how digital competence related to professional development programs impacts special education teachers is essential for improving training strategies. This understanding can inform policymakers, teacher educators, and school administrators in making evidence-based decisions to support inclusive digital education.

2. Literature Review

2.1 Conceptualising Teachers' Digital Competence

Digital competence is one of the fundamental teacher competencies that must be included in teacher education curricula. Recent frameworks such as the European DigCompEdu (Redecker, 2017) and the UNESCO ICT Competence Framework for Teachers (UNESCO, 2018) emphasise that digital competence extends beyond operational capabilities to encompass pedagogical design. However, there is no agreement on how teachers' digital competencies are defined and implemented (Claro et al., 2024).

Some studies emphasise the technical mastery of digital devices and access to infrastructure (Zhang, Sazalli and Nadjwa, 2024), while others focus on the pedagogical and contextual adaptations of technology use in the classroom (Aindriú et al., 2023; Kiryakova and Kozhuharova, 2024). This narrow focus can limit the understanding of how digital skills contribute to inclusive teaching, particularly in special education contexts where technology serves as a tool and instructional support.

2.2 Professional Development for Digital Competence

The ability to competently use digital technology in the teaching process has become a primary goal of teacher professional development (Alarcón, Jiménez and Vicente-Yagüe, 2020; Gurgenidze et al., 2022). Professional development is effective when it is ongoing, collaborative, subject-specific, utilises external expertise, is supported by teachers, has a content focus, and considers the role of context (Avci, O'Dwyer and Lawson, 2020; Sims and Fletcher-Wood, 2021).

However, a comparison of previous studies reveals substantial variability in training outcomes. Some studies have reported increased teachers' confidence and self-efficacy (Pérez and Delgado, 2019; Benigno et al., 2023), whereas others indicate the limited transfer of digital skills into classroom practice due to inadequate contextualisation (Fernández-Batanero, Montenegro-Rueda and Fernández-Cerero, 2022). These results demonstrate the importance of aligning professional development with the teachers' specific contexts and ensuring relevant content and materials.

2.3 Digital Competence in Special Education Context

Research focusing on digital competence among special education teachers remains relatively scarce. Most available studies examine the general education context, with few addressing the unique pedagogical and technological challenges faced by special education teachers (Fernández-Cerero and Montenegro-Rueda, 2023). A comparative analysis across studies reveals a persistent gap including a lack of training in the application of technology in learning to support students with disabilities (Pérez and Delgado, 2019; Graván and Cerero, 2022), a standardised or "one-size-fits-all" training approach (Starks and Reich, 2023), and unequal access to training for teachers (Acuña-Gamboa, Mérida-Martínez and Pons-Bonals, 2023). The use of digital technology in inclusive education can be utilised for training and repetition, to assist learning, and to expand learning opportunities (Drushlyak et al., 2023). To overcome these issues, there is a growing need for targeted professional development that provides teachers working with students with disabilities with appropriate content and experience (Olivencia et al., 2025). The contrast between what is needed (accessibility-oriented assistive competencies) and what is typically provided (general digital skills) reflects a critical research gap that justifies this systematic review.

2.4 Research Gap and Rationale for the Present Study

Although the research on professional development for digital competence has been extensive, several gaps remain:

- First, the literature remains fragmented as studies tend to examine digital competence development in isolation, lacking cumulative evidence.
- Second, there is limited analytical synthesis comparing digital competence development models across contexts and populations.

- Third, limited attention has been given to special education teachers' digital competence, particularly in terms of program design, learning expectations, and assessment instruments.

To fill these gaps, this review systematically analyses empirical studies published between 2014 and 2024 that focus on digital competence development programs among special education teachers. This review expands the existing knowledge by identifying trends and evaluating their effectiveness and contextual relevance.

3. Method

3.1 Research Design

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. The PRISMA framework was chosen because it offers a structured and transparent method that enables authors to conduct systematic and comprehensive analyses. Following this protocol helps to maintain the flow of evidence and enhances the reproducibility and credibility of the review process. As outlined by Page (2021) and Sarkis-Onofre (2021), the PRISMA consists of four phases: identification, screening, eligibility, and inclusion, which were carefully applied throughout this study to ensure methodological integrity.

3.2 Systematic Searching Strategies

Systematic searches were conducted across three major academic databases: Scopus, ScienceDirect, and ERIC databases. These sources were selected because they provide up-to-date, high-quality literature and encompass a range of multidisciplinary perspectives that support a comprehensive analysis. By using multiple databases, this review aimed to ensure comprehensive coverage of relevant studies and the capturing of diverse disciplinary perspectives on the topic.

3.2.1 Identification

In the first step of the PRISMA approach, three main keywords were identified: Digital Competence, Teacher Training, and Special Education. These terms were expanded using related synonyms and combined through Boolean operators (AND, OR). The search strategy accounted for both singular and plural forms of key terms (e.g., “digital competence” and “digital competences”) to capture variations in terminology. Wildcard and truncation operators (e.g., “competenc*”) were applied when supported by the database’s syntax. This step helped minimise the potential omission of studies that used slightly different phrasing. The formulas used in the three databases are listed in Table 1.

Table 1: Keywords of the search strings used in the databases.

Keywords	Database			Total
	Scopus	ScienceDirect	ERIC	
("digital competence" OR "digital skill" OR "technology competence" OR "technology skill")	9822	8743	3475	22040
("digital competence" OR "digital skill" OR "technology competence" OR "technology skill") AND ("teacher training" OR "teacher professional development")	692	646	205	1543
("digital competence" OR "digital skill" OR "technology competence" OR "technology skill") AND ("teacher training" OR "teacher professional development") AND ("special education" OR "inclusive education" OR "student with disabilities")	19	99	9	127

The first search using the keyword “digital competence” and its synonyms yielded 22040 publications. The search was then combined with the second keyword, “teacher training,” resulting in 1543 papers. The last search, utilising Boolean operators, combined the three keywords with their synonyms and yielded 19 papers on Scopus, 99 papers on ScienceDirect, and nine publications on ERIC. A total of 127 search results were included in the screening stage.

3.2.2 Screening

The second stage in the PRISMA protocol was screening. In this phase, several criteria were applied. Articles were selected from 2014 to 2024, and only included papers written in English were included, as English is used as the publication standard. For credibility and relevance, the selected articles had to be journal articles or conference papers. Non-empirical studies that did not align with the review's focus on evidence-based findings were not included. The selected articles had to have full-text access to ensure comprehensive analysis. The inclusion and exclusion criteria are listed in Table 2.

Table 2: Inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Language	English paper	Non-English article
Document type	Article journal, conference paper	Book chapter, review, report, dissertation
Research type	Empirical studies	Literature review
Text access	Full text	Did not have full text
Timeline	2014-2024	Earlier than 2014

Based on the criteria in Table 2, eight articles were excluded because they were not written in English, 22 articles as they were not journal articles or conference proceedings, and five because they were non-empirical studies. Additionally, the authors did not have access to the full text of 33 articles, and 13 articles were written outside the specified time frame. Thus, a total of 46 articles met the eligibility criteria and were included in the subsequent processes.

3.2.3 Eligibility

In the eligibility stage, the authors manually analysed the remaining articles by reading each article's title, abstract, and content to confirm their eligibility. Three articles were excluded as duplicate studies. The content analysis excluded another 31 articles that did not fit the research context, either because they did not focus on the study of teacher training for special education teachers or because they did not focus on teacher training in the field of digital competence.

3.2.4 Inclusion

After conducting three previous processes, at the final PRISMA stage, 17 papers were included in this systematic review. All studies discussed improving the digital competence among teachers of students with disabilities. The complete process of identification, screening, eligibility assessment, and final inclusion is illustrated in Figure 1.

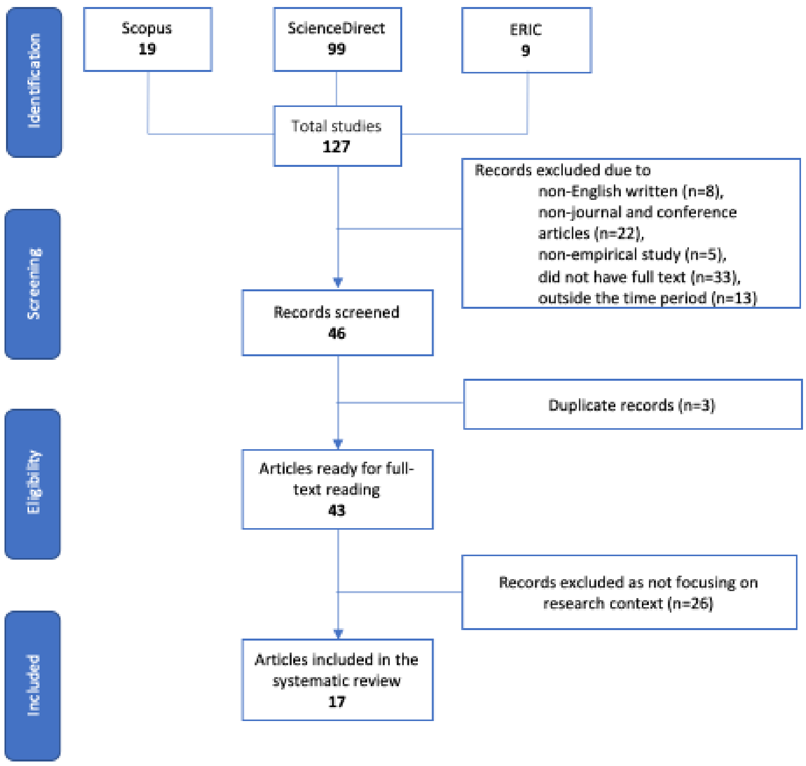


Figure 1: PRISMA flow diagram

3.3 Data Analysis and Extraction

A structured procedure was used for the data extraction and analysis to ensure clarity and transparency. A spreadsheet template was designed to record essential details from each of the 17 included studies. The extracted information covered the study title, year, authors, country, participant characteristics, research objectives, methodological approach, digital competence dimensions addressed, technologies used, and key findings related to teacher training and digital competence development. The lead author carried out the initial data extraction, after which the co-authors cross-checked all entries to ensure accuracy and completeness. Any disagreements were discussed and resolved through consensus, with reference to the original publications as needed. This collaborative checking process enhanced the reliability and transparency of the analytical process. For the content analysis, both quantitative and qualitative techniques were applied. These two approaches were chosen to allow a comprehensive understanding in the literature. The quantitative analysis involved generating various graphical representations to provide a comprehensive overview of the topic's general aspects. For the qualitative component, the VOSviewer tool was used to identify and categorise the primary themes of the study. A table containing all pertinent information from the articles included in the review was also compiled to facilitate the data extraction process (Table 3).

Table 3: Description of the research articles included in the review

Journal Indexing	Journal name	Methodology	Sample	Citation	Reference
Scopus Q1	Education and Information Technologies	Mixed method	114 university teachers and ICT professionals	1	(Román-Graván et al., 2024)
	European Journal of Special Needs Education	Quantitative	21 experts in technology and disability	9	(Montenegro-Rueda and Fernández-Batanero, 2024)
	Education and Information Technologies	Qualitative	13 special education teacher candidates	0	(Kurt and Erden, 2024)
	Heliyon	Quantitative	310 K-12 teachers	5	(Montes, Fuentes and Cara, 2023)
	Computer and Education	Qualitative	20 K-12 teachers	21	(Starks and Reich, 2023)
	Education and Information Technologies	Quantitative	2072 university teachers	16	(Fernández-Batanero et al., 2022)
	Research and Practice in Technology Enhanced Learning	Mixed method	1500 K-12 teachers	25	(Fernández-Batanero, Montenegro-Rueda and Fernández-Cerero, 2022)
	Literacy Research and Instruction	Qualitative	3 K-12 teachers	25	(Ciampa, 2017)
Scopus Q2	Journal of Education and e-Learning Research	Quantitative	130 K-12 teachers	0	(Aldousari and Yuan, 2024)
	Societies	Qualitative	62 K-12 teachers	1	(Montenegro-Rueda and Fernández-Cerero, 2023)
	Education Sciences	Quantitative	25 K-12 teachers	1	(Aindriú et al., 2023)
	International Journal of Educational Research and Innovation	Qualitative	10 experts in technology and disability	4	(Graván and Cerero, 2022)
	Journal of Special Education Technology	Qualitative	3 K-12 special education teachers	8	(Carter and Rice, 2016)

Journal Indexing	Journal name	Methodology	Sample	Citation	Reference
Scopus Q3	Journal of Learning for Development	Mixed method	44 student teachers	1	(Drushlyak et al., 2023)
	Journal of E-Learning and Knowledge Society	Mixed method	91 K-12 teachers	10	(Cappuccio, Compagno and Pedone, 2016)
Other international indexing	The Journal of Continuing Higher Education	Qualitative	64 university teachers	1	(Fernández-Cerero and Montenegro-Rueda, 2023)
	Journal of Online Learning Research	Mixed method	20 K-12 teachers	2	(Du, 2022)

4. Results and Discussion

4.1 What are the Characteristics of the Selected Publications About the Digital Competence of Special Education Teachers?

The first search using the keyword "digital competence" resulted in numerous publications. Likewise, searches related to teacher professional development programs and digital competence yielded numerous publications. However, this number decreased when filtered for the field of special education. Only 17 publications have been published on this topic over the last decade. This phenomenon highlights that digital competence development, particularly for teachers working with students with disabilities, remains poorly studied. Figure 2 shows the number of publications per year. Most publications were published in 2023 (n=6). This surge coincides with the post-pandemic period, during which the integration of digital tools into inclusive education has become more prominent.

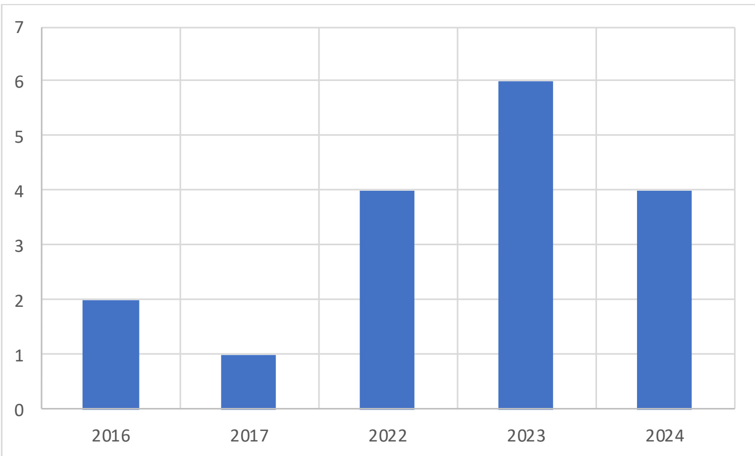


Figure 2: Study representation by year

Figure 3 illustrates the research methods used in the selected studies. Of the 17 articles, seven were qualitative, five were quantitative, and five were mixed methods. The variety of research methods utilised indicates that the topic can be investigated using multiple approaches. However, each method has a different purpose. Quantitative methods allow researchers to collect more data on the teachers' digital competence levels and training. Meanwhile, qualitative approaches enable a detailed and in-depth exploration of how teachers perceive the digital competence training they receive and what they need. At the same time, mixed-method designs collect data using both approaches to obtain comprehensive and in-depth results.

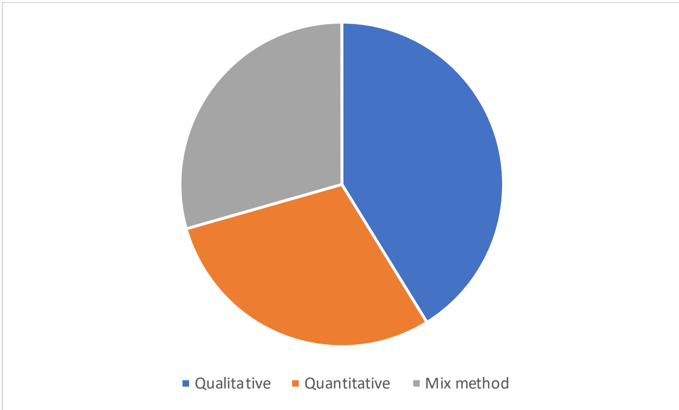


Figure 3: Distribution of the methodology utilised by the selected studies

Figure 4 shows the distribution of studies by country, grouped by first-author affiliation. Most studies were conducted in Europe. The dominance of European studies suggests that digital competence is conceptualised within EU policy frameworks (e.g., DigCompEdu).

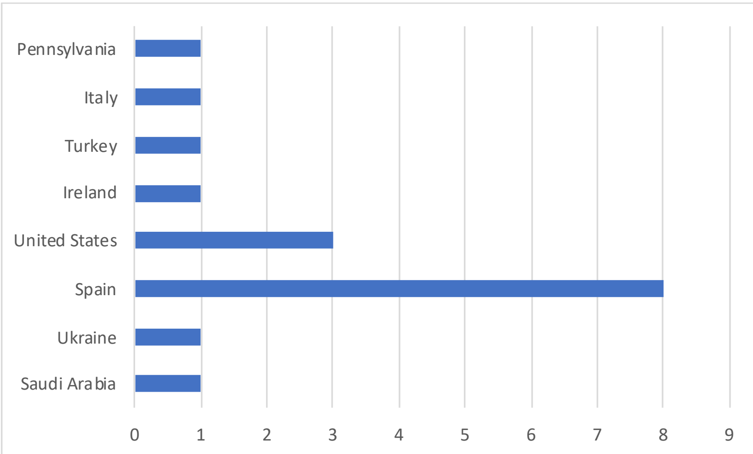


Figure 4: Studies representation by country

From the analysed references, keyword co-occurrence was examined using the VOSviewer software. Keyword co-occurrence analysis enables researchers to identify how two or more terms are interrelated and to reveal the critical points of a particular research area. Figure 5 shows the combined word network or keyword co-occurrence for this study.

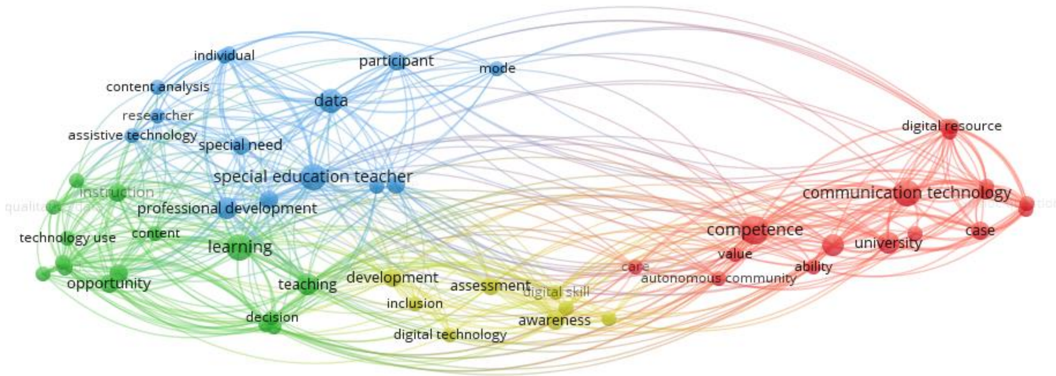


Figure 5: Co-occurrence map

From the 17 studies selected over the past decade, the researchers identified 58 keywords. As illustrated in Figure 5, these keywords were categorised into four distinct clusters based on their similarities, representing the primary research areas in this field. Cluster 1 (green) focuses on professional development, teacher training, and digital technology integration. This cluster emphasises the role of ongoing training programs and institutional support in enhancing teachers' digital competence. Cluster 2 (blue) centres on special education, inclusive education, participants, and learning needs. This cluster highlights the pedagogical and contextual aspects of implementing digital tools for learners with disabilities. Cluster 3 (red) is associated with communication technology, competence, online learning, and autonomous learning. These keywords point to the intersection between the teachers' digital competence and their ability to facilitate remote or technology-mediated instruction. Cluster 4 (yellow) connects digital literacy, resources, and educational tools, reflecting studies that address the teachers' access to and use of digital resources as an enabling factor for competence development. The importance of each descriptor is depicted by the size of its corresponding circle or node, while the connections or spacing between nodes indicate their relationships to one another.

4.2 How Effective is Digital Competence Training on the Abilities of Special Education Teachers Regarding Technology-Based Learning for Students with Disabilities?

The analysis of the selected studies revealed that professional development programs in digital competence produced a limited impact on special education teachers. While there are studies show that special education teachers have a positive attitude toward technology (Pérez and Delgado, 2019; Dalbudak and Yiğit, 2021), their competence remains low according to their own perceptions, that of the school management, and the students (Klapproth et al., 2020; Uromova et al., 2020; Fernández-Cerero and Román-Graván, 2023). The main findings of this systematic review revealed two major problems in digital competence training for teachers. These issues collectively demonstrate why current training initiatives fail to achieve measurable improvements in the teachers' digital competence. The first concerns the low level of digital competence training for special education teachers (Román-Graván et al., 2024). Training is the first step for teachers to implement technology in their teaching (Romero-García, Buzón-García and de Paz-Lugo, 2020). Unfortunately, there are very few training workshops available to them. This low level of training is caused by the unequal access to training (Starks and Reich, 2023) and limited training available for special education teachers (Montes, Fuentes and Cara, 2023; Kurt and Erden, 2024).

The second problem lies in the design of the training received by special education teachers. Teachers report that the training they receive is the same for all, a concept known as the one-size-fits-all approach (Starks and Reich, 2023). This concept assumes that all teachers have the same needs. In reality, teachers have different demands, especially in the field of special education. This uniform approach makes the training the teachers receive less relevant to their needs. Therefore, the main goal of improving digital competence is often not achieved. This observation aligns with previous claims that professional development programs rarely account for contextual teaching differences, particularly within inclusive classrooms. Both of these problems reflect the lack of attention paid to the development of training specifically designed for special education teachers (Graván and Cerero, 2022). The lack of focus on training that meets their needs indicates a gap in supporting teachers looking to meet the challenges of inclusive education in the digital age. There is a need for more targeted training strategies and professional development efforts for teachers to use technology with students with disabilities (Fernández-Batanero et al., 2022; Fernández-Batanero, Montenegro-Rueda and Fernández-Cerero, 2022).

4.3 What Material do Special Education Teachers Expect From Training Workshops Related to Technology-Based Learning for Students with Disabilities?

The literature review revealed a lack of studies specifically related to the development of digital teaching competence training materials for special education teachers. Meanwhile, it is paramount to have relevant and contextualised training for the special education context, as special education teachers face distinct challenges when applying technology to support the learning process of students with disabilities.

Most of the selected studies indicated that the training received by special education teachers employed a generalised approach (Román-Graván et al., 2024), wherein the materials were not specific to using technology to assist students with disabilities. This approach disregards the fact that each teacher operates within a unique teaching context, particularly when implementing digital technology to support students with disabilities (Yıldız et al., 2022).

However, several studies have identified the learning material requirements of teachers in the field of special education. The learning materials required by special education teachers to enhance digital competence include didactic strategies to implement curricular adaptation supported by technology for students with disabilities; specific technological tools, devices, and software for students with disabilities; websites with educational resources for students with special educational needs; practical knowledge of digital tools that enhance accessibility, and guidelines for inclusive practices utilising technology (Fernández-Batanero, Montenegro-Rueda and Fernández-Cerero, 2022; Montenegro-Rueda and Fernández-Cerero, 2023). Additional research has also identified the need for materials related to Understanding by Design (UbD), Universal Design for Learning (UDL), and assistive technology-infused curriculum (Alsolami, 2022; Du, 2022; Aindriú et al., 2023; Schladant et al., 2023). Several studies provided concrete examples of the types of digital tools and assistive technologies that special education teachers expect to be integrated into professional development programs. These include screen readers such as JAWS and NVDA for students with visual impairments; augmentative and alternative communication (AAC) applications like Speech Generating Devices (SGDs) for learners with communication difficulties; interactive whiteboard software, and voice recognition tools (Hilzensauer, Pecher and Angeloni, 2022; Montes, Fuentes and Cara, 2023).

Digital competence training should not only focus on the technical aspects of technology but should also encompass pedagogical aspects by examining how technology can be implemented and prove beneficial for teaching students with disabilities. Professional development for special education teachers requires alignment with frameworks such as UDL and TPACK but with the explicit integration of accessibility and assistive technology layers. This conceptual expansion could form the basis for a new model of 'Inclusive Digital Competence' that bridges pedagogical, technological, and accessibility dimensions.

4.4 What Instruments are Used to Measure the Digital Competence of Special Education Teachers?

An analysis of the empirical research reveals that several instruments can be employed to evaluate the digital competence of special education teachers. One notable reference is DigCompEdu, developed in Europe to assess educators' digital skills in various teaching contexts. The framework comprises 22 competencies from six areas: professional engagement, digital resources, teaching and learning, assessment, empowering learners, and facilitating learners' digital competence. DigCompEdu has become widely used to measure the teacher's level of digital competence (Fernández et al., 2022; Betancur-Chicué and Muñoz-Repiso, 2023; Moreira, Nunes and Casanova, 2023). However, researchers have begun to adapt the framework to the specific needs of teachers in special education. These adaptations ensure that the assessment measures particular skills related to inclusive teaching, such as the use of assistive technology and the design of an accessible digital environment.

Recent studies have highlighted the importance of using instrument tools that reflect the specific digital skills of special education teachers. Montenegro-Rueda and Fernández-Batanero (2024) developed an instrument to assess the digital competencies of special education teachers. This instrument comprises 44 items to evaluate teachers' digital skills across seven areas of disability: visual, hearing, physical, intellectual, autism spectrum disorder, severe behavioural disorder, and attention deficit hyperactivity disorder. The need to adopt the assessment instruments to measure the competence of special education teachers aligns with adjusting the learning materials and training.

The growing diversity of instruments highlights a critical issue: while existing frameworks such as DigCompEdu offer a solid foundation for assessing educators' digital competence, contextual adaptation remains essential. Future studies could focus on validating and refining these instruments across educational contexts. This will ensure that the resulting assessments more accurately reflect the teachers' ability to design digital inclusive learning environments for diverse learners.

4.5 Discussion

This review examined how digital competence among special education teachers has been conceptualised, developed, and assessed in previous research. A review of 17 studies shows the growing interest in this topic. However, most of the research remains concentrated in Europe—particularly in Spain—where the European DigCompEdu framework serves as the primary reference. This dominance suggests that the European policy context shapes the prevailing understandings of teachers' digital competence. This perspective may not be fully applicable to different educational systems with different infrastructure and policies. These findings point to the importance of government efforts to support the improvement of teachers' digital competence through policy, education, training, and ongoing support. The lack of policies on implementing digital learning for students with disabilities is one factor contributing to the under-implementation of technology in education. This aligns with the research findings (Courduff and Moktari, 2022; Hata et al., 2023) which emphasise the need for comprehensive regulations and guidance for implementing technology-based learning in educational institutions for students with disabilities.

The selected publications yielded relatively similar results regarding the effectiveness of teacher training. Most of the selected studies indicate that professional development programs have produced a limited impact on special education teachers. This limited effectiveness can be traced to two interconnected structural problems:

the restricted access to training opportunities and the prevalence of uniform one-size-fits-all" program designs. The limited availability of digital training programs for teachers indicates the need for more accessible and continuous professional development initiatives for all teachers. Policymakers and educational institutions must collaborate to design sustainable digital competence programs supported by adequate infrastructure that considers needs-based training. Training providers have to examine effective training models and identify barriers to special education teachers' participation in digital learning. Additionally, the educational institute can provide guides and self-study materials that teachers can use outside of training sessions, at any time and from anywhere.

A further issue concerns the content of the learning materials used in professional development. The reviewed studies show that existing professional development programs rarely incorporate pedagogical frameworks such as Universal Design for Learning (UDL), Understanding by Design (UbD), or assistive technology–infused curricula. The materials are often generic, lacking context-specific examples, case-based learning, or simulations that mirror real inclusive classroom challenges. Most training initiatives focus on general tools such as Google Classroom rather than assistive and adaptive technologies. For example, very few programs provide hands-on experience with tools such as screen readers, text-to-speech software, or communication boards. This suggests an imbalance in the design of professional development programs, often prioritising the technological aspect of digital competence over its pedagogical and accessibility dimensions. The results highlight the need for teachers to receive pedagogical, technological, and content training to improve their digital skills (Blasco-Serrano, González and Coma-Roselló, 2022). Future training programs should integrate practical case studies, simulated classroom scenarios, and co-designed modules developed in collaboration with special education teachers to increase their relevance and transferability.

Regarding the fourth research question related to teacher digital competence instruments, numerous options are available for utilisation. The DigCompEdu framework has become foundational, even though researchers still need to adapt these instruments by tailoring them to the specific needs of each field. Recent work by Montenegro-Rueda and Fernández-Batanero (2024) proposes a more specialised tool that includes domains such as assistive technology and digital adaptation for particular types of disability. The alignment of measurement tools, training design, and policy priorities will be essential to ensuring the coherence and effectiveness of the professional development system.

From a theoretical perspective, this review broadens the concept of digital competence by emphasising an adaptive dimension. On a practical level, it highlights the need to shift from generic training models to approaches that are grounded in the context of the participants. Integrating accessibility, pedagogy, and technology in this way positions digital competence not only as a technical skill but also as a pedagogical and ethical commitment to inclusion.

This review shows that efforts to develop digital competence among special education teachers remain fragmented and lack a theoretical foundation. To move the field forward, future research should examine diverse cultural and policy contexts, validate inclusive frameworks through empirical studies, and investigate the long-term effects of adaptive, collaboratively designed training programs. Addressing these aspects will help to transform digital competence from a set of technical skills into a meaningful driver of equitable and accessible learning for all students.

5. Conclusion

This review examined 17 studies on the development of digital competence among special education teachers. It has discussed the effectiveness of professional development programs, the training content, and the materials needed to support students with disabilities. This is in addition to instruments used for measuring teachers' digital competence. Overall, the findings highlight that while special education teachers demonstrate openness and positive attitudes toward technology, the opportunities available to them to enhance their digital skills are often limited by the generic nature of the training model. Future programs require embedding accessibility and inclusivity principles into both their content and delivery. Universal Design Learning (UDL) and Technological Pedagogical Content Knowledge (TPACK) framework can be referred to meet this need. Future assessment tools should integrate elements of assistive technology literacy and inclusive digital pedagogy. This would enable a more accurate evaluation of teacher readiness to implement technology in diverse learning environments.

From a practical perspective, these findings underscore the urgent need for contextualised professional development that combines technical training with pedagogical adaptations to different disability categories (visual, auditory, or neurodevelopmental). Such programs should be co-designed with special education experts and practitioners to ensure relevance and sustainability. From a theoretical perspective, the review calls for expanding the existing digital competence frameworks to include explicit indicators of inclusivity and accessibility, bridging the gap between mainstream educational technology and special needs pedagogy.

Nevertheless, several limitations affected this review. First, the review was limited to three database sources. This makes it possible to have missed other studies. Second, the review did not address digital competence building for teachers to support students' learning in relation to one specific learning barrier. It is essential to research digital competence improvement programs that utilise tailored approaches for special education teachers. Further research is recommended on designing digital competence improvement programs for special education teachers who are teaching students with specific learning barriers.

Acknowledgement

We thank the Indonesian Education Scholarship, the Centre for Higher Education Funding and Assessment, and the Indonesian Endowment Fund for Education for the support of this research.

Ethics statement: This study did not require ethical approval as no human subjects were involved.

AI statement: This paper was entirely written and developed by the authors without the use of artificial intelligence tools.

Declaration of Conflict of Interest: There are no conflicts of interest to report.

References

Acuña-Gamboa, L.A., Mérida-Martínez, Y. and Pons-Bonals, L., 2023. COVID-19, educational digital competences and special education in Mexico. *Siglo Cero*, 54(2), pp.29–51. https://doi.org/10.14201/scero202354228945.

Acuña-Gamboa, L.A. and Pons-Bonals, L., 2024. The digital competences of special education teachers in Mexico in times of pandemic. *Revista Colombiana de Educación*, (92), pp.327–346. https://doi.org/10.17227/rce.num92-17206.

Afikah, A., Rohaeti, E., Jumadi, J. and Perdana, R., 2023. Student's higher-order thinking skills and collaboration skills in online learning during pandemic. *International Journal of Evaluation and Research in Education*, 12(1), pp.23–33. https://doi.org/10.11591/ijere.v12i1.23797.

Aindriú, S.N., Connaughton-Crean, L., Duibhir, P.Ó. and Travers, J., 2023. The design and content of an online continuous professional development course in special education for teachers in Irish Immersion Primary and Post-Primary Schools. *Education Scinces*, [online] 13(281). https://doi.org/10.3390/educsci13030281.

Alarcón, R., Jiménez, E. del P. and Vicente-Yagüe, M.I. de, 2020. Development and validation of the DIGIGLO, a tool for assessing the digital competence of educators. *British Journal of Educational Technology*, 51(6), pp.2407–2421. https://doi.org/10.1111/bjet.12919.

Aldousari, A. and Yuan, W., 2024. Teachers' perceptions, attitudes and knowledge of online learning for students with disabilities in Saudi Arabia. *Journal of Education and e-Learning Research*, 11(3), pp.473–480. https://doi.org/10.20448/jeelr.v11i3.5829.

Almenara, J.C., Castillo, J.J.G., Rodríguez, A.P. and Guillén-Gámez, F.D., 2023. Digital Competence of university students with disabilities and factors that determine it. A descriptive, inferential and multivariate study. *Education and Information Technologies*, [online] 28(8), pp.9417–9436. Available at: <https://link.springer.com/article/10.1007/s10639-022-11297-w>.

Alsolami, A.S., 2022. Teachers of special education and assistive technology: teachers' perceptions of knowledge, competencies and professional development. *Sage Open*, 12(1). https://doi.org/10.1177/21582440221079900.

Arif, M., Aziz, M.K.N.A. and Ma'arif, M.A., 2025. A recent study on islamic religious education teachers' competencies in the digital age: a systematic literature review. *Journal of Education and Learning*, 19(2), pp.587–596. https://doi.org/10.11591/edulearn.v19i2.21311.

Assainova, A., Abykenova, D., Aubakirova, Z., Mukhamediyeva, K. and Kozhageldinova, K., 2023. Web technologies in the development of computational thinking of students with mental disabilities. *International Journal of Emerging Technologies in Learning*, 18(11), pp.74–92. https://doi.org/10.3991/ijet.v18i11.38653.

Avci, Z.Y., O'Dwyer, L.M. and Lawson, J., 2020. Designing effective professional development for technology integration in schools. *Journal of Computer and Assisted Learning*, 63(2), pp.160–177. https://doi.org/10.1111/jcal.12394.

Basnayaka, A.I., Epitakaduwa, E.K.G.D., Jayawardena, C.P.U., Zoysa, A., Dharmakeerthi, U. and Jayawardena, S., 2023. Sankalpa - interactive digital learning platform to enrich students with special needs. In: *ICAC 2023 - 5th International Conference on Advancements in Computing: Technological Innovation for a Sustainable Economy, Proceedings*. IEEE. pp.53–58. https://doi.org/10.1109/ICAC60630.2023.10417380.

Bastian, A., Liza, L.O. and Efastri, S.M., 2023. Revolutionizing education: how digital literacy is transforming inclusive classrooms in post-COVID 19. *Journal of Public Health*, 45(3), pp.609–610. https://doi.org/10.1093/pubmed/fdad058.

Baxter, A. and Reeves, L.M., 2023. Inclusion of digital literacy skills in transition planning for students with intellectual disabilities. *Journal of Special Education Technology*, [online] 38(3), pp.384–391. Available at: <https://journals.sagepub.com/doi/10.1177/01626434221120416>.

Benigno, V., Panesi, S., Mutta, E.D., Caruso, G., Fante, C. and Ferlino, L., 2023. Online video training to improve digital competence and computer self-efficacy for support teachers. *Journal of Inclusive Methodology and Technology in Learning and Teaching*, 3(4), pp.1–25. https://doi.org/10.32043/jimtlt.v3i4.109.

Betancourt-Odio, M.A., Sartor-Harada, A., Ulloa-Guerra, O. and Azevedo-Gomes, J., 2021. Self-perceptions on digital competences for M-learning and education sustainability: A study with teachers from different countries. *Sustainability (Switzerland)*, 13(1), pp.1–12. https://doi.org/10.3390/su13010343.

Betancur-Chicué, V. and Muñoz-Repiso, A.G.-V., 2023. Microlearning for the development of teachers' digital competence related to feedback and decision making. *Education Sciences*, 13(7), p.722. https://doi.org/10.3390/educsci13070722.

Blasco-Serrano, A.C., González, I.B. and Coma-Roselló, T., 2022. Incorporation of ICT into preservice teacher training using the flipped classroom so as to enhance inclusive education. *Edutec*, (79), pp.9–29. https://doi.org/10.21556/edutec.2022.79.2393.

Börnert-Ringleb, M., Casale, G. and Hillenbrand, C., 2021. What predicts teachers ' use of digital learning in Germany ? Examining the obstacles and conditions of digital learning in special education. *European Journal of Special Needs Education*, [online] 36(1), pp.80–97. https://doi.org/10.1080/08856257.2021.1872847.

Cappuccio, G., Compagno, G. and Pedone, F., 2016. Digital competence for the improvement of special education teaching. *Journal of e-learning and Knowledge Society*, 12(4), pp.93–108. https://doi.org/10.20368/1971-8829/1134.

Carter, R.A. and Rice, M.F., 2016. Administrator work in leveraging technologies for students with disabilities in online coursework. *Journal of Special Education Technology*, 31(3), pp.137–146. https://doi.org/10.1177/0162643416660838.

Ciampa, K., 2017. Building bridges between technology and content literacy in special education: lessons learned from special educators' use of integrated technology and perceived benefits for students. *Literacy Research and Instruction*, [online] 56(2), pp.85–113. https://doi.org/10.1080/19388071.2017.1280863.

Claro, M., Castro-Grau, C., Ochoa, J.M., Hinostroza, J.E. and Cabello, P., 2024. Systematic review of quantitative research on digital competences of in-service school teachers. *Computers and Education*, 215(May). https://doi.org/10.1016/j.compedu.2024.105030.

Courduff, J. and Moktari, A., 2022. Personal, Cultural, and Institutional Perspectives of Special Education Technology Integrators: A Narrative Inquiry. *Journal of Special Education Technology*, 37(3), pp.413–425. https://doi.org/10.1177/01626434211019393.

Dalbudak, İ. and Yiğit, Ş., 2021. Technology use attitudes of teachers in the field of special education. *Propósitos Y Representaciones*, 9. https://doi.org/10.20511/pyr2021.v9nSPE2.1014.

Drushlyak, M., Semenikhina, O., Kharchenko, I., Mulesa, P. and Shamonia, V., 2023. Effectiveness of digital technologies in inclusive learning for teacher preparation. *Journal of Learning for Development*, 10(2), pp.177–195. https://doi.org/10.56059/jl4d.v10i2.777.

Du, X., 2022. Professional development for virtual environment: designing assistive-technology infused Inquiry-based learning experience for online teaching. *Journal of Online Learning Research*, [online] 8(3), pp.425–446. Available at: <https://files.eric.ed.gov/fulltext/EJ1372630.pdf>.

Fernández-Batanero, J.M., Cabero-Almenara, J., Román-Graván, P. and Palacios-Rodríguez, A., 2022. Knowledge of university teachers on the use of digital resources to assist people with disabilities. The case of Spain. *Education and Information Technologies*, [online] 27(7), pp.9015–9029. https://doi.org/10.1007/s10639-022-10965-1.

Fernández-Batanero, J.M., Montenegro-Rueda, M. and Fernández-Cerero, J., 2022. Are primary education teachers trained for the use of the technology with disabled students? *Research and Practice in Technology Enhanced Learning*, [online] 17(1). https://doi.org/10.1186/s41039-022-00195-x.

Fernández-Cerero, J. and Montenegro-Rueda, M., 2023. Digital competence and disability: a qualitative approach from the perspective of university teachers in Andalusia (Spain). *Journal of Continuing Higher Education*, [online] 0(0), pp.1–17. https://doi.org/10.1080/07377363.2023.2265107.

Fernández-Cerero, J. and Román-Graván, P., 2023. Aspects that explain the digital competence of university teachers in the use of ICT resources to look after students with disabilities. *Edutec. Revista Electrónica de Tecnología Educativa.*, 83, pp.104–119. https://doi.org/10.21556/edutec.2023.83.2759.

Fernández, L.S., Llauradó, E.V., Martínez, L.M. and García, C.R., 2022. Digital competence in the attention of students with special educational needs. An overview from the European Framework for Digital Teaching Competence "DigCompEdu". *Digital Education Review*, (41), pp.284–305. https://doi.org/10.1344/DER.2022.41.284-305.

Fisher, K.M., Standridge, K.E., Echezabal, L.M., Grice, E.G. and Greer, A., 2024. The pandemic experiences of special education teachers in Georgia : a mixed methods study. *The Journal of Special Education*, pp.1–10. https://doi.org/10.1177/00224669241232155.

Gómez-Puerta, M., Chiner, E., Villegas-Castrillo, E. and Suriá-Martínez, R., 2024. Digital and mediation competence for students' safe use of the internet: enhancing teacher training. *Education Sciences*, 14(12), pp.1–14. https://doi.org/10.3390/educsci14121399.

Gonçalves, S. and Ferreira, B.E.B., 2021. Technological and digital convergence, emergency remote education and ADHD students who attend the final years of elementary school. *Texto Livre*, 14(1), pp.1–17. https://doi.org/10.35699/1983-3652.2021.25043.

Graván, P.R. and Cerero, J.F., 2022. Training of university teachers in ICT and disability. The case of the University of Seville. *International Journal of Educational Research and Innovation (IJERI),* 17, pp.135–151. https://doi.org/10.46661/ijeri.6168.

Gurgenidze, M., Makaradze, N., Nakashidze-Makharadze, T., Karmanova, A., Nikiforova, Z. and Sheleiko, V.A., 2022. Enhancing teachers' digital competence for professional development in distance mode. In: *Innovations in Digital Economy*. pp.277–291. https://doi.org/10.1007/978-3-031-14985-6_20.

Hata, A., Wang, H., Yuwono, J. and Nomura, S., 2023. *Teknologi Asistif untuk Anak-anak dengan Disabilitas di Sekolah Inklusif dan Sekolah Luar Biasa di Indonesia*. [online] Washington, D.C. Available at: <https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099431209052334562/idu06ab3657503c280475e0a90009b7aad6329d7>.

Hilzensauer, M., Pecher, A. and Angeloni, F., 2022. *InclUDE technical guidelines for accessible digital higher education*. [online] Available at: <https://easpd.eu/fileadmin/user_upload/Projects/InclUDE_Technical_Guidelines_Full_EN_FINAL.pdf>.

Hsieh, C.-Y., 2024. General and special education teachers' perspectives on distance teaching in post-pandemic in Taiwan. In: *Computers Helping People with Special Needs. ICCHP 2024.* Springer. pp.340–347. https://doi.org/10.1007/978-3-031-62846-7_41.

Kaplarević-Mališić, A., Dimitrijević, S., Radojević, I. and Kovačević, M., 2022. Developing teaching competencies for implementing blended learning in higher education: experiences of faculty of science, University of Kragujevac. In: *9th International scientific conference Technics and Informatics in Education*. pp.352–357. https://doi.org/10.46793/tie22.352k.

Kiryakova, G. and Kozhuharova, D., 2024. The digital competences necessary for the successful pedagogical practice of teachers in the digital age. *Education Sciences*, 14(5). https://doi.org/10.3390/educsci14050507.

Klapproth, F., Federkeil, L., Heinschke, F. and Jungmann, T., 2020. Teachers' experiences of stress and their coping strategies during COVID-19 induced distance teaching. *Journal of Pedagogical Research*, [online] 4(4), pp.444–452. https://doi.org/10.33902/JPR.2020062805.

Kurt, A. and Erden, M.K., 2024. Investigation of the opinions of pre-service special education teachers on the use of assistive technologies in special education. *Education and Information Technologies*, [online] 29(1), pp.51–76. https://doi.org/10.1007/s10639-023-12278-3.

Liao, F., Murphy, D., Wu, J.C., Chen, C.Y., Chang, C.C. and Tsai, P.F., 2022. How technology-enhanced experiential e-learning can facilitate the development of person-centred communication skills online for health-care students: a qualitative study. *BMC Medical Education*, [online] 22(1), pp.1–9. https://doi.org/10.1186/s12909-022-03127-x.

Mali, D. and Lim, H., 2021. How do students perceive face-to-face/blended learning as a result of the Covid-19 pandemic? *International Journal of Management Education*, [online] 19(3), p.100552. https://doi.org/10.1016/j.ijme.2021.100552.

Meinck, Sabine, E., Fraillon, Julian, E. and Strietholt, Rolf, E., 2022. *The Impact of the COVID-19 pandemic on education: international evidence from the Responses to Educational Disruption Survey (REDS).* [online] *International Association for the Evaluation of Educational Achievement*. Available at: <http://www.unesco.org/open-access/terms-use-ccbysa-en>.

Montenegro-Rueda, M. and Fernández-Batanero, J.M., 2022. Digital competence of special education teachers: impact, challenges and opportunities. *Australasian Journal of Special and Inclusive Education*, 46(2), pp.178–192. https://doi.org/10.1017/jsi.2022.8.

Montenegro-Rueda, M. and Fernández-Batanero, J.M., 2024. Adaptation and validation of an instrument for assessing the digital competence of special education teachers. *European Journal of Special Needs Education*, [online] 39(3), pp.367–382. https://doi.org/10.1080/08856257.2023.2216573.

Montenegro-Rueda, M. and Fernández-Cerero, J., 2023. Digital competence of special education teachers: an analysis from the voices of members of school management teams. *Societies*, 13(4). https://doi.org/10.3390/soc13040084.

Montes, C. del P.G., Fuentes, A.R. and Cara, M.J.C., 2023. ICT training for educators of Granada for working with people with autism. *Heliyon*, [online] 9(3), p.e13924. https://doi.org/10.1016/j.heliyon.2023.e13924.

Moreira, J.A., Nunes, C.S. and Casanova, D., 2023. Digital competence of higher education teachers at a distance learning university in portugal. *Computers*, 12(169), pp.1–20. https://doi.org/10.3390/computers12090169.

Moreno-Rodriguez, R., Diaz-Vega, M., Lopez-Bastias, J.L. and Espada-Chavarria, R., 2021. Online training in accessibility and design for all: A tool to train post-COVID inclusive graduates. *International Journal of Environmental Research and Public Health*, 18(23), pp.1–13. https://doi.org/10.3390/ijerph182312582.

Murphy, A., Malenczak, D. and Ghajar, M., 2019. Identifying challenges and benefits of online education for students with a psychiatric disability. *Journal of Postsecondary Education and Disability*, [online] 32(4), pp.395–409. Available at: <https://files.eric.ed.gov/fulltext/EJ1247112.pdf>.

Nino, J., Ochoa, S., Kiss, J., Edwards, G., Morales, E., Hutson, J. and Poncet, F., 2024. Assistive technologies for internet navigation: a review of screen reader solutions for the blind and visually impaired. *International Journal of Recent Engineering Science*, 11(6), pp.260–274. https://doi.org/10.14445/23497157/IJRES-V11I6P122.

Obesso, M. de las M. de, Nú˜nez-Canal, M. and P´erez-Rivero, C.A., 2023. How do students perceive educators ' digital competence in higher education ? *Technological Forecasting & Social*, [online] 188(December 2022). https://doi.org/10.1016/j.techfore.2022.122284.

Ohalezim, N.B., Edwards, B.I. and Aderemi, T.J., 2021. Future of especial education: options for equitable elearning opportunities for learners with special education needs. In: *Emerging Technologies for Next Generation Learning Spaces*. [online] pp.19–30. https://doi.org/10.1007/978-981-16-3521-2_3.

Olakanmi, O.A., Akcayir, G., Ishola, O.M. and Demmans Epp, C., 2020. Using technology in special education: current practices and trends. *Educational Technology Research and Development*, [online] 68(4), pp.1711–1738. https://doi.org/10.1007/s11423-020-09795-0.

Olivencia, J.J.L., Fernández, M.J.A. del O., Sodis, J.L.G. and Villalba, M.J.S., 2025. Digital teaching competence and ICT usability in highly complex educational centers. Practices and opportunities for an inclusive educational transformation. *Revista Electrónica Interuniversitaria de Formación del Profesorado*, 28(1), pp.33–47. https://doi.org/10.6018/reifop.639651.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P. and Moher, D., 2021. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *The BMJ*, 372. https://doi.org/10.1136/bmj.n71.

Pearson, V., Lister, K., McPherson, E., Gallen, A.M., Davies, G., Colwell, C., Bradshaw, K., Braithwaite, N. and Collins, T., 2019. Embedding and sustaining inclusive practice to support disabled students in online and blended learning. *Journal of Interactive Media in Education*, 2019(1). https://doi.org/10.5334/jime.500.

Peng, R., Razak, R.A. and Halili, S.H., 2024. Exploring the role of attitudes, self-efficacy, and digital competence in influencing teachers' integration of ICT: A partial least squares structural equation modeling study. *Heliyon*, [online] 10(13), p.e34234. https://doi.org/10.1016/j.heliyon.2024.e34234.

Pérez, E.M. and Delgado, S.C., 2019. Digital competence, special education teachers'training and attitude towards the ICT. *Profesorado*, [online] 23(1), pp.209–241. Available at: <https://revistaseug.ugr.es/index.php/profesorado/article/view/9151>.

Pinto-Llorente, A.M., Cruz Sánchez-Gómez, M., Teresa Del Moral-Marcos, M. and Martín-Sánchez, Ó.J., 2018. A research into the students' perceptions of technology and inclusive education. In: *ACM International Conference Proceeding Series*. pp.580–586. https://doi.org/10.1145/3284179.3284278.

Podsiadlik, A., 2021. The blended learning experiences of students with specific learning difficulties: a qualitative case study located in one British higher education institution. *International Journal of Disability, Development and Education*, [online] 00(00), pp.1–16. https://doi.org/10.1080/1034912X.2021.1876217.

Redecker, C., 2017. *European framework for the digital competence of educators: DigCompEdu*. [online] *Joint Research Centre (JRC) Science for Policy report*. https://doi.org/10.2760/159770.

Reyes, J.I., Meneses, J. and Xavier, M., 2023. Suitability of online higher education for learners with disabilities: The students' voices. *Journal of Special Education Technology*, [online] 38(3), pp.370–383. https://doi.org/10.1177/01626434221131772.

Román-Graván, P., Fernández-Cerero, J., Montenegro-Rueda, M. and Reyes-Rebollo, M.M., 2024. University teaching skills in ICT and disability. The case of the Autonomous Community of Madrid. *Education and Information Technologies*, [online] 29(10), pp.12653–12676. https://doi.org/10.1007/s10639-023-12314-2.

Romero-García, C., Buzón-García, O. and de Paz-Lugo, P., 2020. Improving future teachers' digital competence using active methodologies. *Sustainability (Switzerland)*, 12(18), pp.1–15. https://doi.org/10.3390/SU12187798.

Santoianni, F. and Ciasullo, A., 2023. Self-efficacy and digital skill of university teachers. In: *Higher Education Learning Methodologies and Technologies Online*. pp.148–167. https://doi.org/10.1007/978-3-031-29800-4_12.

Sarkis-Onofre, R., Catalá-López, F., Aromataris, E. and Lockwood, C., 2021. How to properly use the PRISMA Statement. *Systematic Reviews*, 10(117), pp.13–15. https://doi.org/10.1186/s13643-021-01671-z.

Schladant, M., Ocasio-Stoutenburg, L., Nunez, C., Dowling, M., Shearer, R. and Bailey, J., 2023. Promoting a culture of inclusion: impact of professional development on teachers' assistive technology practices to support early literacy. *Journal of Early Childhood Teacher Education*, 4(2). https://doi.org/10.1080/10901027.2022.2099325.

Silletti, F., Ritella, G., Iacobellis, B., Semeraro, C., Episcopo, E., Cassibba, R. and Coppola, G., 2021. Distance learning in Higher Education during the first pandemic lockdown: The point of view of students with special educational needs. *Qwerty*, 16(2), pp.30–46. https://doi.org/10.30557/QW000042.

Sims, S. and Fletcher-Wood, H., 2021. Identifying the characteristics of effective teacher professional development: a critical review. *School Effectiveness and School Improvement*, 31(1), pp.47–63. https://doi.org/10.1080/09243453.2020.1772841.

Skantz-Åberg, E., Lantz-Andersson, A., Lundin, M. and Williams, P., 2022. Teachers' professional digital competence: an overview of conceptualisations in the literature. *Cogent Education*, [online] 9(1). https://doi.org/10.1080/2331186X.2022.2063224.

Starks, A. and Starks, A., 2022. Serving students with disabilities in K-12 online learning : daily practices of special educators during the COVID-19 pandemic COVID-19 pandemic. *Distance Education*, [online] 43(4), pp.596–620. https://doi.org/10.1080/01587919.2022.2144138.

Starks, A.C. and Reich, S.M., 2023. "What about special ed?": Barriers and enablers for teaching with technology in special education. *Computers and Education*, [online] 193(104665). https://doi.org/10.1016/j.compedu.2022.104665.

Tadesse, S. and Muluye, W., 2020. The Impact of COVID-19 Pandemic on Education System in Developing Countries: A Review. *Open Journal of Social Sciences*, 08(10), pp.159–170. https://doi.org/10.4236/jss.2020.810011.

Thompson, K.M. and Copeland, C., 2020. Inclusive considerations for optimal online learning in times of disasters and crises. *Information and Learning Science*, 121(7–8), pp.481–486. https://doi.org/10.1108/ILS-04-2020-0083.

Tonks, D., Kimmons, R. and Mason, S.L., 2021. Motivations among special education students and their parents for switching to an online school : survey responses and emergent themes. *Online Learning Journal*, 25(2), pp.171–189. https://doi.org/10.24059/olj.v25i2.2141.

UNESCO, 2018. *Unesco ICT competency framework for teachers*. [online] Paris: the United Nations Educational, Scientific and Cultural Organization. Available at: <https://unesdoc.unesco.org/ark:/48223/pf0000265721>.

Uromova, S.E., Medvedeva, E.Y., Dmitrieva, E.E., Olkhina, E.A. and Zhulina, E. V., 2020. The use of information and communication technologies in the practice of special education. In: *Lecture Notes in Networks and System*. [online] Springer. pp.233–238. https://doi.org/10.1007/978-3-030-47945-9_25.

Yıldız, G., Şahin, F., Doğan, E. and Okur, M.R., 2022. Influential factors on e-learning adoption of university students with disability: Effects of type of disability. *British Journal of Educational Technology*, 53(6), pp.2029–2049. https://doi.org/10.1111/bjet.13235.

Zhang, X., Sazalli, N.A.H. and Nadjwa, M.N., 2024. Improving teachers' digital competence in higher education: a systematic literature review. *International Journal of Academic Research in Progressive Education and Development*, 13(1). https://doi.org/10.6007/ijarped/v13-i1/20560.

Agentic RAG for Personalized Learning: Design of an AI-Powered Learning Agent Using Open-Source Small Language Models

Shilpi Taneja, Siddhartha Sankar Biswas, Bhavya Alankar and Harleen Kaur
Department of Computer Science and Engineering, School of Engineering Sciences and Technology, Jamia Hamdard, New Delhi, India

shilpi.asija@gmail.com

https://doi.org/10.34190/ejel.23.4.4044

Abstract: This paper presents the design of a personalized learning agent powered by the Agentic RAG technique. The agent can interpret learners' queries and autonomously decide which tools should be used to generate the most suitable response. When the learner shares an Open Educational Resource (OER) they wish to learn from, the agent first breaks the content into smaller, manageable chunks. These chunks are then indexed sequentially to preserve the natural flow of the text. At the same time, chunks are also converted into vector embeddings that allow semantic retrieval. Depending on the learner's request, different tools are selected by the agent. For example, when the learner requests learning aids like summaries, quizzes, or flashcards, the agent invokes the corresponding tool. This tool passes the sequentially indexed chunks to a small language model to generate the output. For context-specific queries, another specialized tool that relies on vector indexing and retrieval-augmented generation (RAG), is invoked. Visual question answering is handled by a separate tool that leverages multimodal RAG using a multimodal small language model. This agentic setup improves the accuracy and relevance of responses generated by the agent. To test its agentic behaviour, we probed our agent with a diverse set of questions drawn from four different OERs. We thoroughly examined each response and tracked the tools that got invoked autonomously. We also compared the similarity of summaries produced by our agent against those generated by ChatGPT (GPT-4o) using BERT Score as the evaluation metric. Our findings indicate that the agent consistently selected the appropriate tools and the summaries generated by our agent showed close semantic similarity to those produced by GPT-4o, suggesting that the proposed approach can provide performance reasonably close to a state-of-the-art model. The agent being lightweight resides on learner's local machine and avoid dependence on cloud-based AI ensuring the privacy of learner's data. It is affordable as it entirely relies on open source frameworks and small models. As the agent provides personalized support to learners by answering their context-based queries and providing on-demand learning aids, it improves their engagement with the educational content. This research shows that designing agentic AI tools using open-source software to address diverse learning needs is technically and economically feasible as well as educationally valuable.

Keywords: AI in education, LlamaIndex, Agentic RAG, Small language model, Generative artificial intelligence, OER

1. Introduction

The field of personalized learning has seen a number of studies that investigate individuals' learning needs in order to improve learning outcomes through adaptive content delivery and feedback (Holmes, Bialik and Fadel, 2019; Watters, 2023). The recent advances in generative artificial intelligence are impacting education in many ways. Large language models (LLMs), for example, can interact with learners, provide answers to their educational queries with explanations and interactive feedback (Bozkurt, 2023). With the increasing availability of open-source LLMs and small language models (SLMs), it has become technically feasible and economical to design intelligent learning assistants that provide personalized educational support to learners.

Despite their brilliant capabilities, the downside of using LLMs for educational support is that they sometimes fail to provide domain-specific educational information. This is because their responses are based on their pre-training data rather than learning resources. A known drawback of LLMs is hallucinations, responses that appear plausible but are in fact fabricated and not factual. When LLMs do not have the necessary context needed to answer the learners' query, they often end up hallucinating and may mislead learners. Retrieval-Augmented Generation (RAG) mitigates this limitation to a large extent as it grounds the LLM's responses in domain-specific knowledge and improves completeness, accuracy and relevance of the responses (Lewis et al., 2020).

In practice, AI-powered personalized learning is largely dependent on cloud-based LLMs (Chimezie, 2024; Sajja et al., 2024; Slade, Hyk and Gurung, 2024) that have notable limitations, such as privacy concerns and cost. This paper demonstrates how open-source small language models combined with Agentic AI techniques can be used to build autonomous learning agents that preserve privacy and are affordable. These models can run on modest hardware; for instance, running a less than 7b parameter model with Ollama typically requires 8 to16 GB RAM and a modern CPU with at least 4 cores, making it feasible for standard personal computers (GPU Mart, 2025).

Cite this article: Taneja, S.et al. 2025. "Agentic RAG for Personalized Learning: Design of an AI-Powered Learning Agent Using Open-Source Small Language Models", *Electronic Journal of e-Learning* , 23(4), pp 69-80, https://doi.org/10.34190/ejel.23.4.4044

In our earlier work, we outlined the architecture of an AI-powered personal learning assistant using multi-modal Retrieval Augmented Generation (RAG) with small language models (Taneja et al., in press). The present study builds on that design by integrating an emerging approach 'Agentic RAG' in it (Singh et al., 2025). With this addition, the agent not only answer the learner's queries from an Open Educational Resource (OER) in natural language, but autonomously decide which tool is most relevant for the query. In educational context, this helps learners by answering their context-specific queries and providing on-demand learning aids such as summaries, flashcards, and quizzes.

To simplify the interaction between learner and agent, we implemented a chatbot interface. This was designed using Gradio, which is an open-source Python package used for quickly building AI applications (DeepLearning.AI, 2024b). The chatbot maintains the context of the conversations, which allows learners to ask follow-up questions based on the ongoing interaction.

The study is guided by the following primary research question: How can open, locally-deployable Agentic RAG-based AI systems be designed to match or surpass the pedagogical utility of cloud-based AI tools, while preserving learner privacy and minimizing cost? The study further explores the following sub-questions, in order to answer this main question:

Q1. How can Agentic RAG enhance the learning agents by answering context-specific educational queries and providing learning-aids such as summaries, flashcards, and quizzes?

Q2. Are there any design and deployment guidelines for creating affordable, multimodal and context-aware learning agents that run locally using open-source tools and how these learning agents compare with cloud-based AI tools?

The rest of the paper is organized as follows: Section 2 discusses related work that has already been done in this field and identifies the gaps in current research which can be filled by our work. Section 3 explains the system design of proposed agent in detail. Section 4 presents development methodology and provide practical guidelines on the implementation. Section 5 reports the analysis and results, while Section 6 summarizes key findings and discusses limitations of the current study. Finally, Section 7 points to the potential directions for future research.

2. Related Work

In this section, we review prior work in the fields of AI-powered personalized learning based on language models. We highlight the main contributions of these studies and state how our approach differs from them.

2.1 Cloud-Hosted LLM Based Learning Assistants

Several studies have proposed intelligent assistants built on cloud-hosted LLMs. For instance, an AI enabled intelligent assistant presented in a recent work provides many features similar to our proposed agent, such as summaries, quizzes, flashcards, and context-relevant responses (Sajja et al., 2024). However, their system uses GPT 3.5, which is hosted on the cloud, and hence it doesn't provide data confidentiality. Moreover, GPT 3.5 is a text-based model, so the assistant lacks multimodal capabilities. Other cloud-based learning assistants/intelligent tutors have been proposed for teaching Data Structures & Algorithms and Introductory Psychology courses using a RAG approach (Chimezie, 2024; Slade, Hyk and Gurung, 2024). While these works demonstrate the utility of cloud-based LLMs in education, they raise concerns of privacy, cost, and accessibility.

2.2 Open-Source SLM Based Learning Assistants

Recent studies have started exploring the efficacy of small language models with RAG for educational purpose. For instance, a recent work used is neural-chat-7b-v3, a fine-tuned version of Mistral-7B-v0.1 to provide learning support for computing education (Liu et al., 2024).The model they have used is text-based, therefore limiting its use to non-visual question answering.

Recent advances in multimodal open source small models such as gemma3, llava, mini-cpm-v present a promising opportunity which combines vision and language capabilities in learning assistants. Our proposed agent uses a multimodal small language model for image-based question answering in one of its tools. The Agentic RAG technique enhances the agent's ability to understand and respond to user queries with high contextual accuracy by invoking the dedicated tools for specific tasks (DeepLearning.AI, 2024a).

2.3 Contribution Beyond Existing Work

While prior studies have largely focused on cloud-based, text-only assistants, our work emphasizes local deployment of the proposed Learning Agent by using open-source small language models and a multimodal model. This ensures that sensitive user data remains on personal devices, thereby enhancing privacy, security and affordability. Moreover, unlike existing literature, we share detailed guidelines and instructions for implementing the proposed personal learning agent, which are not available to the best of our knowledge.

From a pedagogical point of view, our proposed agent enables learner-driven exploration of the educational resources, generates personalized explanations, quizzes, and other learning aids. It provides feedback in natural language, resulting in improved learner engagement and interest in the subject matter. These aspects align with the well-known ideas of personalized learning that encourage learners to take charge of their own learning and actively participate in the learning process (Reeve and Tseng, 2011) and that providing formative feedback can help enhance learning outcomes (Shute, 2007).

3. System Design

The design of the proposed AI-powered personal learning agent is based on an Agentic AI technique, namely Agentic Retrieval Augmented Generation. Agentic AI refers to artificial intelligence systems that can autonomously perform tasks, make decisions, and solve complex problems without constant human intervention (Pounds, 2024). Agentic RAG incorporates agentic behaviour into the RAG-based AI systems by adding intelligence that can autonomously analyze queries, select the most effective tools for data retrieval, and refine responses (DeepLearning.AI, 2024a), which allows for more accurate and comprehensive answers.

3.1 Technical Building Blocks

Our previous work shared the detailed technology stack required to implement the learning assistant (Taneja et al., in press). All the tools and resources contained in this stack are open source. We have used one additional tool, Gradio, for chatbot interface development for our agent. To summarize, we have used the following open-source tools/packages/frameworks for our design:

- **Small language model**, gemma 2:2b (Ollama, 2024a), for question answering and natural language interaction with the learner (Team et al., 2024).
- **Small Multimodal models,** Llava (Ollama, 2024b) or minicpm-v (Ollama, 2024c)for visual question answering.
- **Ollama** (Ollama, 2025) for hosting these small models on a local machine.
- **LlamaIndex** (LlamaIndex, 2025g), for Agentic RAG implementation.
- **Gradio** for chatbot interface and chat history implementation.

3.1.1 LlamaIndex components

From LlamaIndex, we have primarily used the following components: Index (Sequential, Vector Store, and Multimodal Vector Store), Query Engine, Response Synthesizer, and Router Query Engine. A brief description of these components is discussed below and is summarized in Figure 1.

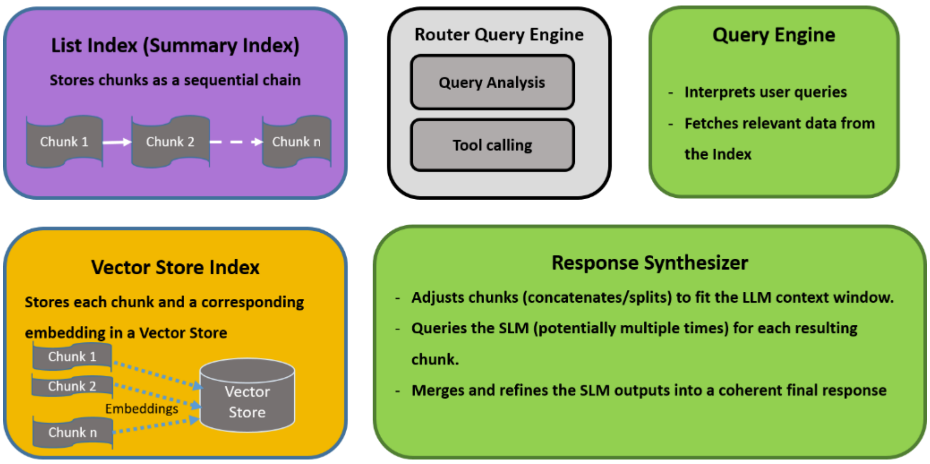


Figure 1: LlamaIndex Components for Agentic RAG

- **List Index / Summary Index** organizes chunks in a sequential list format, making it easy to manage and retrieve chunks (LlamaIndex, 2024e). In the LlamaIndex library, what was earlier referred to as a List Index is now called a Summary Index. For clarity, we continue to use the term List Index in this paper because it better reflects its sequential structure. In the proposed agent, List Index is used when a learner requests the summary of OER or other learning-aids, like flash cards and quizzes. Unlike the Vector Store Index which focuses on retrieving semantically similar chunks, List Index is helpful in cases when there is a need to access the entire content for a holistic view of the material**.**
- **Vector Store Index** converts text chunks into vector embeddings, which enables semantic search and supports RAG (LlamaIndex, 2024f). This mechanisms helps the agent to generate contextually relevant answers to learners' queries. This helps in enhancing the quality of interactions between the learner and the AI agent (Taneja et al., in press). **Multimodal Vector Store Index** is a special type of Vector Store Index that uses multimodal embeddings such as CLIP to represent both images and text. In this paper, we discuss the multimodal vector store index in one of the approaches for visual question answering.
- The **Query Engine** is the interface through which a user query is processed. It interprets the input query, retrieves relevant information from an Index, and then passes the user's query and retrieved data to the Response Synthesizer for generating a coherent response (LlamaIndex, 2024b). Thus, it acts as the coordinator that connects the user's query to the Index and the Response Synthesizer.
- The **Response Synthesizer** in LlamaIndex is a component responsible for transforming the retrieved data into a clear, human-readable final response (LlamaIndex, 2024d). It uses Large/Small Language Models to synthesize information, ensuring that the final output is contextually relevant, complete, and concise. There are three main response modes for the synthesizer that we have used in our implementation-Refine, Compact, and Tree Summarize (LlamaIndex, 2024c). In the **Refine** mode, the synthesizer sequentially processes the chunks, beginning with an initial response produced from the first chunk. It makes a separate SLM call per chunk. The previous answer and the next chunk are integrated with the original question to be used in the next query iteratively, until all chunks are used. In contrast, the **Compact** mode focuses on efficiency by reducing the SLM calls, concatenating as many chunks as possible into a single input prompt such that the total text fits within the context window. Our agent uses Compact mode for generating flashcards and quizzes and context-specific Question Answering. The **Tree Summarize** mode takes a hierarchical approach, where chunks are recursively summarized and merged. Summaries are generated at each stage, combined into larger summaries, and refined until a single, coherent response emerges. This method is used by our agent to create summaries.
- The **Router Query Engine** is a specialized Query Engine that interprets and analyzes users' queries and routes them to the appropriate tools by identifying which tool is best suited to handle the user query(Zhang et al., 2020). It allows for modular and efficient query processing by integrating multiple independent tools in a single application, which are specialized in their tasks.

3.1.2 Front-end chatbot interface

To develop a web-based front-end interface, we have used Gradio (DeepLearning.AI, 2024b), which is an open-source Python package to build the chatbot interfaces. This interface allows learners to upload any OERs that they wish to learn from. It also maintains chat history and allows learners to ask follow-up questions based on the previous chat. A screenshot of the chatbot interface of the learning agent is shown in Figure 2.

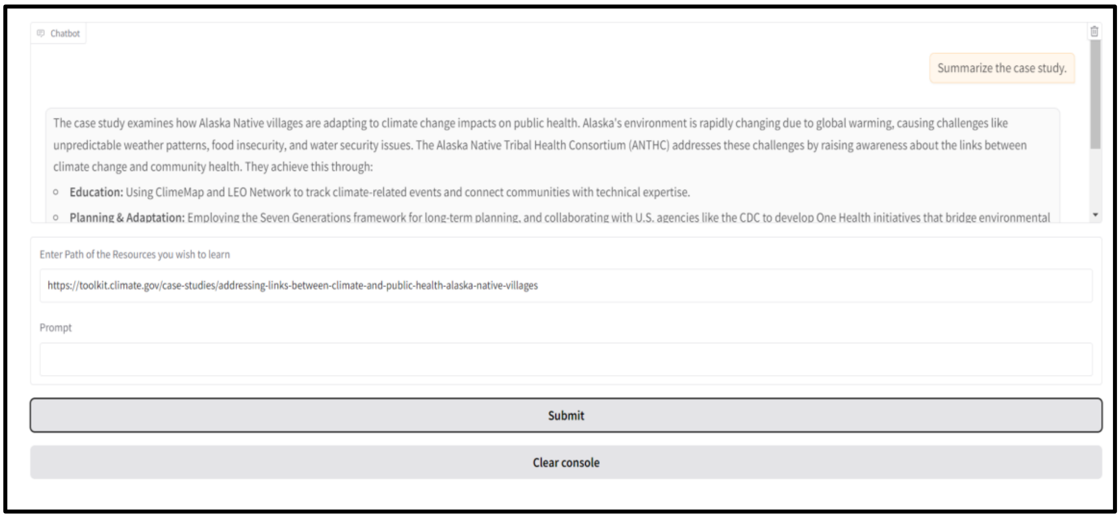


Figure 2: Chatbot Interface built using Gradio

3.2 Educational Rationale Behind Design Choices

The design of our learning agent is based on the educational theory and instructional design practices. We have included features such as flashcards, quizzes, and summaries because they are recognized to encourage active recall and improve comprehension (Dunlosky et al., 2013; Putnam, Sungkhasettee and Roediger, 2016). Moreover, multimodal interaction (text and images) makes the system more inclusive and engaging as learners can work with both textual and visual educational resources they typically encounter in classrooms and digital learning environments.

4. Development Methodology

The methodology involves initial data preparation (chunking and indexing) at the time of data loading by learners, followed by Agentic Retrieval-Augmented Generation process while question-answering and generating learning aids.

4.1 Data Preparation

The OER documents that the learner wishes to learn are chunked into smaller segments to facilitate processing. This approach, known as **Chunking**, is very important due to the context window limitations of language models, which can only process a finite number of tokens at a time. By creating smaller, more coherent chunks, the system ensures that each segment fits within the model's context window, thereby enabling more effective and accurate responses. After Chunking, the next step is **Indexing**, a method of organizing data in a way that makes searching and retrieving information faster and more efficient. LlamaIndex offers several types of indexes (LlamaIndex, 2024a) to be used in different use cases, as discussed in section 3.1.1. Figure 3 demonstrates the process of Chunking and Indexing.

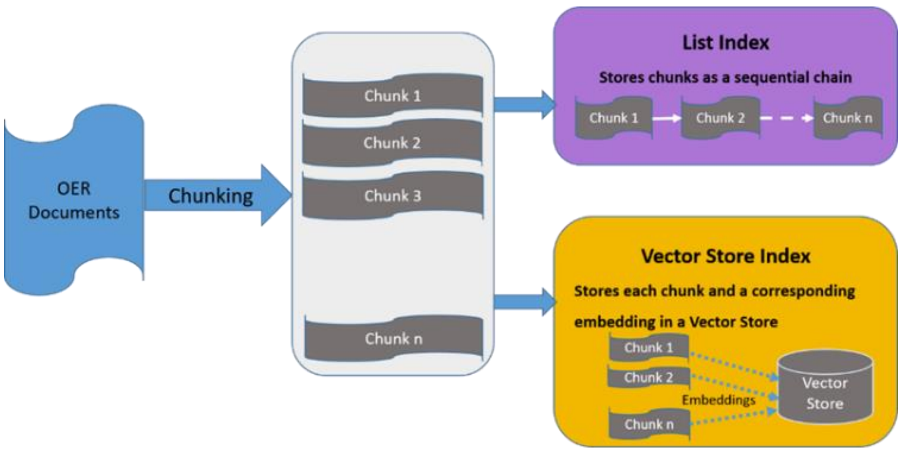


Figure 3: Indexing Techniques

4.2 Agentic RAG Process

During the learning time, the Agentic RAG approach is used by our agent to respond to learners' queries. Learner's query is passed to a Router Query Engine, which analyses it and, based on the intent of the query, an appropriate tool is invoked. There is an exclusive tool for each type of learner's request. Each tool has its dedicated query engine that works along with the Index and Response synthesizer to create the final response. This design is presented in Figure 4.

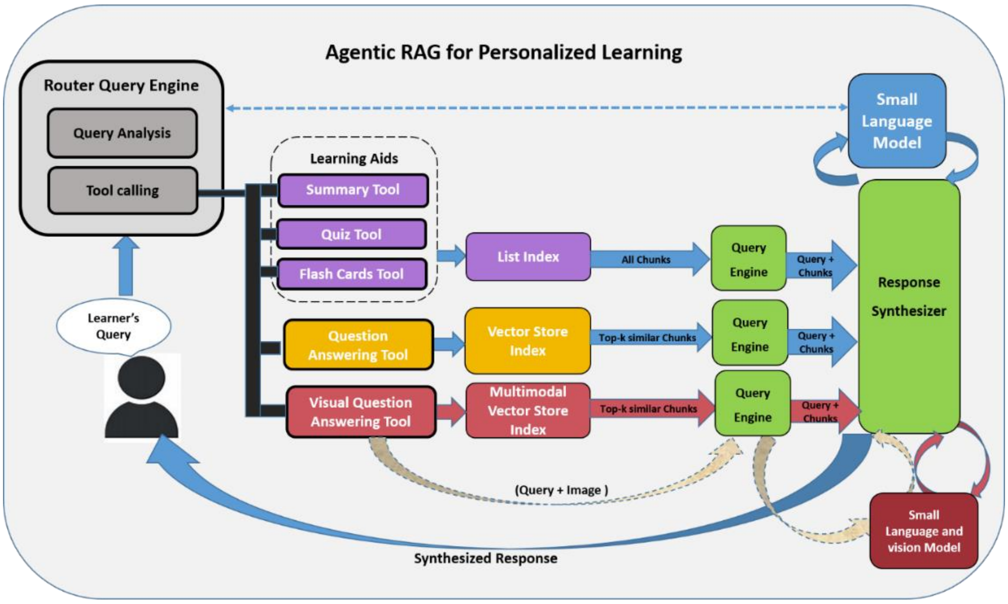


Figure 4: Agentic RAG Design

If the learner is interested in obtaining a summary of the OER, the Summary tool is invoked by the Router. When a learner asks for flashcards or a quiz, the agent are activates the corresponding tool. For content-specific questions, Question Answering tool is used while image-based questions are routed to the Visual Question Answering tool by the Router Query Engine. A brief description of these tools is given below:

- **Tools for Learning aids (Summary Tool, Flashcards Tool, Quiz Tool):** Whenever the learner requests the agent for learning aids, it uses one of these tools. These learning aids are recognized in educational practice for their role in helping learners understand, practice, and retain key ideas. Summary condense the main points of an educational resource so that learners can revisit important concepts without rereading the entire content. Flashcards convert complex topics into smaller units, making them easier to remember. Quizzes foster active engagement and help learners in strengthening their understanding of the topic (Dunlosky et al., 2013; Putnam, Sungkhasettee and Roediger, 2016). Collectively, these tools allow the agent to provide structured support to the learners across different stages of learning. The process that our Learning agent undertakes to generate these learning aids is demonstrated in Figure 5. The learner's query is passed to the Router Query Engine, which analyzes it and then calls the appropriate tool for learning by forwarding the query to the Query Engine. The Query Engine pulls the sequentially indexed chunks from the List Index. All learning-aid tools rely on the List Index and Response Synthesizer described in Section 3.1.1

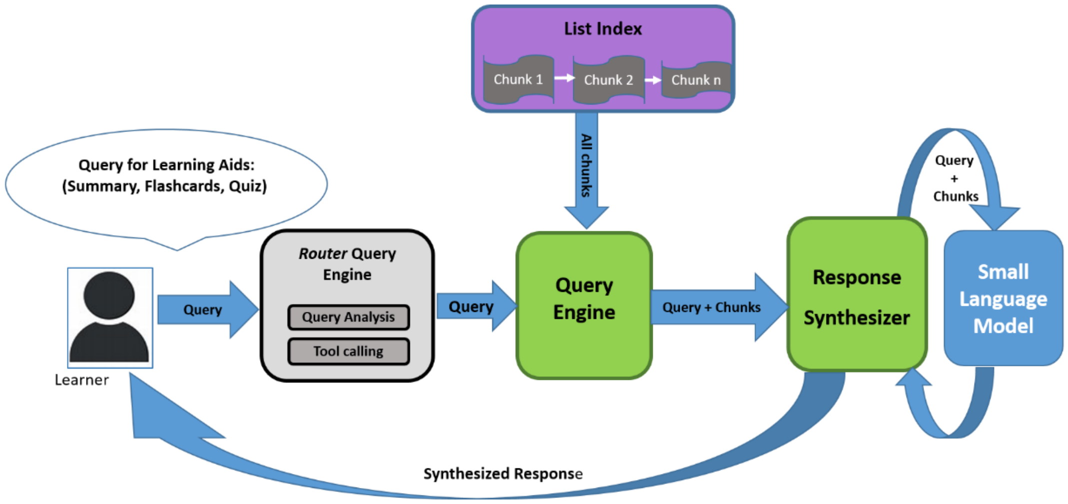


Figure 5: Tools for Learning Aids

- **Question Answering Tool (RAG Tool):** Figure 6 illustrates the RAG process used by the Question Answering Tool. Vector Store Index stores embeddings of all the chunks in a vector store. When a learner asks a query, it is passed to the Router Query Engine, which then chooses to invoke the Question-Answering Tool. The Router Query Engine forwards the query to the Query Engine. The top-k chunks that are most similar to the learner's query are retrieved by the Query Engine. These similar chunks, along with the Query, are passed on to the Response synthesizer, which adjusts the chunks and passes them to the SLM along with the query and returns the synthesized response to the learner.

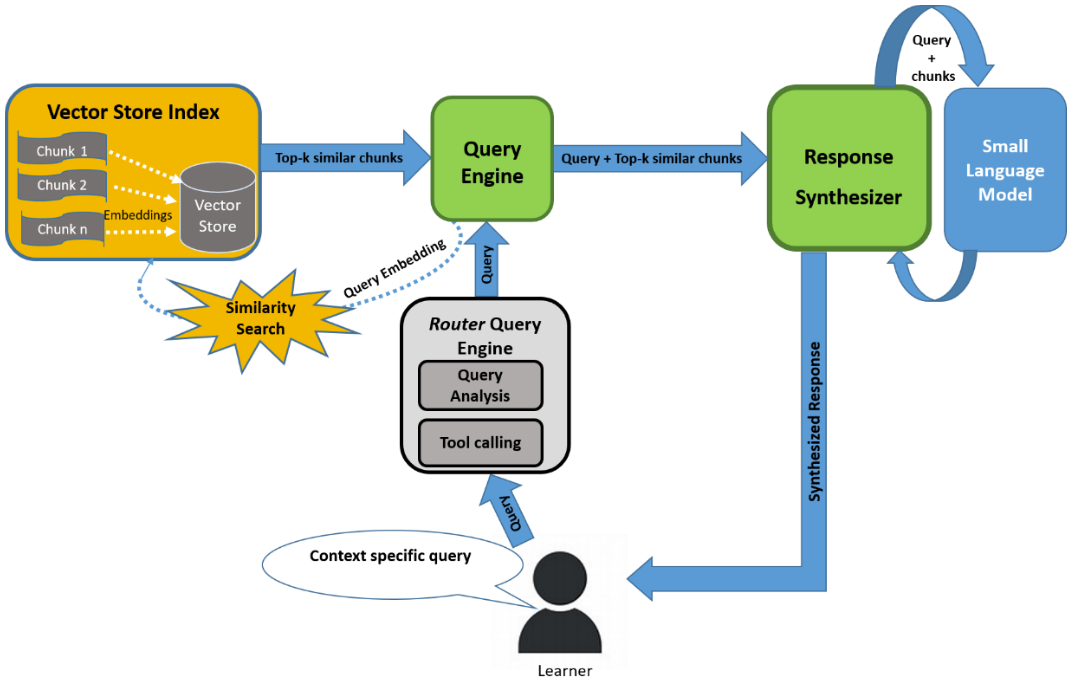


Figure 6: Question-Answering Tool (RAG-Tool)

- **Visual Question Answering Tool (Image Tool):** We experimented with two different methods for building the Visual question answering tool. In the first method, process is very similar to text-based question answering. We used a multimodal embedding model (CLIP) to create a multimodal vector index for images and text. When learner submitted a query, is was also embedded with the same model and most relevant chunks were retrieved from the vector space. These were then combined with the query and passed to a multimodal SLM such as Llava, which also uses CLIP embedding. Though this multimodal RAG approach functioned as expected, but the quality of responses were inferior as compared to our second approach. In the second approach, we developed a Custom Query Engine in place of the default one provided by LlamaIndex. Normally, creating a Query engine requires building an index, but we bypassed this requirement by using the Custom Query Engine. Instead, we directly passed the learner's query and the associated image to a more efficient small multimodal model, minicpm-v. The model's output was wrapped into a LlamaIndex response object so that it could be integrated smoothly with rest of our system. This approach generated better image-based responses and aligned well into our broader agentic design.

5. Results and Discussion

For RAG-based question answering, i.e., to answer context-specific queries of the learner, our previously proposed assistant demonstrated satisfactory performance. We have reported the results of RAG evaluation concerning Faithfulness, Answer relevance, and Context Relevance as well as human evaluation in our previous work. Hence, we decided to go ahead with our findings of the previous study and chose the Gemma 2 model with 2b parameters, with a chunk-size of 512 tokens, and integrate it in the question answering tool of our agent.

To evaluate the quality of summaries generated by the proposed agent, we obtained 4 OERs (case study/Readings) from different subject areas from OER Commons and summarized them using the Summary tool of our agent. A small set of four OERs was chosen to cover a diverse range of content types and structures, ensuring a focused and manageable study while still allowing us to observe the agent's behaviour across varied content. We generated the reference summaries of the same OERs using ChatGPT (GPT4o) and compared both using BERTScore. BERTScore (Zhang et al., 2020) is a metric for evaluating quality of text generation. It computes the cosine similarity between token embeddings of reference and candidate sentences using pre-trained BERT representations. It evaluates Precision, Recall, and F1 score, where Precision focuses on how much of the candidate's content is relevant compared to the reference. Recall focuses on how much of the reference's content is captured by the candidate. F1 Score, the harmonic mean of Precision and Recall, balances the two and measures the overall quality of the match. Table 1 shows the results of our experiment.

Table 1: BERTScore Evaluation

Subject Area	OER Details	BERTScore
Environmental Science	Addressing Links Between Climate and Public Health in Alaska Native Villages (https://toolkit.climate.gov/case-studies/addressing-links-between-climate-and-public-health-alaska-native-villages)	Precision: 0.88 Recall: 0.89 F1: 0.88
Business Communication	Adjusting for Inflation (https://www.stlouisfed.org/publications/page-one-economics/2023/01/03/adjusting-for-inflation)	Precision: 0.90 Recall: 0.89 F1: 0.89
Law	Equity vs. Equality (https://oercommons.org/courseware/lesson/97984/overview)	Precision: 0.90 Recall: 0.91 F1: 0.90
Life Sciences	Anatomy and Physiology of the Respiratory System (https://oercommons.org/authoring/26964-1-1-anatomy-and-physiology-of-respiratory-system/view)	Precision: 0.85 Recall: 0.84 F1: 0.84

As seen in Table 1, the Bert Score, F1 Score are 0.84 or more for all the OERs summaries generated by GPT as reference and summaries generated by our agent as candidate. This clearly shows that the assistant's performance is quite reasonable and similar in terms of semantic similarity and relevance to that of the state-of-the-art model like GPT4o, for summarizing the content. From educational point of view, this means that learners can rely on the summaries generated by our agent to quickly review the main ideas of a resource before diving into details.

To test the autonomous (tool selection) behaviour of the agent, we challenged it with a diverse set of questions drawn from each of the four OERs. Table 2 lists a representative sample of twenty-five questions. We selected 25 queries to reflect common learning tasks such as summarization, retrieval, quiz generation, and flashcard creation. This number was appropriate for an exploratory study, allowing us to examine the system's behaviour across different tasks and content types without making the evaluation unwieldy. The set was designed so that each question naturally aligned with a different tool- Summary Tool (ST), RAG Tool (RT), Quiz Tool (QT), and

Flashcard Tool (FT). We have included visual question answering-based questions, which are expected to invoke Image Tool (IT), from the Environmental Sciences and Life Sciences OER, as these resources contained multiple images from which meaningful questions could be asked.

To assess the agent's responses, we applied a 3-point scoring system. Each response was evaluated both on whether the correct tool was activated (verified through analysis of logs) and the correctness of the generated response. Each answer is rewarded points based on the following scoring scheme:

- *2 points* → Response is Satisfactory & Actual Tools used are the same as the Expected Tools.
- *1 point* → Response is Partially Satisfactory (in terms of completion, correctness, or relevance) or mismatch between the expected and the Actual Tool
- *0 point* → Unsatisfactory Response.

As can be seen from Table 2, for most of the questions (24 out of 25) from our sample dataset, the Actual Tools used were the same as the Expected Tools. The only case where there is a mismatch was Q5, where we expected the agent to call the RAG tool, followed by the quiz tool to generate the response. The Agent autonomously decided to call the Quiz tool directly and generated a response that was still reasonable. This instance shows that while the agent occasionally bypasses a tool (RAG) in favour of another (Quiz), it may still produce a pedagogically useful output. This may be positive in some learning contexts, though further investigation is needed to assess how such deviations effect learning outcomes. In the case of the Image Tool (IT), the agent performed well in retrieving visual information (Q6 - Q8, Q24 - Q25). However, the accuracy of interpretation of images depends heavily on image clarity, domain-specific labels, and alignment between text and image context. The outputs of other tools (flashcards, quizzes) produced simpler and structured learning aids that may be helpful to learners and support them in an educational environment where clarity and alignment with source content are essential. Therefore, we saw that the proposed prototype of the agent was working satisfactorily with the OERs and questions on which it was assessed.

These findings show that the proposed agent is technically viable and pedagogically significant. It answers context-specific text-based questions as well as questions based on image understanding. This implies that learners can engage with the content in multiple ways like reading, question-answering, summarizing, practicing, and testing their knowledge. When the learning material is very technical or image-heavy, the agent may miss small but important details which is a matter of investigation in future research. By addressing these areas, the system could further increase learner engagement and provide them stronger support.

Table 2: Agentic Behaviour Analysis

Q. No.	Queries from OERs	Expected Tool	Score
	OER- Addressing Links Between Climate and Public Health in Alaska Native Villages (**Link**: https://toolkit.climate.gov/case-studies/addressing-links-between-climate-and-public-health-alaska-native-villages**)**		
1	Summarize the case study.	ST	2
2	What are the climate change impacts on public health in Alaska Native Villages?	RT	2
3	Make flashcards for this case study.	FT	2
4	Create a multiple-choice questions-based assessment from this case study	QT	2
5	Create a short quiz on health adaptation strategies.	RT+QT	1 (only QT called)
6	Analyze the image to identify the primary challenges and explain their significance. (**Image Link**: https://toolkit.climate.gov/image/1108)	IT	2
7	Describe the key visual elements in the provided image. What do they convey about climate change? (**Image Link**: https://toolkit.climate.gov/image/1110)	IT	2
8	Does the image show temperature trends or anomalies? (**Image Link**: https://toolkit.climate.gov/image/1108)	IT	2

Q. No.	Queries from OERs	Expected Tool	Score
	OER- Adjusting for Inflation (**Link**: https://www.stlouisfed.org/publications/page-one-economics/2023/01/03/adjusting-for-inflation)		
9	Give a brief overview of the document in three to four sentences	ST	2
10	Why is it important to compare real values rather than nominal values when analyzing economic data over time?	RT	2
11	Can you turn this document into a set of flashcards for learning?	FT	2
12	Create a comprehensive quiz from the entire content of this document	QT	2
13	Please provide a summary of key concepts mentioned in this article, and also answer from the text: What does adjusting for inflation involve, and what term do economists use to describe dollar amounts that have been adjusted for inflation?	ST+RT	2
	OER- Equity Vs. Equality (**Link**: https://oercommons.org/courseware/lesson/97984/overview)		
14	Please summarize the concepts explained in this text.	ST	2
15	How can misunderstanding the concepts of equality and equity impact societal institutions?	RT	2
16	Create flashcards to review the concepts covered in this material	FT	2
17	Prepare a practice quiz to reinforce the learning from this document.	QT	2
18	Provide a quick summary suitable for a presentation slide, and create a quiz having 5 multiple-choice questions for assessing learners.	ST+QT	2
	OER- Anatomy and Physiology of the Respiratory System (**Link**: https://oercommons.org/authoring/26964-1-1-anatomy-and-physiology-of-respiratory-system/view)		
19	Provide a bullet-point summary of the key points from the given article	ST	2
20	How does air follow from the nasal cavity to the larynx during inhalation?	RT	2
21	Generate flashcards to help study the main points of this text.	FT	2
22	Generate a short 5-question quiz covering the key points of this text	QT	2
23	Give me a 100-word summary of this text and generate flashcards	ST+FT	2
24	Describe the image. (**Image Link:** https://img.oercommons.org/oercommons/media/editor/153219/8cd649589ce741b39f269c72837e7910.jpg)	IT	2
25	What are the labelled parts of the respiratory system in this image? (**Image Link**: https://img.oercommons.org/oercommons/media/editor/153219/47628ec67eb441df8f9a195aaf0d69e5.jpg)	IT	2

6. Conclusion

We presented the detailed design, methodology, and technical guidelines for designing an Agentic RAG-based multimodal agent, which is based on open-source software and hence is likely highly cost-effective compared to cloud-based systems. It is lightweight as it is powered by small language models and can run on a learner's local machine, ensuring privacy without the need for any special computation-intensive resources. Based on learners' request, the agent can generate summaries, flashcards, and quizzes from the OERs they provide and also allows context-aware interactions with those resources.

Our work adopts Agentic RAG architecture and sets out practical design & deployment guidelines for affordable, locally operated educational AI agents. Compared with cloud-based systems, this approach offers benefits in privacy, cost, and contextual relevance. That said, the proposed agent has its own limitations. While hallucinations are reduced to a large extent by using RAG, some responses may still be irrelevant and fabricated by the SLM, which is a known drawback of language models. The quality of responses may also vary for highly technical or image-intensive OERs, where fine details or complex diagrams are harder to interpret. Another concern (shared with other SLMs and LLMs) is the occasional possible use of offensive, insensitive or inappropriate language, which poses ethical and safety concerns.

Our research supports the broader use of AI in education and learning by showing that learning agents can be build without requiring costly computational resources. It presents the detailed technical guidelines to develop pedagogically valuable AI agents and deploy them on local machines, opening the opportunities for future research in the field of AI in education.

7. Recommendations for Future Research

Looking ahead, several areas invite further research and exploration in this field. On the technical side, incorporating guardrails could ensure that output remain safe and pedagogically appropriate. Stronger domain-specific grounding can be achieved by integrating structured resources such as glossaries, ontologies, or knowledge graphs for technical subjects or complex visual reasoning. Extending multimodal capabilities to include video, or enabling voice interaction, could make the system more versatile. Another promising avenue is optimizing the agent by using efficient techniques and lighter models to allow it to run on low-resource mobile devices like smartphones as well.

From educational standpoint, future research could study how agents can be aligned closely with learning theories and instructional design principles. For example, quiz questions can be mapped to different levels of Bloom's Taxonomy. Additionally, agents could provide adaptive feedback and recommendations to learners by scoring quiz responses. Adding gamification features such as badges, progress milestones, and challenges might increase motivation. Finally, multi-agent designs could be explored in instructional design, where different agents handle different stages of developing learning experiences. For example, following the ADDIE model one agent could analyze the existing content based on the learning requirements and share its results, observations and ideas. Based on this agent's analysis second agent could design and develop the learning design; finally third agent could review and evaluate the results of previous agents and iteratively interact with them for improvements. These directions offer opportunities for technical improvements as well as learning enhancements to advance personalized and ethical AI applications in education and learning.

AI Statement: The authors declare that no AI tools were used in the conceptualization, preparation, interpretation or conclusions in this paper.

Ethics Statement: This research did not involve human participants, animal subjects, or any material that requires ethical approval.

References

Bozkurt, A., 2023. Generative artificial intelligence (AI) powered conversational educational agents: The inevitable paradigm shift. *Asian Journal of Distance Education*, [online] 18(1). Available at: <https://www.asianjde.com/ojs/index.php/AsianJDE/article/view/718> [Accessed 23 July 2024].

Chimezie, M.O., 2024. LEVERAGING RETRIEVAL-AUGMENTED GENERATION IN LARGE LANGUAGE MODELS FOR EFFECTIVE LEARNING: A DATA STRUCTURES & ALGORITHMS LEARNING ASSISTANT.

DeepLearning.AI, 2024a. *Building Agentic RAG with Llamaindex*. [online] DeepLearning.AI - Learning Platform. Available at: <https://learn.deeplearning.ai/courses/building-agentic-rag-with-llamaindex/lesson/1/introduction> [Accessed 29 December 2024].

DeepLearning.AI, 2024b. *Building Generative AI Applications with Gradio*. [online] DeepLearning.AI - Learning Platform. Available at: <https://learn.deeplearning.ai/courses/huggingface-gradio/lesson/1/introduction> [Accessed 29 December 2024].

Dunlosky, J., Rawson, K.A., Marsh, E.J., Nathan, M.J. and Willingham, D.T., 2013. What Works, What Doesn't. *Scientific American Mind*, 24(4), pp.46–53. https://doi.org/10.1038/scientificamericanmind0913-46.

GPU Mart, 2025. *How to Run LLMs Locally with Ollama AI*. [online] GPU Servers Mart. Available at: <https://www.gpu-mart.com/blog/run-llms-with-ollama> [Accessed 13 June 2025].

Holmes, W., Bialik, M. and Fadel, C., 2019. Artificial Intelligence In Education.

Liu, S., Yu, Z., Huang, F., Bulbulia, Y., Bergen, A. and Liut, M., 2024. Can Small Language Models With Retrieval-Augmented Generation Replace Large Language Models When Learning Computer Science? In: *Proceedings of the 2024 on Innovation and Technology in Computer Science Education V. 1*, ITiCSE 2024. [online] New York, NY, USA: Association for Computing Machinery. pp.388–393. https://doi.org/10.1145/3649217.3653554.

LlamaIndex, 2024a. *Index Guide*. [online] Available at: <https://docs.llamaindex.ai/en/stable/module_guides/indexing/index_guide/> [Accessed 13 December 2024].

LlamaIndex, 2024b. *Query Engine*. [online] Available at: <https://docs.llamaindex.ai/en/stable/module_guides/deploying/query_engine/?utm_source=chatgpt.com> [Accessed 30 December 2024].

LlamaIndex, 2024c. *Response Modes*. [online] Available at: <https://docs.llamaindex.ai/en/stable/module_guides/deploying/query_engine/response_modes/> [Accessed 13 December 2024].

LlamaIndex, 2024d. *Response Synthesizer*. [online] Available at: <https://docs.llamaindex.ai/en/stable/module_guides/querying/response_synthesizers/> [Accessed 30 December 2024].

LlamaIndex, 2024e. *Summary*. [online] Available at: <https://docs.llamaindex.ai/en/stable/api_reference/indices/summary/?form=MG0AV3> [Accessed 13 December 2024].

LlamaIndex, 2024f. *Vector Store Index*. [online] Available at: <https://docs.llamaindex.ai/en/stable/module_guides/indexing/vector_store_index/> [Accessed 30 December 2024].

LlamaIndex, 2025g. *Build Knowledge Assistants over your Enterprise Data*. [online] Available at: <https://www.llamaindex.ai/framework> [Accessed 2 January 2025].

Ollama, 2024a. *gemma2:2b*. [online] Available at: <https://ollama.com/gemma2:2b> [Accessed 2 January 2025].

Ollama, 2024b. *llava*. [online] Available at: <https://ollama.com/llava> [Accessed 2 January 2025].

Ollama, 2024c. *minicpm-v*. [online] Available at: <https://ollama.com/minicpm-v> [Accessed 2 January 2025].

Ollama, 2025. *Ollama*. [online] Available at: <https://ollama.com> [Accessed 2 January 2025].

Pounds, E., 2024. What Is Agentic AI? *NVIDIA Blog*. Available at: <https://blogs.nvidia.com/blog/what-is-agentic-ai/> [Accessed 12 December 2024].

Putnam, A.L., Sungkhasettee, V.W. and Roediger, H.L., 2016. Optimizing Learning in College: Tips From Cognitive Psychology. *Perspectives on Psychological Science*, 11(5), pp.652–660. https://doi.org/10.1177/1745691616645770.

Reeve, J. and Tseng, C.-M., 2011. Agency as a fourth aspect of students' engagement during learning activities. *Contemporary Educational Psychology*, 36(4), pp.257–267. https://doi.org/10.1016/j.cedpsych.2011.05.002.

Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D. and Demir, I., 2024. Artificial Intelligence-Enabled Intelligent Assistant for Personalized and Adaptive Learning in Higher Education. *Information*, 15(10), p.596. https://doi.org/10.3390/info15100596.

Shute, V.J., 2007. Focus on Formative Feedback.

Singh, A., Ehtesham, A., Kumar, S. and Khoei, T.T., 2025. *Agentic Retrieval-Augmented Generation: A Survey on Agentic RAG*. https://doi.org/10.48550/arXiv.2501.09136.

Slade, J.J., Hyk, A. and Gurung, R.A.R., 2024. Transforming Learning: Assessing the Efficacy of a Retrieval-Augmented Generation System as a Tutor for Introductory Psychology. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 68(1), pp.1827–1830. https://doi.org/10.1177/10711813241275509.

Taneja, S., Biswas, S.S., Alankar, B. and Kaur, H., in press. Architecture and prototype of a lightweight AI-powered personal learning assistant using open source small language model and multi-modal retrieval augmented generation. *International Journal of Technology Enhanced Learning*. https://doi.org/10.1504/IJTEL.2025.10069095.

Team, G., Riviere, M., Pathak, S., Sessa, P.G., Hardin, C., Bhupatiraju, S., Hussenot, L., Mesnard, T., Shahriari, B., Ramé, A., Ferret, J., Liu, P., Tafti, P., Friesen, A., Casbon, M., Ramos, S., Kumar, R., Lan, C.L., Jerome, S., Tsitsulin, A., Vieillard, N., Stanczyk, P., Girgin, S., Momchev, N., Hoffman, M., Thakoor, S., Grill, J.-B., Neyshabur, B., Bachem, O., Walton, A., Severyn, A., Parrish, A., Ahmad, A., Hutchison, A., Abdagic, A., Carl, A., Shen, A., Brock, A., Coenen, A., Laforge, A., Paterson, A., Bastian, B., Piot, B., Wu, B., Royal, B., Chen, C., Kumar, C., Perry, C., Welty, C., Choquette-Choo, C.A., Sinopalnikov, D., Weinberger, D., Vijaykumar, D., Rogozińska, D., Herbison, D., Bandy, E., Wang, E., Noland, E., Moreira, E., Senter, E., Eltyshev, E., Visin, F., Rasskin, G., Wei, G., Cameron, G., Martins, G., Hashemi, H., Klimczak-Plucińska, H., Batra, H., Dhand, H., Nardini, I., Mein, J., Zhou, J., Svensson, J., Stanway, J., Chan, J., Zhou, J.P., Carrasqueira, J., Iljazi, J., Becker, J., Fernandez, J., Amersfoort, J. van, Gordon, J., Lipschultz, J., Newlan, J., Ji, J., Mohamed, K., Badola, K., Black, K., Millican, K., McDonell, K., Nguyen, K., Sodhia, K., Greene, K., Sjoesund, L.L., Usui, L., Sifre, L., Heuermann, L., Lago, L., McNealus, L., Soares, L.B., Kilpatrick, L., Dixon, L., Martins, L., Reid, M., Singh, M., Iverson, M., Görner, M., Velloso, M., Wirth, M., Davidow, M., Miller, M., Rahtz, M., Watson, M., Risdal, M., Kazemi, M., Moynihan, M., Zhang, M., Kahng, M., Park, M., Rahman, M., Khatwani, M., Dao, N., Bardoliwalla, N., Devanathan, N., Dumai, N., Chauhan, N., Wahltinez, O., Botarda, P., Barnes, P., Barham, P., Michel, P., Jin, P., Georgiev, P., Culliton, P., Kuppala, P., Comanescu, R., Merhej, R., Jana, R., Rokni, R.A., Agarwal, R., Mullins, R., Saadat, S., Carthy, S.M., Cogan, S., Perrin, S., Arnold, S.M.R., Krause, S., Dai, S., Garg, S., Sheth, S., Ronstrom, S., Chan, S., Jordan, T., Yu, T., Eccles, T., Hennigan, T., Kocisky, T., Doshi, T., Jain, V., Yadav, V., Meshram, V., Dharmadhikari, V., Barkley, W., Wei, W., Ye, W., Han, W., Kwon, W., Xu, X., Shen, Z., Gong, Z., Wei, Z., Cotruta, V., Kirk, P., Rao, A., Giang, M., Peran, L., Warkentin, T., Collins, E., Barral, J., Ghahramani, Z., Hadsell, R., Sculley, D., Banks, J., Dragan, A., Petrov, S., Vinyals, O., Dean, J., Hassabis, D., Kavukcuoglu, K., Farabet, C., Buchatskaya, E., Borgeaud, S., Fiedel, N., Joulin, A., Kenealy, K., Dadashi, R. and Andreev, A., 2024. *Gemma 2: Improving Open Language Models at a Practical Size*. https://doi.org/10.48550/arXiv.2408.00118.

Watters, A., 2023. *Teaching Machines: The History of Personalized Learning*. MIT Press.

Zhang, T., Kishore, V., Wu, F., Weinberger, K.Q. and Artzi, Y., 2020. *BERTScore: Evaluating Text Generation with BERT*. https://doi.org/10.48550/arXiv.1904.09675.

e-DigCompEdu: Validation of a Framework for Online Higher Education Through a Delphi Panel

Cassio Santos[1,2], Neuza Pedro[1] and Julio Cabero-Almenara[3]

[1]Unidade de Investigação e Desenvolvimento em Educação e Formação (UIDEF), Instituto de Educação (IE), Universidade de Lisboa (ULisboa), Portugal

[2]Escola Superior de Educação, Instituto Politécnico de Santarém, Portugal

[3]Universidad de Sevilla, Spain

cassiosantos@ie.ulisboa.pt (corresponding author)
nspedro@ie.ulisboa.pt
cabero@us.es

https://doi.org/10.34190/ejel.23.4.4156

Abstract: This paper addresses the growing importance of digital competence for higher education professors due to the increasing technology integration in this sector. Existing frameworks, such as the European Framework for the Digital Competence of Educator (DigCompEdu), present limitations for higher education, particularly regarding the use of online and blended learning approaches, immersive technologies, and artificial intelligence. Such limitations motivated the development and validation of the e-DigCompEdu, an extended framework specifically designed for this context. The validation process employed a Delphi panel with international experts in distance education, initially involving 29 participants. The selection of specialists was based on their publication records across 40 high-impact distance education journals, involving the analysis of 25,980 authors. The experts evaluated the extended version of the DigCompEdu, with 12 new competencies, specifically considering three aspects: title and description, related activities, and proficiency levels. Experts were asked to rate the competence adequacy on a five-point scale and to offer qualitative feedback. Results showed overall improved adequacy scores, from the first to the second round, as well as an increasing positive evaluation of the competences relevancy. Although some competences experienced a slight reduction in mean scores, they showed decreased variance, demonstrating greater expert consensus. Ultimately, all 12 new competences were enhanced by expert contributions (qualitative) and subsequently validated (quantitative). The validated e-DigCompEdu framework effectively addresses the digital competence requirements from professors in the online education setting. It provides a robust resource for guiding professional development and informing institutional policies regarding the digital transformation of higher education practices.

Keywords: Digital competence, Teacher digital competence, DigCompEdu, Online education, e-Learning, Higher education

1. Introduction

Since the 1990s, the integration of digital technologies into higher education has grown substantially; presently the digital competence of educators is seen as paramount, given the escalating role of technology within educational practices (Palacios-Rodríguez et al., 2024). This expansion has been accelerated by the advancement of new digital technologies, broadening the scope of teaching and learning and fostering innovative pedagogical approaches in onsite and online education. In an increasingly digital society, these technologies are not merely supplementary, they have been reshaping educational practices, expanding access, and supporting new forms of knowledge creation and dissemination. Their integration into higher education frameworks ensures that both educators and learners develop the necessary digital competencies to navigate and thrive in contemporary academic environments (Modise & Molotsi, 2022; Nadzir & Bakar, 2023). In this context, technology and innovation have become increasingly crucial to the success of online learning. In the current digital era, technological advancements have transformed education, presenting new opportunities and challenges for students, educators, as well as institutions. With a wide range of digital tools and platforms available, students can access educational resources and engage in learning activities at their own pace and convenience. The ability to harness these competencies enhances students' capacity to benefit from the flexibility and convenience of online education, ultimately leading to a more positive and enriching learning experience (Nadzir & Bakar, 2023; Sattayaraksa et al., 2023).

Professors (meaning academics, lectures or other teaching professionals) face continuous challenges in integrating emerging technologies into the educational process, such as Learning Management Systems (LMS), mobile phones, and more recently, artificial intelligence-based solutions (Alainati et al., 2023; Farooq, Zaidi &

Cite this article: Santos, C., Pedro, N. and Cabero-Almenara, J. 2025. "e-DigCompEdu: Validation of a Framework for Online Higher Education Through a Delphi Panel", *Electronic Journal of e-Learning*, 23(4), pp 81-101, https://doi.org/10.34190/ejel.23.4.4156

Shah, 2024). In the context of online higher education, the increasing use of digital devices and web-based learning technologies highlights the importance of students' digital competences, as they play a crucial role in facilitating effective engagement and academic success (Kallas & Pedaste, 2022). Digital competence stands out as an essential skill, indispensable across all spheres of academic and professional life. It is also fundamental for the exercise of a full citizenship and for problem-solving in various daily life situations. Furthermore, it is recognised as one of the key competences for 21st-century learning (Chatwattana, 2021; Kassymova, Tulepova & Bekturova, 2023; Morachat & Seechaliao, 2024). Within the European Union context, since 2006, digital competence has been listed as one of the eight key competences for lifelong learning (Council of the European Union, 2018; European Parliament and Council of the European Union, 2006). It is also considered transversal to other key competences, as it is closely linked to the understanding and the use of digital technologies within these (Chatwattana, 2021; Karakış, 2022).

Just as the term 'digital competence' lacks consensus within the scientific community, a fact evidenced by the interchangeable use of terms such as Digital Literacy, eLiteracy, e-Skills, eCompetence, Technology Literacy, and Media and Information Literacy (Ferrari, Punie & Redecker, 2012), the same applies to the concept of Teacher Digital Competence (Benali & Mak, 2022; Cabero-Almenara, Romero-Tena & Palacios-Rodríguez, 2020; Horváth et al., 2025), which is the terminology adopted in this study.

Teacher Digital Competence (TDC) is defined as the set of knowledge, skills, and attitudes related to technological, informational, and communicative aspects applied within the professional context of teaching staff at all levels and sectors of a country's educational system (Benali & Mak, 2022; Cabero-Almenara, Romero-Tena & Palacios-Rodríguez, 2020; Horváth et al., 2025). This competence integrates scientific/content, pedagogical and didactic criteria to ensure the conscious and effective use of these elements in the teaching and learning processes, considering their implications for the development of students' digital competence.

It is important to highlight that the concept of digital competence is considered highly dynamic as it evolves and updates in parallel with the sociotechnological advancements (Moreno-Guerrero et al., 2021). This fact highlights the need for constant adaptation by both professors and students as new tools, platforms, and digital methodologies transform the teaching and learning process.

Digital competence, both of professors and students, plays a crucial role in performance within online learning environments, where technology-mediated interaction is essential. Proficiency in technology facilitates adaptation to the different challenges that may arise in these environments. When they possess adequate levels of digital competence, all individuals involved in online learning platforms become effective agents in the educational process, contributing to a more integrated and successful teaching and learning experience (Zabun, 2022).

This proficiency is even more significant in higher education, where timely and targeted interventions aimed at enhancing students' digital preparedness can lead to higher academic performance, greater satisfaction with courses, and a more positive perception of their own competences (Cabero-Almenara, Barroso-Osuna & Palacios-Rodríguez, 2021; Reyes-Millán et al., 2023; Santos, Pedro & Mattar, 2021; Moreira, Nunes & Casanova, 2023). Esteve-Mon, Llopis-Nebot and Adell-Segura (2020) further highlight that professors in higher education must increase their level of proficiency in digital competences to respond to new challenges and demands—an issue that has been widely discussed since the turn of the century and more intensively in the post-pandemic context (de Wit & Altbach, 2023).

To effectively address these new challenges and demands in technologically advanced learning environments, professors must integrate new technologies into their teaching practices (Aydın & Çelik, 2020). The development of digital competence among higher education professors thus plays a strategic role in fostering these competences in students, enabling them to meet the academic and professional demands of the contemporary world (Rintamäk, 2019). It is important to consider that many young people enter university without the minimum digital competence required to operate effectively in academic and professional contexts (Biel & Ramos, 2019). This scenario underscores the urgent need to train professors to promote the development of these competences in students, ensuring that technological management in the educational domain aligns with the demands of the 21st century.

Students' motivation in online learning environments is directly linked to their digital competence. According to Karakış (2022), there is a positive and statistically significant relationship between students' levels of digital competence and their motivation in online learning. Also, the quality of education, enhanced by the professors' mastery of digital knowledge and competences, plays a fundamental role in increasing student satisfaction and engagement (Maulana & Arli, 2022). It is essential for the success of distance education to emphasise the importance of preparing both students and professors for the effective use of digital technologies.

Using a scale adapted from Ng (2012), which considers attitudinal, technical, cognitive, and social dimensions of digital literacy, Kayaduman, Battal and Polat (2023) found that students with higher levels of digital competence demonstrate greater self-regulation in online interactions, a crucial aspect in distance education. These skill sets are positively correlated with students' perceptions and have a direct influence on online learning. When combined with positive attitudes towards technology and advanced technical skills, they contribute to more effective interactions between student-content, student-professor, and student-student.

It is important to highlight the clear distinction between Emergency Remote Teaching (ERT) and planned, structured online education. While ERT was implemented as an improvised measure to ensure the continuity of lessons during the COVID-19 crisis, relying on available resources in an ad-hoc manner and without in-depth pedagogical planning, properly prepared online education requires an advanced set of digital competences (Bond et al., 2021; Hodges et al., 2020). Planned online education requires educators to strategically apply carefully selected pedagogical strategies and properly configured digital tools to design meaningful learning experiences, assess outcomes, and adapt methodologies to learners' needs (Holik et al., 2023).

High-quality online learning depends not only on institutional support and access to digital technologies, but also on educators' digital competence, which are essential for effective mediation, engagement, and student support in virtual environments. Online learning tools are only effective if users possess the skills to operate them; hence, it is crucial that educators continuously refine their digital competences through their everyday teaching practices, particularly in a rapidly evolving technological landscape (Getenet et al., 2024; Mudau & Modise, 2022; Nadzir & Bakar, 2023).

1.1 Frameworks

The development of frameworks focused on digital competence in education, whether for professors or educational organisations, has gained momentum through the support of official institutions that both promote and demand the advancement of these competences in a society increasingly immersed in digital Technologies (Díaz, Reche & Rodríguez, 2019).

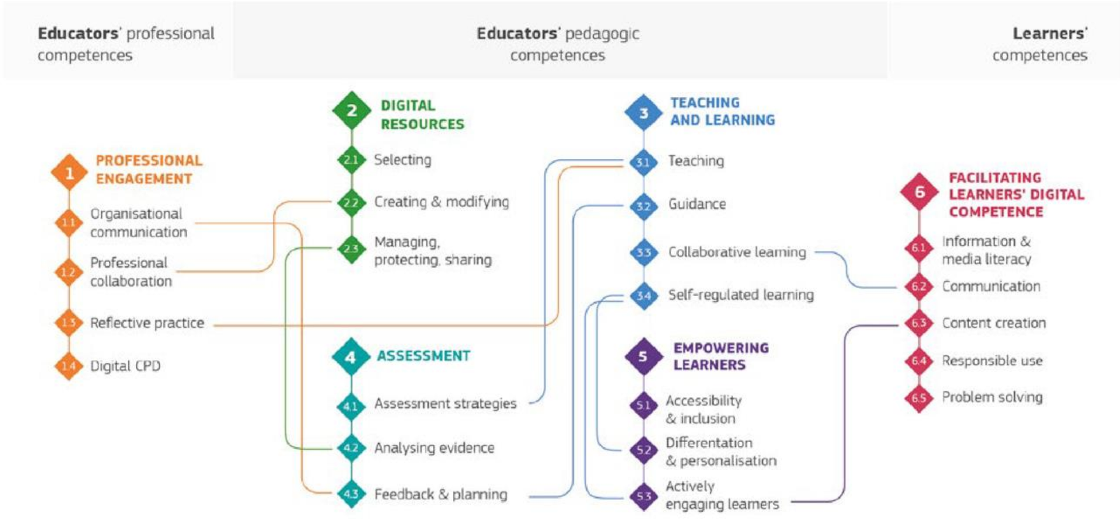
Based on the *DIGCOMP A Framework for Developing and Understanding Digital Competence in Europe* (Ferrari, 2013), several other frameworks have been developed for education, including the *European Framework for the Digital Competence of Educators: DigCompEdu* (Redecker, 2017), and the *European Framework for Digitally-Competent Educational Organisations* (DigCompOrg), aimed at educational organisations (Kampylis, Punie & Devine, 2015). Additionally, *DigComp 2.2: The Digital Competence Framework for Citizens* (Vuorikari, Kluzer & Punie, 2022), although primarily intended for the public, started to be applied to both professors and students, given that the former are responsible for fostering these competences in the latter (Pedro, Santos & Mattar, 2023).

1.2 DigCompEdu

Inspired by the *DigComp 2.1: The Digital Competence Framework for Citizens* (Carretero, Vuorikari & Punie, 2017), DigCompEdu focuses on enhancing the digital competences of educators across all levels of the educational system. This framework is structured into 22 competences, divided into six areas (Figure 1), encompassing six proficiency levels and employing a model of cumulative progression of the digital competence development.

DigCompEdu reflects a growing awareness among European member states of the importance of establishing specific actions for the promotion of digital competences for the teaching professionals. This framework aims to guide education professionals in adopting practices that harness the potential of digital technologies to enhance and innovate the educational process.

Although the European Union has developed several frameworks on digital competences for education, no specific framework explicitly considers online higher education. While DigCompEdu is designed to be applicable across all educational levels, it lacks key elements for addressing distance learning or blended learning (Mattar et al., 2020; Viñoles-Cosentino, Sánchez-Caballé & Esteve-Mon, 2022); also, it does not address emerging technologies such as Generative Artificial Intelligence, Immersive environments, among others.



Source: Redecker (2017, p. 8).

Figure 1: DigCompEdu

It has also been used as a central element in the development of extensions, incorporating new competences and transforming them into a highly specialised framework. Examples include the *Supplement to the DigCompEdu Framework: Outlining the skills and competences of educators related to AI in education* (Bekiaridis, 2024), and the present study, which aims to validate the *e-DigCompEdu: Digital Competencies for Online Higher Education extension*.

1.3 DigCompEdu as Reference for new Frameworks and Extensions

This framework has been widely used both within the European Union and world-wide. As an intrinsic characteristic of DigCompEdu, its applicability across all levels of education has allowed it to serve as a foundational framework for the development of new frameworks, as well as a central element for the creation of extensions. Notably, DigCompEdu has emerged in the literature as a central reference for the development of more specialised competence frameworks, both at macro and institutional levels. Some examples consider:

- "DigCompEdu-FyA", targeting university educators (Castañeda et al., 2023);
- *"Marco de Referencia de la Competencia Digital Docente"*, aimed at non-university Educators (INTEF, 2022);
- "*Pedagogical DigCompEdu Reloaded*", which focuses exclusively on the pedagogical dimension and is applicable across all levels of education (Moreira et al., 2024);
- *DigCompEdu Supplement: Defining Educators' AI Skills and Competences* (Bekiaridis, 2024);
- *Defining XR-Specific Teacher Competencies: Extending the DigCompEdu Framework for Immersive Education* (Rutten & Brouwer-Truijen, 2025).

The e-DigCompEdu presented in this article offers an extension of the original DigCompEdu framework, expanding and adapting its structure to address a specific educational context.

1.4 e-DigCompEdu

The development of e-DigCompEdu was carried out in three distinct phases, as illustrated in Figure *2*.

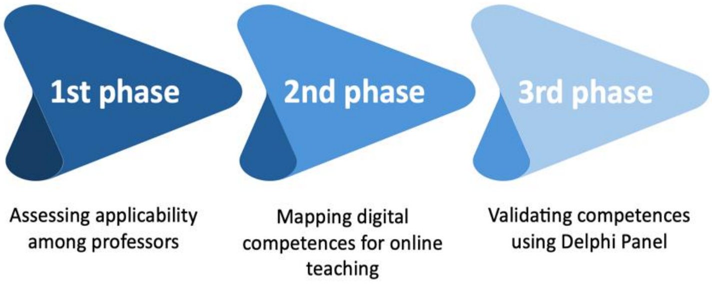


Figure 2: Phase of e-DigCompEdu construction

The e-DigCompEdu is structured around 12 new competences, with six of them being distributed across four existing areas of DigCompEdu, and numbered sequentially. The remaining six competences, due to their specific characteristics, have been grouped into two newly established areas: the scientific digital literacy and the digital management of online teaching and learning, as illustrated in Figure 3.

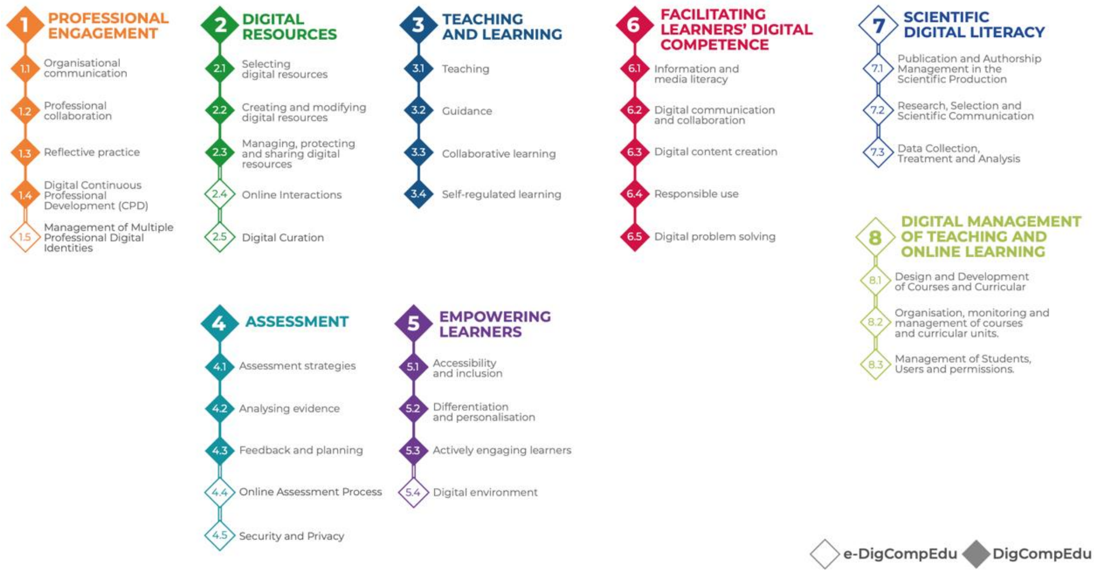


Figure 3: Integration of new competences and areas on DigCompEdu, resulting in the creation of e-DigCompEdu

In addition to expanding the scope of DigCompEdu, e-DigCompEdu emphasises the application of digital pedagogical strategies that foster accessibility, inclusion, and personalised learning. It provides detailed descriptors, activities, and proficiency levels, enabling professors and online higher education institutions to utilise the framework as a tool for training, assessment, and strategic planning.

The absence of a specific digital competence framework, tailored to the particularities of online higher education (Santos, 2023), has posed challenges to institutions and educators seeking structured guidance for pedagogical practices in virtual environments. While several frameworks address digital competences more broadly or across general educational levels, they often fail to incorporate essential components of fully online and blended learning contexts (Mattar et al., 2020). The development of the e-DigCompEdu aims to mitigate this absence by proposing a dedicated structure that integrates these missing elements and supports educators in navigating the specificities of distance higher education settings.

Accordingly, the aim of this article is to present the validation of e-DigCompEdu, an extension of the DigCompEdu specifically developed for online higher education. To that end, a Delphi panel of international experts in distance education is employed to appraise the clarity and adequacy of such a framework, i.e., its pedagogical relevance and utility, considering its alignment with the needs felt in higher education online teaching.

1.5 Validation Practices in Digital Competence Frameworks

The validation of any theoretical or conceptual framework is a fundamental pillar for ensuring its relevance, robustness, and scientific credibility. Validation processes typically involve a range of methodological strategies designed to guarantee the applicability and recognition of these models within educational and policy contexts.

A prevalent approach in such processes involves the collaborative consultation of groups of experts and stakeholders. The *DigCompConsumers, Digital Competence Framework for Consumers* (Brečko & Ferrari, 2016), for instance, was validated through workshops with experts and online consultations, engaging a select group of professionals in the areas of digital and consumer education. Similarly, the DigCompEdu (Redecker, 2017) underwent a rigorous scientific process, based on structured discussions and deliberations with European experts and dedicated working groups. Similarly, The *GreenComp: the European sustainability competence framework* (Bianchi et al., 2022) followed a consensus-building process, involving several rounds of consultations and workshops with experts in sustainability education.

Other commonly used methods for validation processes are literature reviews, inventories, and in-depth analysis of existing frameworks. These approaches were central to the development and validation of the DigCompOrg (Kampylis, Punie & Devine, 2015) and was complemented by expert consultations and thematic workshops. Similarly, the *EntreComp: The entrepreneurship competence framework* (Bacigalupo et al., 2016) employed a robust mixed-methods research design, validated through iterative consultation stages involving multiple stakeholders and online panel discussions.

In some cases, frameworks also integrate broad public engagement in their validation processes. The DigComp 2.2 (Vuorikari, Kluzer & Punie, 2022), and its update DigComp 3.0, currently under development, involved consultations with a wide range of stakeholders via a Community of Practice and interactive workshops, culminating in a public online survey to assess the relevance of the new proposed knowledge, skills, and attitudes.

1.6 Research Focus and Aims

Although multiple European initiatives address digital competence in education, there is no framework specifically oriented to online higher education. While transversal and widely adopted, DigCompEdu lacks key elements for fully or partially developed online education and does not incorporate new technological domains such as immersive technologies or generative artificial intelligence. These gaps motivated the development of the e-DigCompEdu presented in this article, which extends DigCompEdu with 12 new competences, organised across existing areas and two newly created areas, complemented by descriptors, activities, and proficiency statements targeted to the online higher-education context.

The aim of this article is to present the validation of the e-DigCompEdu as an extension of the DigCompEdu, specifically developed for online higher education, by using a Delphi panel. This validation process aims to ensure that the digital competences listed in such framework are aligned with the practical demands of online teaching, considering the specificities of this modality within the higher education context.

In this study, the term "adequacy" refers to the pedagogical relevance, usability, and alignment with the practical demands of online teaching in higher education. Specifically, this study seeks to: i. assess the adequacy of the proposed competences within the e-DigCompEdu, and ii. identify the level of consensus achieved regarding the framework.

By consulting a panel of international experts in distance education, this study seeks to refine and consolidate the framework, and, consequently, to assess its content validity for online higher education. The research question guiding this study is: To what extent does the e-DigCompEdu demonstrate content validity for online higher education, based on expert consensus on the adequacy of its title and description, related activities, and proficiency statements?

2. Methodology

This study adopts a mixed methodological approach, employing the Delphi panel as its data collection and analysis strategy. This method was selected for the validation and continuous refinement of the e-DigCompEdu through these experts' contributions. The panel of specialists iteratively reviewed and refined their assessments and recommendations throughout the different stages of the panel process.

This methodological choice was motivated by five main factors:

- Usefulness in the development of frameworks, one of the key expected outcomes of this approach when applied to educational and technological contexts (Almaiah et al., 2022; Oxley, Nash & Weighall, 2024):
- Ability to achieve consensus among experts, through a structured group communication process (Almaiah et al., 2022),
- Specific application in the validation of structures related to DigCompEdu (Munar-Garau, Oceja, & Salinas Ibáñez, 2024);
- Ability to incorporate multiple rounds of iterative feedback, allowing experts to review and refine their responses throughout the process, thereby enhancing the accuracy of the analysis (Malkawi, Bakar & Dahalin, 2023; Oxley, Nash & Weighall, 2024);
- Wide application to various scientific domains, including Education (Malkawi, Bakar & Dahalin, 2023; Niederberger & Renn, 2023; Oxley, Nash & Weighall, 2024), although its use is more firmly established in fields such as health, business, and technology (Malkawi, Bakar & Dahalin, 2023).

2.1 Delphi Panel

The name of this technique originates from the Oracle of Delphi, a sacred site dedicated to the god Apollo, where the ancient Greeks went to seek answers to complex questions. Its modern development began in the 1950s within U.S. defence institutions during the Cold War, with the objective of obtaining reliable consensus among experts on military strategies (Malkawi, Bakar & Dahalin, 2023).

In essence, the Delphi panel enables a structured, iterative, and systematic process, involving experts organised into a group, allowing for the progressive review and refinement of their assessments and recommendations. This process facilitates the development of informed consensus on complex issues and is widely applied in academic research, educational policymaking, as well as technological innovation (Almaiah et al., 2022; Malkawi, Bakar & Dahalin, 2023; Oxley, Nash & Weighall, 2024).

The iterative process, conducted across multiple rounds, allowed the consolidation of opinions between a carefully selected panel of experts, fostering a well-founded and robust consensus. This method is widely recognised for its ability to structure and progressively refine expert knowledge, enhancing decision-making through a structured and anonymous feedback process that reduces individual biases (Oxley, Nash & Weighall, 2024). The Delphi Panel is organised in rounds, where a group of experts is consulted to explore or resolve complex issues through the aggregation of their opinions. This process is typically iterative, allowing participants to adjust their responses based on the aggregated feedback received in previous rounds. The primary aim is to achieve a consensus or enhance understanding of a specific topic through the convergence of expert opinions.

According to Malkawi, Bakar and Dahalin (2023), the application of the Delphi panel requires the consideration of specific methodological parameters, such as the careful selection of the experts, the number of participants, the quality of the panel, the structuring of the iterative process in multiple rounds, and the criteria established for achieving the completion of the process. These aspects were rigorously followed in the present study to ensure the validity and reliability of the results, as recommended by Oxley, Nash and Weighall (2024).

Anonymity is a core feature of the Delphi panel, minimising the influence of social pressures and power dynamics, and promoting impartial contributions (Malkawi, Bakar & Dahalin, 2023). This principle was rigorously upheld throughout all stages of the panel, ensuring that expert feedback was guided solely by the merit of the content, free from external influence (Oxley, Nash & Weighall, 2024).

Regarding the number of rounds, Oxley, Nash and Weighall (2024) indicate that the exchange process may involve 3-4 rounds, since the results tend to stabilise rapidly after the third round. This iterative process offers experts multiple opportunities to adjust their responses based on aggregated feedback, sent between rounds, which promotes further refinement of contributions. On the other hand, Malkawi, Bakar and Dahalin (2023) emphasise that, unlike other methods, the primary aim of Delphi is not necessarily to reach a single response or an absolute consensus. Instead, the goal is to obtain a diversified, rich and high-quality set of insights.

In line with the commitment to ensuring anonymity throughout the process, a limited set of demographic data was collected exclusively for the purpose of profiling the specialists.

For this study, the Delphi panel was structured into five main stages (Figure 4), designed to obtain qualified contributions from experts. The following stages were carried out:

- Stage 1: Careful selection of experts, based on their expertise on the topic at hand, aligned with best practices described in recent references on Delphi panel (Malkawi, Bakar & Dahalin, 2023).
- Stages 2, 3, and 4 (Rounds): Focused on the iterative process of rounds, which is crucial for achieving consensus among experts, during which they had the opportunity to track and evaluate improvements based on the collective feedback obtained. Stage 2 involved the initial data collection from the panel, as suggested in best Delphi practices. During stage 3, suggestions and contributions collected previously across all rounds were analysed and integrated, promoting continuous improvement. At Stage 4, the consensus parameters were applied, and consolidation of opinions and identifications of points of convergence among the experts were developed. This iterative cycle allowed for a grounded and systematic progression towards reliable and consensual results.
- Stage 5: Consisted of drafting a final document based upon the consolidate inputs of the panel (final framework).

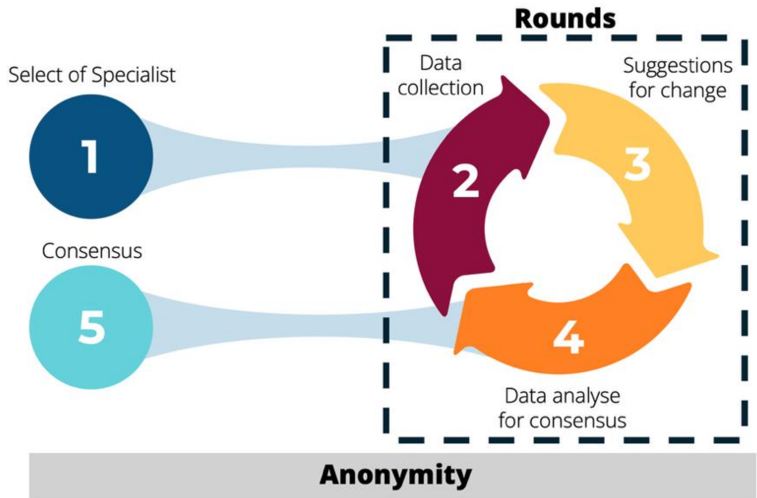


Figure 4: Five stages of the Delphi Panel

2.2 Stage 1: Selection of Specialist

Based on a bibliometric analysis conducted by Santos, Pedro and Mattar (2024), 40 high-impact journals in the field of distance education were selected according to SCImago rankings. The analysis of articles published in these journals from 2018 to 2023 revealed a total of 25,980 authors across 12,947 articles published in such journals. Taking that number of authors in consideration, for this study, a specialist was defined as any researcher who contributed with at least five publications of this dataset, averaging one publication per year. Using this criterion, we identified 888 eligible authors. An exploratory web-search facilitated the mapping of names, affiliations, and email addresses for 816 of these authors, who were then invited by email to participate in the study. In the first round, 29 specialists participated (3.5%). In the second round, only the 29 specialists who had participated in the first round were contacted, and ultimately, 16 specialists took part in the second round. In Figure 5, we quantitatively display the selection and participation in the two rounds of the Delphi panel.

This criterion ensured impartiality and academic merit, functioning as a bias-reduction mechanism and reinforcing the credibility and methodological rigour of the expert panel involved in the validation process.

The literature suggests that the number of experts participating in a Delphi panel study typically ranges from 10 to 30. Numbers lower than 10 may compromise the effective consensus and the relevance of the information obtained, while numbers exceeding 30 make the administration and analysis excessively complex, which tends to result in limited production of new ideas (Malkawi, Bakar & Dahalin, 2023; Oxley, Nash & Weighall, 2024).

The invitations to experts were nominal, with the platform allowing the identification of specialists who completed each round. This information enabled the fact that, in subsequent rounds, only participants who had contributed to previous stages were invited to continue, thereby ensuring consistency and continuity in the expert group throughout the iterative rounds.

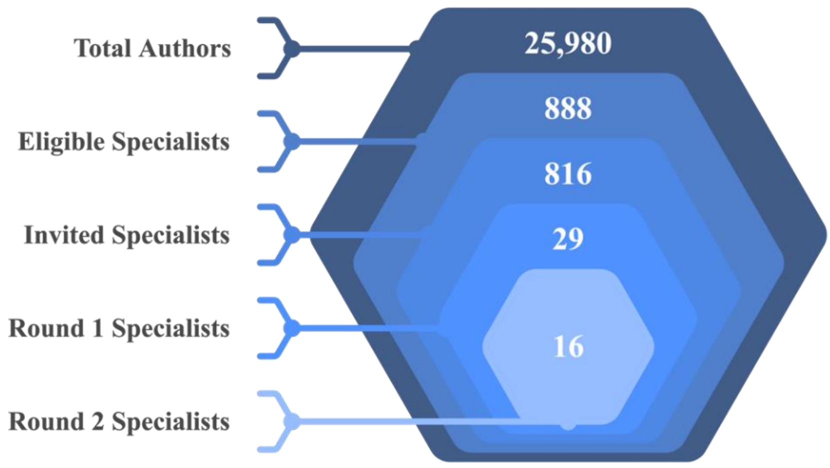


Figure 5: Selection of Specialists

2.3 Stage 2: Data Collection (Rounds)

Quantitative and qualitative (mixed methods approach) data were collected. The Delphi panel and the list of specialists (n=816), which includes names, affiliations, and email addresses, were integrated into the online data collection system LimeSurvey. This enabled personalised and individualised contact with the specialists, including personalised reminders for those who had not yet participated.

The survey was structured into two main blocks: "Block 1: Legal and Ethical Requirements and Participant Demographics", which included the study presentation, the informed consent, and the data protection policy, ensuring fully compliance of the study with ethical standards. It also collected basic demographic information solely for characterising the panel, and "Block 2: Competence Validation", which focused on the evaluation of the newly proposed e-DigCompEdu competences. Experts assessed each competence across three topics: title and description, related activities, and proficiency levels.

2.3.1 Question block 1: Legal and ethical requirements and participant's demographics

This section began with a brief description of the study, content that had already been provided in the email invitation. To proceed, participants were required to select the option "I accept to participate." On this page, the "Data Protection Policy" and the "Informed Consent Form" were also available for the specialists to read and to accept.

For the demographic characterisation of the specialist, only one question was presented focusing exclusively on the geographical location of their research activities ("In which region have you predominantly practised your research in the last 5 (five) years?") The options included regions such as Asia, Africa, America, Europe, Oceania, and Antarctica.

2.3.2 Question block 2: Competence validation

As previously mentioned, 12 new competencies were submitted for validation to the panel, with six integrated into the existing areas of the original framework (DigCompEdu) and six allocated across two completely new areas. Each digital competence (e.g. competence 1.5. Management of Multiple Professional Digital Identities) was assessed across three topics: 1. title and description (Figure 6); 2. related activities (Figure 7); and 3. proficiency statements (Figure 8).

This New Digital Competence, ***Management of Multiple Professional Digital Identities***, is proposed as the fifth (1.5) competence of ***Area 1: Professional Engagement*** , specifically for teachers in Online Higher Education. See more details (DigCompEdu) of the area or the complete framework.

*

How would you rate the adequacy of the title and description of this competence?

Competence: Management of Multiple Professional Digital Identities

Description: To manage multiple professional digital identities, whether in internal systems or outside the organisation. To promote the security of digital identities using several resources and strategies. To assess the data privacy and protection policies of external digital identities, as well as their access management tools, before creating any of them.

Very poor | Poor | Acceptable | Good | Very good

Figure 6: Example of competence title and description

*

How would you rate the adequacy of the activities related to this competence?

Competence: Management of Multiple Professional Digital Identities

1. To adopt several basic strategies to protect my identities, e.g., alphanumeric passwords with special characters;
2. To adopt several strategies to protect my identities, e.g., using different passwords to different systems and two-factor authentication whenever possible; to recognise the risks of centralised authentication;
3. To recognise invasive practices regarding the privacy of my personal data in systems outside the organisation, e.g., data sharing;
4. To identify digital evidence regarding potential intrusions into digital identities, e.g., date of last access or an automatic e-mail reporting access from a "new device";
5. To use specific digital identities to access through various internal systems (e.g., academic management system, virtual learning environment) and external ones (e.g., digital tools such as those used for synchronous and asynchronous communication, content production, students' assessment, and scientific repositories);
6. To assess the need, benefits and risks of creating a digital identity prior to its creation based on several factors, e.g., data privacy protection and access policies.

Very poor | Poor | Acceptable | Good | Very good

Figure 7: Example of competence related activities

How would you rate the adequacy of progression and the proficiency statements to this competence?

Competence: Management of Multiple Professional Digital Identities

Proficiency Level	**Progression**	**Proficiency statements**
A1 – Newcomer	Making limited management of digital identities.	I manage my digital identities to a limited extent. I always use the same easy-to-remember password, e.g., my date of birth.
A2 – Explorer	Being aware of the inherent risks associated with the use of digital identities.	Before I create a digital identity, I become aware of the data security and privacy policies. Before I create a digital identity, I verify which information is required.
B1 – Integrator	Using diversified strategies to protect digital identities.	I use passwords with alphanumeric and special characters. I use different e-mail accounts for personal and professional matters.
B2 – Expert	Using efficient strategies in a structured and appropriate way to protect digital identities.	I use two-factor or biometric authentication systems to protect my digital identities. I identify invasive practices related to the privacy of my data.
C1 – Leader	Assessing and discussing security strategies considering privacy policies and data protection	I critically assess each online system before creating a new digital identity in regard to its data privacy security and protection policies. I identify digital evidence of potential intrusion attempts in a digital identity.
C2 – Pioneer	Developing advanced security strategies for digital identities.	I do not use authentication systems with centralised login (national/federal). I create an account with protected password for each system.

Proficiency statements: A series of proficiency statements exemplifying typical activities at each proficiency level. This list of statements is subject to continuous revision and should only be considered as a means of illustrating the proficiency progression. Since the progression of proficiency levels is cumulative, a person competent at an advanced level should be able to perform the activities at this level and all lower levels, with the exception of the lowest level (A1).

See the Description for two proficiency levels (Link A1 to C2)

Very poor | Poor | Acceptable | Good | Very good

Figure 8: Example of competence proficiency statements

The specialists were consulted on each of these dimensions regarding three specific questions:

- Dimension 1: "How would you rate the adequacy of the <<topic>> of this competence?" Specialists could assess using a five-point scale ranging from a) Very poor, b) Poor, c) Acceptable, d) Good, to e) Very good, numerically corresponding from 1 to 5 points. Quantitative data were collected.
- Dimension 2: "Would you propose any changes to the <<topic>>?" Specialists had the options "Yes" or "No". If "Yes" was selected, dimension 3 would be activated; if "No", the contribution was concluded. Dichotomic data (Yes: 1; No: 0) were collected.
- Dimension 3: "What changes would you propose to the <<topic>>?" If changes were suggested (dimension 2 = "Yes"), a text box was made available for the specialist to detail their proposed modifications. This response field was conditional. Qualitative data were collected.

In Figure 9, we present the example of competence “1.5 - Digital Identity Management and Security”, specifically within the "title and description" topic, across its three dimensions.

Thus, considering the 12 competencies, the experts responded to 24 mandatory questions, and 12 conditional ones. The two new areas were assessed only in dimension 1, "title and description", resulting in four mandatory questions and two conditional ones. In total, the validation question block comprised 42 questions, of which 28 were mandatory and 14 were conditional.

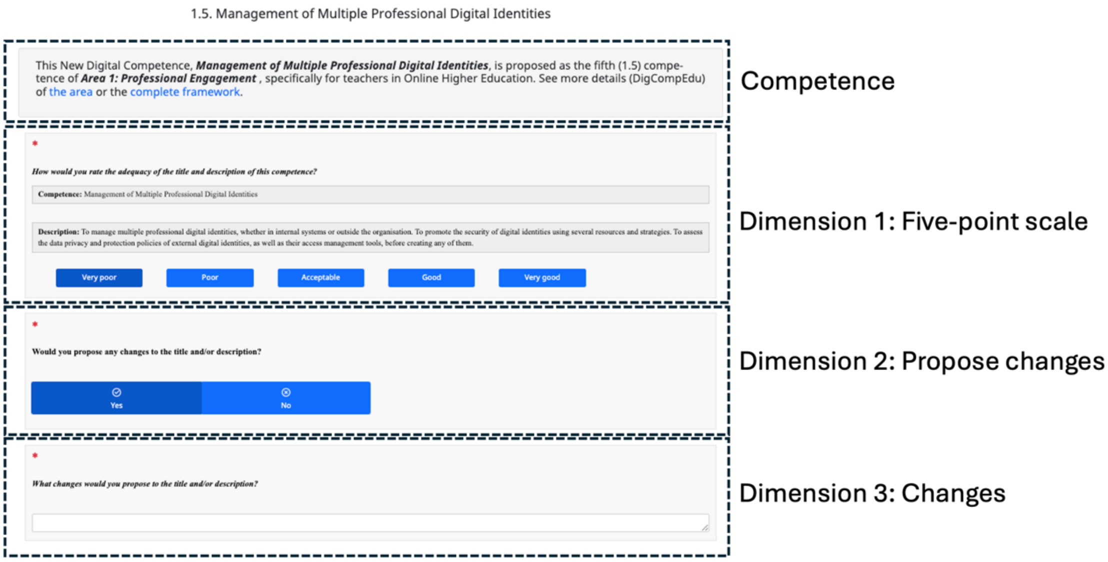


Figure 9: Example of the questions presented to experts

2.4 Stage 3: Suggestions for Change Analysis (Rounds)

During the analysis process, suggestions were reviewed for each dimension of the competencies and areas assessed. In Figure 10, we can observe the analysis and incorporation of suggestions from the specialists regarding the competency "4.5 Security, Privacy and Ethical Conduct" of topic "title and description", which received change suggestions from four specialists.

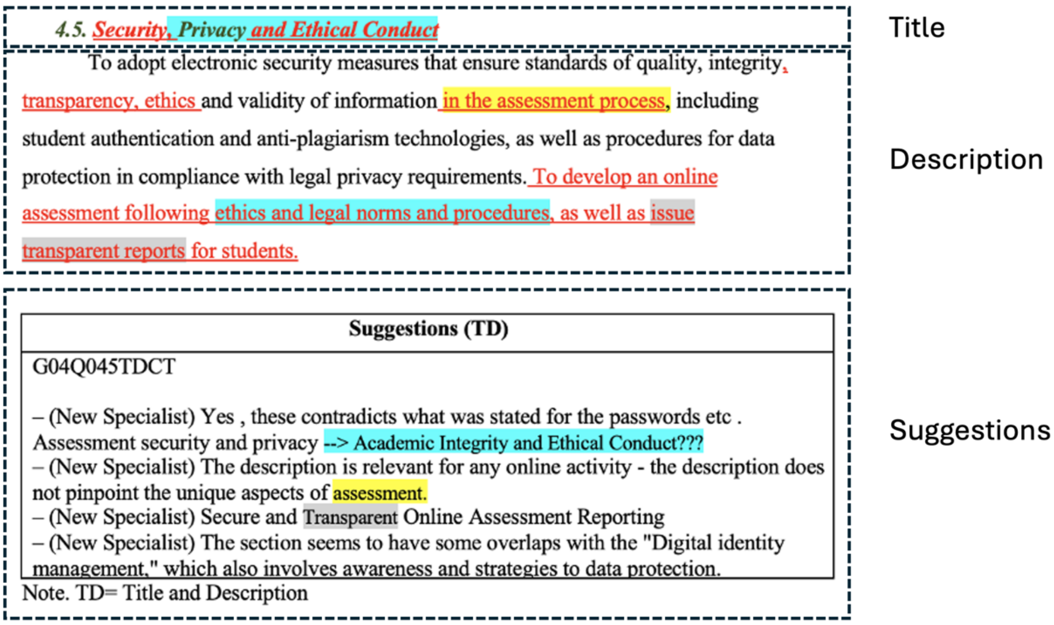


Figure 10: Example of the process of incorporating the suggestions

2.5 Stage 4: Data Analysis for Consensus (Rounds)

Throughout the rounds, both quantitative and qualitative (mixed methods approach) data were collected. The integration of these qualitative and quantitative insights across successive rounds enriches the process and improves the overall quality of the results. Quantitative analyses were performed in IBM SPSS Statistics, version 29, using descriptive parameters (mean and variance, i.e., the square of standard deviation) of consistency as defined by Delphi best practice. Qualitative data were organised and coded in NVivo, version 14, following thematic content analysis aligned with the three topics assessed for each competence (title and description; related activities; proficiency statements).

Qualitative analysis procedure

In rounds, participants were invited to submit improvement suggestions for each of the 12 new competences and two new areas. These suggestions were treated as structured qualitative feedback for refinement. The analysis followed a reflexive thematic approach as proposed by Braun and Clarke (2022). Themes were reviewed to identify areas of convergence and actionable refinement, supporting the revision of the framework for Round 2. All contributions were anonymised, analysed and considered without any differentiation from authors' country/region.

Quantitative analysis procedure

Quantitative data were collected using a five-point (1-5) scale for Dimension 1, ranging from 1 "Very Poor" to 5 "Very Good". Descriptive statistical techniques, means (evaluation score) and variance (consensus score), were applied. This choice is supported by Malkawi, Bakar and Dahalin (2023), who reviewed 60 Delphi studies in higher education and identified mean, median, and standard deviation as the most frequently used statistical parameters.

2.6 Stage 5: Stopping Criteria

Descriptive statistical techniques were established as parameters for scoring panel's evaluation and consensus. Based on a 5 points scale, statistical parameters were calculated to quantify the assessment of the items adequacy and the consensus level achieved between specialists.

- **Evaluation of adequacy:** The adequacy of the competences was determined by the arithmetic mean of the responses on the scale. A high mean score indicates a positive evaluation of the item, suggesting that the specialists view it favourably (> 3.50 points). Conversely, a reduced mean score points to a less favourable evaluation.
- **Level of Consensus:** The variance of the responses measures consensus among the specialists. A higher variance indicates a reduced level of agreement, reflecting diverse opinions and a lack of consensus. On the other hand, a lower variance indicates a high degree of agreement, suggesting that the specialists are aligned in their assessments.

3. Results

The results obtained in this study are presented in three main sections, providing a detailed overview of the validation process of the e-DigCompEdu.

3.1 Characterisation of Specialists

In the first round, the respondents (n=29) included participants from all five continents. However, in the second round (n=16), only specialists from Asia (n=8) and Europe (n=8) participated (Figure 11).

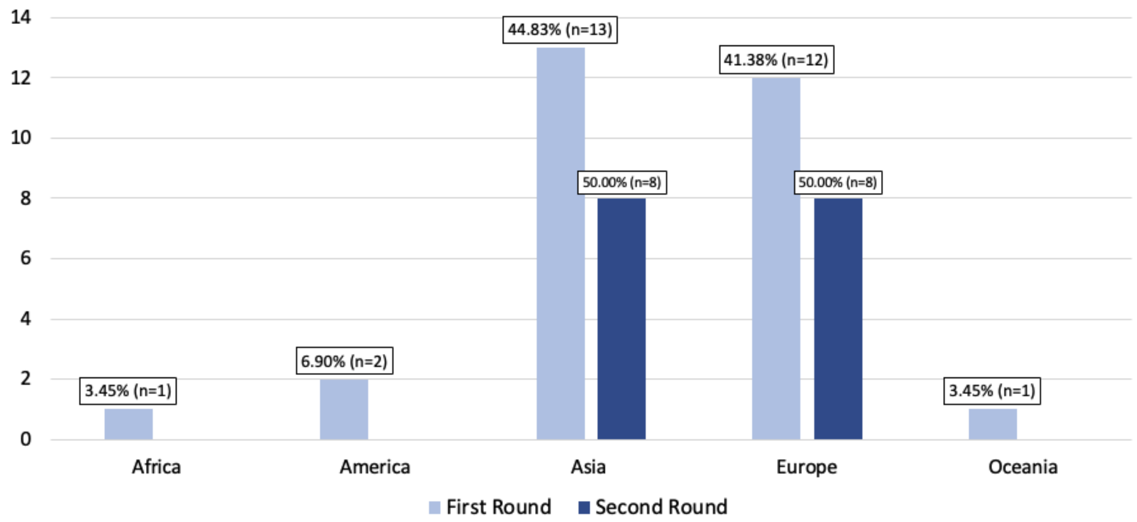


Figure 11: Geographic distribution of specialists

3.2 Evaluation and Consensus (Dimension 1)

In this study, two rounds were conducted:

- 1st Round – Data collection took place from September to December 2023. January 2024 was dedicated to processing this data and preparing for the second round.
- 2nd Round – Collection occurred between February and May 2024. The results of this round were pivotal in making the final decisions: the closure of the process.

3.2.1 Overall

Considering the overall terms the mean score in the first round was 3.89, which is close to the "good" (4) rating on the scale. In the second round, the global results showed a mean of 4.07, thus consolidating the "good" classification and indicating an increase in the global mean between rounds.

3.2.2 Competences and areas

The general adequacy of the competences was calculated by averaging the scores assigned to the three topics evaluated for each item: title and description, related activities, and proficiency statements. Differently, on areas 7 and 8, the mean adequacy refers to the "title and description".

Results indicate that the mean adequacy was high in all the new competences (> 3.5 points) and also that it increased between the first and second Delphi rounds for 11 of the 12 competences demonstrating an overall improvement in clarity and alignment with the experts' expectations. The only exception was Competence 4.4, which maintained the same mean score across rounds. This trend is illustrated in Figure 12, which summarises the comparative means and highlights the progression toward consensus.

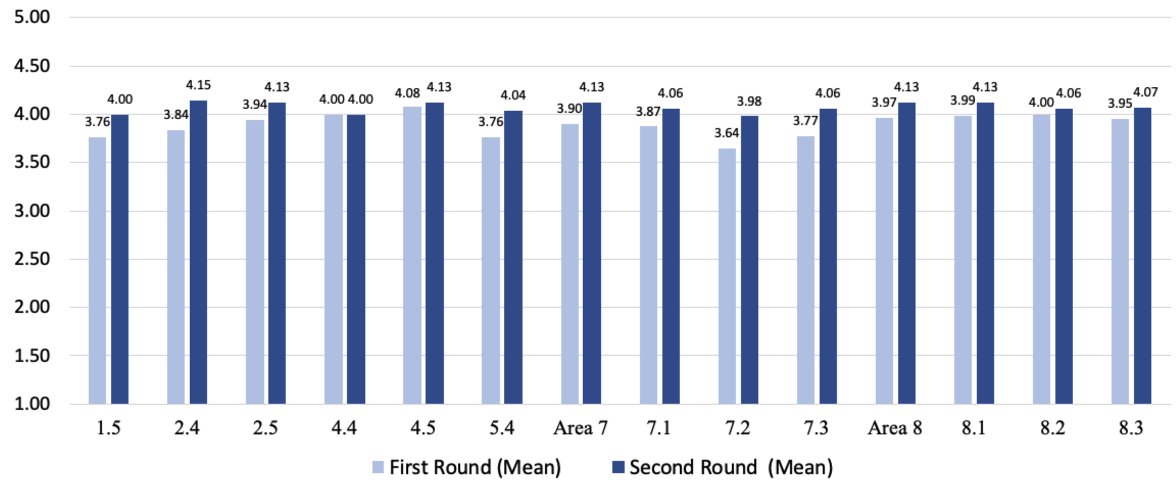


Figure 12: Means scores found in competences and areas on the two rounds

3.2.3 Topics (title and description, related activities, and proficiency levels)

As an initial parameter for analysing the determination to close the rounds of the Delphi panel, an increase in the mean across the various dimensions in which the competencies were assessed was considered. This suggests that the specialists view favourably the new version presented in the second round (Table 1). In cases where the mean did not show an increase, variance was checked, where lower variance indicates a higher degree of agreement (Table 2)

Table 1: Mean Competence

Competence / topic	First Round			Second Round		
	Title and description	Related activities	Proficiency statements	Title and description	Related activities	Proficiency statements
1.5. Digital Identity Management and Security	3.69	3.79	3.79	3.94	4.13	3.94
2.4. Online Engagement	3.76	3.83	3.93	4.13	4.38	3.94

Competence / topic	First Round			Second Round		
	Title and description	Related activities	Proficiency statements	Title and description	Related activities	Proficiency statements
2.5. Digital Curation	4.10	3.90	3.83	4.13	3.88 [a]	4.38
4.4. Online Assessment Process	4.00	4.03	3.97	4.06	3.88 [a]	4.06
4.5. Security, Privacy and Ethical Conduct	4.21	4.10	3.93	4.06 [a]	4.13	4.19
5.4. Digital Learning Environments Literacy	3.69	3.72	3.86	4.13	4.06	3.94
Area 7: Scientific Digital Literacy	3.90	-	-	4.13	-	-
7.1 Written and Management of Scientific Outputs	3.76	3.93	3.93	4.13	4.13 [a]	3.94
7.2. Research, Selection and Scientific Dissemination	3.45	3.76	3.72	3.94	4.00	4.00
7.3. Research Data	3.72	3.83	3.76	4.06	4.06	4.06
Area 8: Digital management of teaching and online learning	3.97	-	-	4.13	-	-
8.1. Design and Create Online Courses	4.03	3.97	3.97	4.06	4.13	4.19
8.2 Implement Online Courses	3.97	4.07	3.97	4.13	3.88	4.19
8.3. Management of Student's enrolment	4.03	3.90	3.93	4.06	4.00	4.06

Note. [a] Reduction in the mean between the first and second rounds.

Table 2: Mean and Variance of Competence

Competence	Topic	First Round Mean (Variance)	Second Round Mean (Variance)
2.5 Digital Curation (Area 2)	Activities	3.90 (0.645)	3.88 (0.359)
4.4 Online Assessment Process (Area 4)	Activities	4.03 (0.585)	3.88 (0.484)
4.5 Security, Privacy and Ethical Conduct (Area 4)	Title and description	4.21 (0.647)	4.06 (0.434)
8.2 Implement Online Courses (Area 8)	Activities	4.07 (0.409)	3.88 (0.234)

Of the 12 competencies submitted to the validation of experts through the use of the Delphi panel methodology, eight were considered validated based on the initial parameter, which is the high scores found in both rounds, and the increase in the mean scores from the first to the second round considering the three-topic analysed. The other four competences (Table 2), which showed a reduction in at least one of the topics, were analysed in terms of variance reduction, demonstrating a decrease in it. Based on these parameters, after the second round, it was considered unnecessary to conduct further rounds, concluding with the incorporation of the contributions in the last round and the full validation of the e-DigCompEdu.

3.3 Suggestions for Improvement (Dimension 2 and 3)

Regarding suggestions for changes to the topics presented in the first round, the specialists submitted 211 suggestions, averaging 7.24 suggestions per specialist. In the second round, 101 suggestions were received, averaging 6.31, thus representing a decrease in the mean number of suggestions made by the specialists. This reduction in both the total number of suggestions and the average per specialist can be interpreted as a possible indication of increase in consensus.

3.4 Final Version of e-DigCompEdu

The e-DigCompEdu was developed to complement the original DigCompEdu framework, incorporating 12 new digital competencies specifically created considering online higher education; six were integrated into the existing areas of DigCompEdu, and the other six were distributed across two new areas created specifically to address such context.

The competences integrated into the existing areas included: Competence 1.5 which was incorporated into Area 1; 2.4 and 2.5 which were added to Area 2; 4.4 and 4.5 which were included in Area 4; and 5.4 which was integrated into Area 5. Additionally, Area 7, 'Scientific Digital Literacy,' and Area 8, 'Digital Management of Teaching and Online Learning, were created, integrating three competences each. In Figure 3, as mentioned above, it is possible to observe the integration of the 12 new competencies with the 22 existing competences of DigCompEdu.

4. Discussion

The methodological approach adopted in this study aligns with validation standards already established in the development of other digital competence-related frameworks, particularly in terms of expert consultation. Similar to frameworks such as DigCompEdu, GreenComp, and DigCompConsumers, this study involved a panel of specialists to ensure that the framework reflects relevant and context-sensitive competences for its intended domain. However, this work extends the common practice of qualitative expert feedback by incorporating quantitative adequacy assessments for each competence element, including titles and descriptions, related activities, and proficiency statements. By integrating both qualitative and quantitative methods within a Delphi panel structure, the study offers a methodologically robust validation process. This dual approach strengthens the reliability of the findings and contributes to the framework’s credibility for potential adoption in varied institutional and international contexts. This methodology, widely recognised in research requiring complex analysis and evidence-based consensus (Malkawi, Bakar & Dahalin, 2023), proved to be particularly effective for the validation of the framework.

The careful selection of specialists was central to ensuring the credibility of the results. Defining the inclusion criterion as academic production in high-impact journals in the field of 'Distance Education' enabled the formation/selection of a highly qualified and representative panel. Additionally, the geographical diversity of participants enhanced the validity of the data by considering the inputs for subjects from different contexts and backgrounds. This methodological approach ensured that the contributions reflected a broad spectrum of practices and demands in online higher education.

Another important aspect of using the Delphi panel was its ability to integrate both quantitative and qualitative contributions. The combination of a numerical scale of responses with open-ended suggestions resulted in a robust analysis process, enabling the identification of points of convergence and divergence among the experts, and leading to the refinement of the framework. This iterative exchange of contributions among the experts fostered a collective and evidence-based construction process, demonstrated by the increase in mean ratings and the reduction in variances between rounds.

Variations in the digital competence levels among faculty have direct implications on their performance, particularly in the context of distance education (Maulana & Arli, 2022). According to Sever and Çatı (2021), there is a positive relationship between digital competence levels and faculty attitudes and satisfaction regarding online teaching and infrastructure. These findings reinforce that the increase in digital competences is directly associated with relevant improvements. To implement digital education effectively, it is essential to develop faculty digital competences, with an emphasis not only on the use of tools but also on pedagogically suitable content creation (Holik et al., 2023).

During the validation process of the competences, it was observed that some items showed a reduction in the mean rating scores (1-5) between the first and second rounds, which required careful analysis. Among these items are Digital Curation (Area 2 - Topic activities), in which there was a mean decrease from 3.90 to 3.88, while the variance dropped from 0.644 to 0.359; Online Assessment Process (Area 4 - Topic activities), with a reduction in the mean from 4.03 to 3.88 and in the variance from 0.585 to 0.484; Security, Privacy and Ethical Conduct (Area 4 - Topic title and description), which also had its mean decreased from 4.21 to 4.06, while the variance dropped from 0.647 to 0.434; and Implement Online Courses (Area 8 - Topic activities), which mean reduced from 4.07 to 3.88, while the variance dropped from 0.409 to 0.234.

Although the decrease in means initially suggests a less favourable evaluation, the reduction in variance indicates a greater alignment in the experts’ opinions, signalling that the contributions made between rounds refined the items, promoting greater clarity and consensus. The Delphi panel allowed for a productive management of divergences, transforming the varied opinions into valuable contributions for adjustments, enabling the dimensions comprising each of the 12 competencies and the two new areas created, to be better defined and to become more applicable within the context of online higher education.

Although there was a reduction in the number of specialists participating (attrition) in the second round, this phenomenon is a common and expected feature of the Delphi panel methodology, due to the demanding nature of iterative consultation (Almaiah et al., 2022; Malkawi, Bakar & Dahalin, 2023; Oxley, Nash & Weighall, 2024). This attrition does not compromise the validity of the results, as the expert panel in the first round already comprised specialists from all five continents, ensuring broad international representation. Furthermore, the foundation of the e-DigCompEdu was not built upon a single national search, but rather it was grounded in international literature and a generic competence mapping for online higher education. These elements strengthen the framework's global applicability and support its adaptability across diverse institutional and cultural contexts.

The progressive refinement and expert consensus achieved across the three core topics (title and description, related activities, and proficiency statements) indicate that the e-DigCompEdu demonstrates validity for the context of online higher education. The observed increase in mean adequacy, the decrease in variance and in the suggestions for improvement across rounds reflect not only a growing alignment among experts, but also the internal consistency and clarity of the framework's descriptors.

The organisation of the 12 validated competences in e-DigCompEdu reflects a logical and functional structure aimed at addressing the specificities of online higher education, following the DigCompEdu model. The competences were integrated into both the existing areas of DigCompEdu and the new areas created to fill the identified gaps. This organisation was based on the need to align the competences with the specific characteristics of online higher education, such as the management of virtual environments and the production of scientific content in digital formats. The distribution of competences across different areas enhances the clarity and applicability of the framework, making it practically useful for teachers and institutions.

The e-DigCompEdu is designed not only to support teachers' professional growth but also to guide the formulation of institutional strategies that foster the digital transformation of online higher education. Its application is considered essential to overcome challenges related to the quality of online education, such as the design of pedagogically thoughtfully planned online activities and the promotion of ethical and inclusive practices in virtual learning environments. To ensure effective and engaging online teaching experiences, it is necessary to invest in the continuous training of teaching staff as well as other support services (Maulana & Arli, 2022; Sattayaraksa et al., 2023). Changes in how teachers teach and how students learn in digital environments demand that today's educators not only enhance their academic profiles but also acquire and update their digital knowledge, essential for thriving on social media, immersive worlds and artificial intelligence-based solutions. These competencies, along with other professional attributes, are fundamental components for delivering quality online instruction (Lantaya, 2024).

5. Conclusion

Considering the study's objectives: i. assessing the adequacy of the proposed competences within the e-DigCompEdu framework and ii. identifying the level of consensus achieved regarding its structure, this concluding section reflects on the key findings and their implications.

The Delphi panel has proven to be an effective methodological approach for the validation of e-DigCompEdu. Its application facilitated the structured and iterative integration of contributions from international experts, resulting in a comprehensive and robust framework that effectively addresses the practical and global needs of online higher education.

The results directly address the research question by confirming that the e-DigCompEdu demonstrates content validity for online higher education. This was evidenced by the growing expert consensus on the adequacy of its three core components: title and description, related activities, and proficiency statements.

The results proved the complementarity between the e-DigCompEdu and the DigCompEdu frameworks, and validated the integration of specific aspects of online higher education. The e-DigCompEdu is intended to be globally applicable with contextual adaptation. Its core competence structure is conceived as universal, while descriptors, activity examples, and proficiency statements should be localised to national regulations and institutional arrangements. This intention (the global applicability) is supported by three elements of the study design and evidence: (i) the framework was grounded in international literature and in a generic mapping of competences for online higher education rather than any national syllabus; (ii) the validation drew on an international expert panel—Round 1 included specialists from all five continents, and Round 2 involved two continents; and (iii) the mean adequacy scores generally increased while variances decreased between rounds, indicating a growing convergence. Together, these features provide evidence of content validity and transferability beyond Europe, while preserving room for contextual tailoring.

The contextual adaptation can be by national or institutional types, according to legal, cultural, or institutional constraints. For example, some digital competences within the framework may be delegated to technical teams or academic support staff rather than to educators themselves. This highlights the need for contextual adaptations to ensure the framework's relevance and applicability.

Given the rapid advancement of emerging technologies (such as generative artificial intelligence, data analytics, and immersive environments), it is essential that its descriptors undergo regular evaluation and adjustments. The continuous incorporation of new technological demands will not only ensure that the framework remains up to date but will also strengthen its alignment with the structural transformations in online higher education.

Despite the methodological robustness of the Delphi panel, this study is not without limitations. Participant attrition across multiple rounds is a common challenge due to the demanding nature of the process. Additionally, there is a potential for non-response bias, particularly related to participant dropout between rounds. While strategies such as personalized invitations and individual reminders were used to encourage continued participation, the absence of responses from part of the original panel may have, to some extent, influenced the final representativeness of the results. Nevertheless, the international composition of the first-round panel and the consistency of the procedures throughout the process help mitigate this limitation. The pursuit of consensus may also reduce the visibility of minority viewpoints, although all contributions were systematically analysed. The subjective nature of expert judgment, and potential individual biases, such as *pro domo* tendencies, may influence the outcomes, even though measures were taken to preserve anonymity and reduce such risks.

The e-DigCompEdu not only guides and structures the professional development of educators but can also serve as a foundation for the formulation of institutional policies aimed at faculty training and digital transformation. Institutions may begin its implementation by conducting a self-assessment or diagnostic process based on the framework, followed by the contextual adaptation of descriptors, if necessary, to local and institutional settings, and the progressive integration into training programs, faculty appraisal systems, and curriculum design processes. Its adoption may be strategic for the development of structured programmes focused on pedagogical innovation and the enhancement of online higher education quality. However, challenges related to institutional implementation must be considered, including resistance to the adoption of new technologies, gaps in teacher training, and limitations in technological infrastructure.

Future studies could explore strategies to overcome these barriers, such as institutional incentives, continuous training based on learning analytics, and policies tailored to the diverse realities of institutions. Another direction is the development of a proficiency-level assessment instrument based on the e-DigCompEdu framework, enabling educators and institutions to diagnose individual or collective gaps and to implement more targeted and effective training initiatives, to be piloted with distance education teachers and to undergo reliability and validity testing through structural equation modelling.

AI Statement: The authors declare that they have not used generative or assisted artificial intelligence tools at any stage of the paper's conception and revision. All content presented results exclusively from the author's autonomous work, which guarantees originality, integrity, and compliance with ethical and scientific principles.

Ethics Committee: The Ethics Committee of the Institute of Education of the University of Lisbon granted approval for the various stages of this research process (approval No. 2906)

Funding: This work was supported by National Funds through FCT-Portuguese Foundation for Science and Technology, I.P., under the scope of UIDEF - Unidade de Investigação e Desenvolvimento em Educação e Formação, UIDB/04107/2025, https://doi.org/10.54499/UIDB/04107/2020

Acknowledgements

The authors are sincerely thankful to Prof. Silvia Roda for her comprehensive proofreading of this manuscript. Her expertise and careful review helped to refine the arguments and correct numerous oversights, ensuring a polished final submission.

References

Alainati, S., Al-Hunaiyyan, A., Alhajri, R., Alahmad, F. and Alkhatib, H, 2023. Perceptions of Online Learning Among Instructors: How to Maximise Instructors' Competencies in Virtual and Blended Learning. *International Journal of Professional Business Review*, *8*(11), e03924. https://doi.org/10.26668/businessreview/2023.v8i11.3924

Almaiah, M. A., Hajjej, F., Lutfi, A., Al-Khasawneh, A., Alkhdour, T., Almomani, O. and Shehab, R, 2022. A Conceptual Framework for Determining Quality Requirements for Mobile Learning Applications Using Delphi Method. *Electronics (Switzerland)*, *11*(5). https://doi.org/10.3390/electronics11050788

Aydın, M. and Çelik, T., 2020. Impact of the Digital Literacy Courses Taken by the Prospective Social Studies Teachers by Distance Learning on Digital Citizenship Skills. *Research on Education and Media*, *12*(1), 42–57. https://doi.org/10.2478/rem-2020-0006

Bacigalupo, M., Kampylis, P., Punie, Y., and Van den Brande, G., 2016. EntreComp: the entrepreneurship competence framework. In Luxembourg: Publication Office of the European Union. Publication Office of the European Union. https://doi.org/10.2791/593884

Bekiaridis, G., 2024. Supplement to the DigCompEDU Framework: Outlining the skills and competences of educators related to AI in education. https://aipioneers.org/supplement-to-the-digcompedu-framework/

Benali, M. and Mak, J., 2022. A comparative analysis of international frameworks for Teachers' Digital Competences. *International Journal of Education & Development Using Information & Communication Technology*, *18*(3), 122–138. https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,uid&db=eue&AN=161133228&lang=pt-pt&site=eds-live&scope=site

Bianchi, G., Pisiotis, U., Cabrera, M., Punie, Y., and Bacigalupo, M., 2022. GreenComp - The European sustainability competence framework (M. Bacigalupo and Y. Punie, Eds.). Publications Office of the European Union. https://doi.org/10.2760/13286

Biel, L. A. and Ramos, E. Á., 2019. La Competencia Digital Docente del professor Universitario 3.0. Caracteres. Estudios Culturales y Críticos de La Esfera Digital, 8(2), 205–236. http://revistacaracteres.net/wp-content/uploads/2019/11/Caracteresvol8n2noviembre2019.pdf

Bond, M., Bedenlier, S., Marín, V. I. and Händel, M., 2021. Emergency remote teaching in higher education: mapping the first global online semester. In *International Journal of Educational Technology in Higher Education* (Vol. 18, Issue 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1186/s41239-021-00282-x

Braun, V., and Clarke, V., 2022. Thematic Analysis: A Practical Guide (1st ed.). SAGE.

Brečko, B., and Ferrari, A., 2016. The Digital Competence Framework for Consumers (R. Vuorikari and Y. Punie, Eds.). https://doi.org/10.2791/838886

Cabero-Almenara, J., Barroso-Osuna, J., Gutiérrez-Castillo, J. J. and Palacios-Rodríguez, A., 2021. University teaching in times of pandemic. Reflection on the digital skills of Spanish university teachers according to DigCompEdu Framework. *Revista da Escola Superior de Educação*.

Cabero-Almenara, J., Romero-Tena, R. and Palacios-Rodríguez, A., 2020. Evaluation of teacher digital competence frameworks through expert judgement: The use of the expert competence coefficient. *Journal of New Approaches in Educational Research*, *9*(2), 275–283. https://doi.org/10.7821/naer.2020.7.578

Carretero, S., Vuorikari, R. and Punie, Y., 2017. DigComp 2.1: The Digital Competence Framework for Citizens. With eight proficiency levels and examples of use. In *Publications Office of the European Union*. Publications Office of the European Union. https://doi.org/10.2760/38842

Castañeda, L., Vanaclocha, N., Velasco, J. R., Ruiz, P., Hartillo, M. I., Pereira, E. and Ruiz, A., 2023. *Marco de Competencia Digital Docente Universitario. Creación y validación DIGCOMPEDU-FyA*. http://hdl.handle.net/10201/136836

Chatwattana, P., 2021. Massive open online courses model with self-directed learning to enhance digital literacy skills. *International Journal of Engineering Pedagogy*, *11*(5), 122–137. https://doi.org/10.3991/IJEP.V11I5.22461

Council of the European Union., 2018. Council recommendation on key competences for lifelong learning (2018/C 189/01). *Official Journal of the European Union*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ.C_.2018.189.01.0001.01.ENG

de Wit, H., and Altbach, P. G., 2023. International Higher Education for the Future: Major Crises and Post-Pandemic Challenges. *Change: The Magazine of Higher Learning*, 55(1), 17–23. https://doi.org/10.1080/00091383.2023.2151799

Díaz, I. A., Reche, M. P. C. and Rodríguez, J. M. R., 2019. Competencia digital de un tutor e-learning: un modelo emergente de buenas prácticas docentes en TIC. *Texto Livre: Linguagem e Tecnologia*, *12*(3), 49–68. https://doi.org/10.17851/1983-3652.12.3.49-68

Esteve-Mon, F. M., Llopis-Nebot, M. A. and Adell-Segura, J., 2020. Digital Teaching Competence of University Teachers: A Systematic Review of the Literature. *Revista Iberoamericana de Tecnologias Del Aprendizaje*, *15*(4), 399–406. https://doi.org/10.1109/RITA.2020.3033225

European Parliament and Council of the European Union., 2006. *Recommendation 2006/962/EC - On key competencies for lifelong learning*. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2006:394:0010:0018:en:PDF

Farooq, E., Zaidi, E. and Shah, M. M. A., 2024. The Future Classroom: Analysing the Integration and Impact of Digital Technologies in Science Education. *Jurnal Penelitian Dan Pengkajian Ilmu Pendidikan: E-Saintika*, *8*(2), 280–318. https://doi.org/10.36312/esaintika.v8i2.1957

Ferrari, A., 2013. DIGCOMP: A Framework for Developing and Understanding Digital Competence in Europe. *European Commission*. https://doi.org/10.2788/52966

Ferrari, A., Punie, Y. and Redecker, C., 2012. Understanding Digital Competence in the 21st Century: An Analysis of Current Frameworks. *21st Century Learning for 21st Century Skills*, 79–92. https://doi.org/10.1007/978-3-642-33263-0_7

Getenet, S., Haeusler, C., Redmond, P., Cantle, R. and Crouch, V., 2024. First-year Preservice Teachers' Understanding of Digital Technologies and Their Digital Literacy, Efficacy, Attitude, and Online Learning Engagement: Implication for Course Design. *Technology, Knowledge and Learning*. https://doi.org/10.1007/s10758-023-09724-z

Hodges, C., Moore, S., Lockee, B. B., Trust, T. and Bond, A., 2020, November 10. *The Difference Between Emergency Remote Teaching and Online Learning*. https://er.educause.edu/articles/2020/3/the-difference-between-emergency-remote-teaching-and-online-learning

Horváth, L., M. Pintér, T., Misley, H. and Dringó-Horváth, I., 2025. Validity evidence regarding the use of DigCompEdu as a self-reflection tool: The case of Hungarian teacher educators. Education and Information Technologies, 30(1), 1–34. https://doi.org/10.1007/s10639-024-12914-6

Holik, I., Kersánszki, T., Molnár, G. and Sanda, I. D., 2023. Teachers' Digital Skills and Methodological Characteristics of Online Education. *International Journal of Engineering Pedagogy (IJEP)*, *13*(4), 50–65. https://doi.org/10.3991/ijep.v13i4.37077

Instituto Nacional de Tecnologías Educativas y Formación del Profesorado [INTEF]., 2022. *Marco de Referencia de la Competencia Digital Docente: Enero 2022*. http://aprende.intef.es/mccdd

Kallas, K. and Pedaste, M., 2022. How to Improve the Digital Competence for E-Learning? *Applied Sciences*. https://doi.org/doi.org/10.3390/app12136582

Kampylis, P., Punie, Y. and Devine, J., 2015. *Promoting Effective Digital-Age Learning: A European Framework for Digitally-Competent Educational Organisations*. Publications Office of the European Union. https://doi.org/10.2791/54070

Karakış, Ö., 2022. Examining online learning motivations of university students studying via distance education in the Covid-19 pandemic by digital literacy variable. *Kastamonu Eğitim Dergisi*, *30*(3), 587–608. https://doi.org/10.24106/kefdergi.927496

Kassymova, G. M., Tulepova, S. B. and Bekturova, M. B., 2023. Perceptions of digital competence in learning and teaching English in the context of online education. *Contemporary Educational Technology*, *15*(1). https://doi.org/10.30935/cedtech/12598

Kayaduman, H., Battal, A. and Polat, H., 2023. The relationship between undergraduate students' digital literacy and self-regulation in online interaction. *Innovations in Education and Teaching International*, *60*(6), 894–905. https://doi.org/10.1080/14703297.2022.2113113

Lantaya, G. A., 2024. *An Assessment of Professional Attributes and 21st Century Digital Skills of Teachers Implementing Biology Laboratory Courses in an Online Distance Learning Mode*.

Malkawi, A. R., Bakar, M. S. A. and Dahalin, Z., 2023. Review of the Delphi Method in The Higher Educational Research. *Kongzhi Yu Juece*. *38*(01)

Mattar, J., Piovezan, M. B., Souza, S., Santos, C. and Santos, A., 2020. Apresentação crítica do Quadro Europeu de Competência Digital (DigComp) e modelos relacionados. *Research, Society and Development (RSD)*(4). https://doi.org/10.33448/rsd-v9i4.3062

Maulana, A. E. and Arli, D., 2022. Contextualizing Lecturer Performance Indicators to Online Teaching and Learning Activities: Insights for Application during the COVID-19 Pandemic and Beyond. The Electronic Journal of E-Learning, 20(5), 554–569. https://academic-publishing.org/index.php/ejel/article/view/2644/2101

Modise, M.-E. P. and Molotsi, A., 2022. The perceptions of new lecturers towards adopting a learning management system for facilitating modules online in a South African ODeL institution. International Journal of Education and Development Using Information and Communication Technology (IJEDICT), 18(1), 27–41. http://ijedict.dec.uwi.edu/include/getdoc.php?id=9448&article=3016&mode=pdf

Morachat, W. and Seechaliao, T., 2024. The Development of an Instructional Model Based on Flipped Using Technology-Based Learning to Enhance the Digital Literacy for Undergraduate Students in the Faculty of Education, Rajabhat University. *Higher Education Studies*, *14*(3), 189. https://doi.org/10.5539/hes.v14n3p189

Moreira, J. A., Dias-Trindade, S., Knuppel, M. A. and Serra, I., 2024. *Quadro de Referência das Competências Pedagógico-Digitais de Professores. Pedagogical Digcompedu Reloaded*. www.whitebooks.pt

Moreira, J. A., Nunes, C. S. and Casanova, D., 2023. Digital Competence of Higher Education Teachers at a Distance Learning University in Portugal. *Computers*, *12*(9). https://doi.org/10.3390/computers12090169

Moreno-Guerrero, A. J., López-Belmonte, J., Pozo-Sánchez, S. and López-Núñez, J. A., 2021. Usability and prospective of distance learning in Vocational Training determined by digital competence. *Aula Abierta*, *50*(1), 471–480. https://doi.org/10.17811/RIFIE.50.1.2021.471-480

Mudau, P. K. and Modise, M. E. P., 2022. Using e-portfolios for active student engagement in the odel environment. *Journal of Information Technology Education: Research*, *21*, 425–438. https://doi.org/10.28945/5012

Munar-Garau, J., Oceja, J., and Salinas Ibáñez, J., 2024. Equivalencias entre los indicadores de la herramienta SELFIE y el marco DigCompEdu a partir de la técnica Delphi. Pixel-Bit, Revista de Medios y Educación, 69, 131–168. https://doi.org/10.12795/pixelbit.101775

Nadzir, M. M. and Abu Bakar, J., 2023. A Digital Literacy Predictive Model in The Context of Distance Education. Journal of ICT in Education, 10(1), 118–134. https://doi.org/10.37134/jictie.vol10.1.10.2023

Ng, W., 2012. Can we teach digital natives digital literacy? Computers and Education, 59(3), 1065–1078. https://doi.org/10.1016/j.compedu.2012.04.016

Niederberger, M. and Renn, O., 2023. Delphi Methods In the Social and Health Sciences: Concepts, applications and case studies. Springer. https://doi.org/10.1007/978-3-658-38862-1

Oxley, E., Nash, H. M. and Weighall, A. R., 2024. Consensus building using the Delphi method in educational research: a case study with educational professionals. *International Journal of Research and Method in Education*. https://doi.org/10.1080/1743727X.2024.2317851

Palacios-Rodríguez, A., Llorente-Cejudo, C., Lucas, M. and Bem-haja, P., 2024. Macroassessment of teachers' digital competence. DigCompEdu study in Spain and Portugal. *RIED-Revista Iberoamericana de Educación a Distancia*, *28*(1), 177–196. https://doi.org/10.5944/ried.28.1.41379

Pedro, N., Santos, C. and Mattar, J., 2023. Competências Digitais na Educação: Uma introdução global. In N. Pedro, C. Santos and J. Mattar (Eds.), *Competências Digitais: desenvolvimento e impacto na educação atual* (1st ed.). Instituto de Educação da Universidade de Lisboa.

Redecker, C., 2017. *European Framework for the Digital Competence of Educators: DigCompEdu* (Y. Punie, Ed.). Publications Office of the European Union. https://doi.org/10.2760/159770

Reyes-Millán, M., Villareal-Rodríguez, M., Murrieta-Flores, M. E., Bedolla-Cornejo, L., Vázquez-Villegas, P. and Membrillo-Hernández, J., 2023. Evaluation of online learning readiness in the new distance learning normality. *Heliyon*, *9*(11). https://doi.org/10.1016/j.heliyon.2023.e22070

Rintamäk, K., 2019. From Teachers to Students: Digital Literacy Course for University Teachers. Qualitative and Quantitative Methods in Libraries (QQML), 8(4), 457–477. https://www.qqml-journal.net/index.php/qqml/article/view/525.

Rutten, N., and Brouwer-Truijen, K., 2025. Defining XR-Specific Teacher Competencies: Extending the DigCompEdu Framework for Immersive Education. Trends in Higher Education, 4(1), 11. https://doi.org/10.3390/higheredu4010011

Santos, C., 2023. Desenvolvimento do e-DigCompEdu: Quadro de referência das competências digitais docentes do ensino superior online. http://hdl.handle.net/10451/58016

Santos, C., Pedro, N. and Mattar, J., 2021. Digital Competence of Higher Education Professors: Analysis of Academic and Institutional Factors. *Obra Digital*, *21*, 67–92. https://doi.org/10.25029/od.2021.311.21

Santos, C., Pedro, N. and Mattar, P., 2024. Current Distance Education Research Landscape: A Bibliometric Study. *Revista de Educacion a Distancia (RED)*, *80*(24). https://doi.org/10.6018/red.610861

Santos, C., and Pedro, N., 2024. What is the applicability of the DigCompEdu Framework for online higher education? A study with Portuguese teachers. Revista Digital de Investigación En Docencia Universitaria, 18(1), 1–18. https://doi.org/https://doi.org/10.19083/ridu.2024.1816

Sattayaraksa, W. D, Luangrangsee, P., Ratsameemonthon, C., and Sulisworo, D., 2023. Understanding how demographic factors influence faculty member's perceptions of online learning success: A case study in Thai private higher education. *Journal of Pedagogical Research*, *7*(5), 48–68. https://doi.org/10.33902/JPR.202323519

Sever, S. and Çatı, K., 2021. The Mediating Role of Attitude towards Distance Education in the Effect of Digital Literacy Level on Satisfaction with Distance Education. Journal of Higher Education and Science, 11(3), 559–574. https://doi.org/10.5961/jhes.2021.475

Viñoles-Cosentino, V., Sánchez-Caballé, A. and Esteve-Mon, F. M., 2022. Desarrollo de la Competencia Digital Docente en Contextos Universitarios. Una Revisión Sistemática. *REICE. Revista Iberoamericana Sobre Calidad, Eficacia y Cambio En Educación*, *20*(2), 11–27. https://doi.org/10.15366/reice2022.20.2.001

Vuorikari, R., Kluzer, S. and Punie, Y., 2022. *DigComp 2.2: The Digital Competence Framework for Citizens* (1st ed.). Publications Office of the European Union. https://doi.org/10.2760/115376

Zabun, E., 2022. An investigation of the relationship between digital literacy of social studies teachers and their roles and competencies in distance online education. International Journal of Curriculum and Instruction, 14(3), 2093–2114. https://ijci.net/index.php/IJCI/article/view/106

Adoption Of Adaptive Gamified Learning Systems: A Push-Pool-Mooring Model Perspective

Eddy Triswanto Setyoadi[1,2], Syaad Patmanthara[1], Heru Wahyu Herwanto[1], Hartarto Junaedi[3], Alexander Wirapraja[2] and Titasari Rahmawati[2]

[1]Department Of Electrical Engineering and Informatics, Faculty of Engineering, Universitas Negeri Malang, Indonesia

[2]Department Of Information System, Faculty of Information Technology, Institut Informatika Indonesia Surabaya, Indonesia

[3]Department Of Information System, Faculty of Science and Technology, Institut Sains dan Teknologi Terpadu Surabaya, Indonesia

eddy.triswanto.2305349@students.um.ac.id, eddy@ikado.ac.id
syaad.ft@um.ac.id (Corresponding Author)
heru_wh@um.ac.id
aikawa@stts.edu
alex@ikado.ac.id
tita@ikado.ac.id

https://doi.org/10.34190/ejel.23.4.4295

Abstract: The adoption of digital learning systems is closely related to user engagement and system relevance. This quantitative research aims to explore the factors influencing students' switching intention from traditional Learning Management Systems (LMS) to a gamified LMS platform, using the Push-Pull-Mooring (PPM) framework. A conceptual model was developed to examine how negative experiences with previous systems (push factors), the appeal of a new gamified platform (pull factors), and personal constraints (mooring factors) influence switching behavior. The gamified LMS, named Learning Nova, was designed based on six types of goal orientation, enabling personalization according to students' motivational profiles. Data were collected through a two-stage process: an initial classification using a modified AGQ-R questionnaire, followed by a large-scale survey involving 1,054 university students from various institutions across Indonesia who interacted with the prototype. The findings confirmed the significant influence of both push and pull effects on switching intention. While mooring factors did not moderate these effects, they had a direct impact on students' decisions to switch. These insights offer practical implications for educational institutions and system developers seeking to enhance LMS adoption through motivation-aligned, gamified experiences.

Keywords: Gamified learning, Learning management system, Push-Pull-Mooring model, Goal orientation, Switching intention, Educational technology, Adoption

1. Introduction

The digital transformation in higher education, accelerated by the COVID-19 pandemic, has positioned Learning Management Systems (LMS) as the backbone of online learning. LMS platforms enable flexible distribution of course materials, assessment management, and interaction between instructors and students (Nguyen, 2021; Yuen, Cheng, Chan, 2019;Rau, Hösel, Roschke, Thomanek, Ritter, 2019) However, the widespread adoption of LMS has also revealed several fundamental issues, particularly concerning users' psychological experiences. Students often report stress, decreased engagement, and a loss of control over learning processes that are perceived as overly rigid and structured (Cao, Fang, Hou, Han, Xu, Dong, Zheng., 2020; Xue, Li, Xu., 2022; Lim, Regencia, Dela Cruz, Ho, Rodolfo, Ly-Uson, Baja., 2022). Consequently conventional LMS often fail to deliver learning experiences that are enjoyable, contextual, and meaningful.

One emerging approach to addressing these challenges is gamification—the integration of game elements into learning processes. Numerous studies have shown that gamification can enhance student motivation, engagement, and satisfaction, especially through features such as points, challenges, badges, and reward systems (Hamari, Koivisto, Sarsa., 2014; Khan, Ahmad, Malik., 2017; Robson, Plangger, Kietzmann, McCarthy, Pitt., 2015). However, the effectiveness of gamification is heavily influenced by individual student characteristics. When implemented uniformly without regard to user preferences and motivation, gamification may backfire, leading to boredom, competitive stress, or even manipulative behavior aimed solely at achieving higher scores (Saleem, Noori, Ozdamli., 2022; Almeida, Kalinowski, Feijo., 2021; Antonaci, Klemke, Specht., 2019).

Cite this article: Setyoadi, E.T.et al. 2025. "Adoption Of Adaptive Gamified Learning Systems: A Push-Pool-Mooring Model Perspective", *Electronic Journal of e-Learning*, 23(4), pp 102-125, https://doi.org/10.34190/ejel.23.4.4295

Therefore, an adaptive gamification approach that aligns with students' learning goal orientations is essential. Previous research has identified various student orientation types—such as mastery-intrinsic, mastery-extrinsic, performance-only, and non-achiever—that demonstrate different preferences for gamified elements (Hakulinen & Auvinen, 2014; Hakim Firdaus & Hendradjaya, n.d.). Even hybrid types, such as mastery ex-in, reflect the complex motivations that cannot be addressed through a single design strategy. This underscores the importance of LMS designs that respond to the emotional, motivational, and cognitive needs of students on a personalized level.

Previous work has developed a gamified LMS tailored to six student orientation types. However, a critical unanswered question remains: does the system actually encourage students to switch from their previous LMS to this new gamified version? This study specifically investigates students' switching intention toward the gamified LMS using the Push-Pull-Mooring (PPM) model through a multiple linear regression approach.

This study specifically investigates students' switching intention toward the gamified LMS using the Push-Pull-Mooring (PPM) model through a multiple linear regression approach. The PPM model is highly relevant as it offers a robust theoretical framework for understanding the interplay of three forces: Push factors (reasons to leave the old system, e.g., dissatisfaction) , Pull factors (attractions of the new system, e.g., features, ease of use) , and Mooring factors (psychological barriers or anchors, e.g., habits or emotional attachment). This application is supported by previous findings in related contexts, for example, studies indicating that perceived enjoyment and comfort positively contribute to switching intention, while prior learning experiences and habits serve as significant moderating factors (Lisana, 2023). In the Indonesian context, (Pramana, 2018) where perceived ease of use and usefulness are key determinants in technology adoption, a comprehensive understanding of how new LMS features are interpreted is crucial.

By testing an LMS prototype personalized based on six types of student goal orientations, this research addresses a literature gap by shifting the focus of the Pull factor from general usefulness to deep motivational alignment, a key driver of technology adoption. Thus far, no study has explicitly examined switching intention toward a gamified LMS using the PPM model that is grounded in user motivation orientation classifications. This research gap establishes the urgency of the present study—not merely to assess whether a gamified LMS is preferred, but to explore why and how students decide to transition from an old system to a new one within a framework that holistically considers technical, psychological, and motivational factors.

Based on survey data collected from 1,054 students, this study applies multiple linear regression analysis, this study aims to provide empirical contributions to the design of personalized, adaptive, and user-centered learning systems. Theoretically, it extends the application of the PPM model to the field of higher education and addresses a notable gap in gamified LMS literature, which has so far overlooked the complexity of users' goal orientations in system design and adoption strategies. This PPM application theoretically bridges the gap by integrating motivational segmentation as a personal and profound key driving factor (Pull Effect) in technology adoption studies.

2. Theoretical Background

2.1 Learning Management System

A Learning Management System (LMS) is defined as a web-based interface that facilitates the delivery of educational content, organizes learning procedures, and enables interaction between educators and learners. LMS platforms support online learning management through the integration of various e-learning modules and are commonly used to complement face-to-face instruction within blended learning models (Felea, Albastroiu, Vasiliu, Georgescu., 2018). Through functions such as discussion forums, self-assessments, and content management, LMS enables adaptive and structured digital learning approaches.

In the context of higher education, LMS has become a primary instrument for integrating technology into the learning process. It allows flexible and real-time access to course materials, supports two-way communication, and enables automated class management. However, the implementation of LMS also demands a higher level of technical competence and self-discipline from students compared to traditional classroom settings. This underscores the need to evolve LMS from being merely a content management tool into an interactive platform that actively fosters learning engagement. Studies in vocational education also emphasize the need for teachers to develop Technological Pedagogical Content Knowledge (TPACK) to optimize LMS usage in instructional delivery (Septian Ferdiansyah, Patmanthara and Suswanto, no date).

Furthermore, project-based and team-based approaches have gained popularity in vocational and applied science courses to improve students' collaboration and problem-solving skills in digital learning environments. The application of team-based project models in LMS settings has shown to significantly improve academic learning outcomes and student engagement (Patmanthara, Hidayat, Anugerah, Ichwanto., 2024). Likewise, the integration of collaborative tools within LMS supports not only content management but also deeper learning experiences through peer interaction and shared goal setting.

LMS typically operates within the framework of e-learning, which refers to the use of electronic devices to access educational content outside conventional classroom environments. E-learning formats include web-based learning, virtual classrooms, computer-based instruction, and digital collaboration through the internet, intranet, or other media (Fang, Li and Wu, 2023). In this context, LMS serves as a central component that coordinates content delivery, monitors participation, and measures learning outcomes.

Beyond content access, LMS-supported e-learning provides rapid feedback on students' learning activities and facilitates personalized learning pathways. E-learning–based LMS offers flexibility in time and location, improves access to up-to-date content, and incorporates advanced learning technologies. According to (Meskhi, Ponomareva and Ugnich, 2019), LMS enables the creation of adaptive and personalized learning environments, allowing students to develop customized learning solutions that suit their individual needs.

Nevertheless, many conventional LMS platforms are designed primarily for technical and administrative efficiency, rather than addressing the affective and motivational needs of users. Therefore, a new approach is needed in LMS development—one that integrates motivational principles such as gamification and is responsive to individual user characteristics, including their learning goal orientations. This is where the urgency arises for adopting gamification-based design strategies and evaluating students' switching intentions using the Push-Pull-Mooring model in this study.

2.2 Gamification in Education

Gamification refers to the application of game elements in non-game contexts, including education, with the aim of enhancing learners' motivation, engagement, and performance. This approach leverages psychological aspects that are inherently present in games—such as challenge, reward, immediate feedback, and a sense of achievement—to create a more engaging and interactive learning environment (Limantara, Meyliana, Gaol, Prabowo., 2022). Within the context of Learning Management Systems (LMS), gamification is integrated to bridge the rigidity of online learning with a more humanistic and participatory approach.

Gamification in LMS is implemented through the integration of various mechanisms such as points, badges, leaderboards, challenges, and real-time feedback. These elements are designed to stimulate intrinsic motivation and increase students' attention to the learning content (Hamari, Koivisto, Sarsa., 2014; Robson, Plangger, Kietzmann, McCarthy, Pitt., 2015). Practical implementations of this approach can be seen in applications like Kahoot!, Quizizz, and Wooclap, which successfully create a competitive and enjoyable atmosphere in online classrooms.

Moreover, gamification has been successfully applied in various learning models, such as flipped learning, where students engage with learning materials prior to face-to-face sessions. Research has shown that gamified flipped classrooms enhance student participation, intensify interaction with learning content, and improve academic achievement (Khaldi, Bouzidi and Nader, 2023). Even in technical fields such as biometrics, the integration of game elements into learning platforms has been shown to significantly improve the learning experience.

Gamification-based mobile learning designs have also demonstrated promising results in digital business education and other vocational contexts (Hidayat, Ulya, Patmanthara, Sari., 2024). Additionally, problem-based learning strategies using digital gamified modules have proven effective in enhancing outcomes in design and programming courses (Yusril Firmansyah, Patmanthara, Gatot Sutapa., 2022; Hidayat, Patmanthara, Tosepu, Sutikno, Wakhidah., 2021). Adaptive gamification platforms like "Learn Web Dev" further show the importance of user-centered design in vocational learning (Soraya, Patmanthara, Hidayat, Damayanti., 2024)

Nevertheless, the success of gamification in online education heavily depends on the careful selection, combination, and adaptation of game elements to suit learners' individual characteristics. Not all students respond positively to point systems or leaderboards; for some, competition may lead to pressure or demotivation. Therefore, adaptive gamification approaches—which align game elements with students' learning goal orientations—are receiving increasing attention in the development of motivation-based learning systems.

In this regard, gamification is not merely the addition of game-like features to educational systems, but rather a pedagogical strategy that is deeply integrated with instructional and psychological design. In this study, the gamification approach is directly linked to students' orientation profiles (e.g., mastery-intrinsic, performance-only, etc.) and its influence on students' switching intention toward a new LMS is evaluated using the Push-Pull-Mooring (PPM) framework.

2.3 Achievement Goal Orientation

The achievement goal orientation theory explains students' internal motives in directing their learning behavior. According to (Elliot and Church, 1997), goal orientation can be classified into several types: mastery-intrinsic (focused on mastering content for personal satisfaction), performance (focused on outcomes and recognition), and avoidance (aimed at avoiding failure). In this study, the classification is expanded into six types—super-achiever, mastery-intrinsic, mastery-extrinsic, mastery ex-in, performance-only, and non-achiever—to more comprehensively capture the diversity of students' learning motivations.

Adapting LMS design to these orientation types allows the system to be more responsive and relevant to users' needs. For example, students with a mastery-intrinsic orientation are more motivated by challenges and content exploration, whereas those with a performance-only orientation respond more positively to reward-based systems such as leaderboards or badges.

A recent systematic review has emphasized the importance of aligning gamification strategies with students' goal orientation types to improve academic performance and LMS engagement (Setyoadi and Patmanthara, 2024). Their review highlights that gamification, when tailored to students' dominant motivational profiles—such as mastery versus performance orientation—results in significantly higher satisfaction and persistence in online courses. The study also notes that mismatched gamification elements can inadvertently reduce learner engagement, particularly among students with avoidance or non-achiever orientations. Therefore, integrating gamification with goal orientation theory is critical to ensure meaningful and effective adoption of gamified LMS platforms.

2.4 Push-Pull-Mooring (PPM) Model in Evaluating LMS Switching Intention

The Push-Pull-Mooring (PPM) model was originally developed by (Bansal, 2005) in the context of customer migration studies and has since been adapted in various technology-related research, including online learning environments. The adaptation of the PPM model has been further extended by (Hou, Chern, Chen, Chen., 2011; Xu, Wang, Tai, Lin., 2021;Lin, Jin, Zhao, Yu, Su., 2021) in studies related to online and mobile learning system adoption.

This model explains switching behavior—or users' intention to move from one system to another—by analyzing three main categories of factors: push, pull, and mooring.

Push Effect

In this study, the push effect refers to the negative conditions perceived by users in the current system, which drive their desire to abandon it. In the LMS context, push factors may include perceptions of low service quality, inconvenient interface design, lack of interactive features, and technology-related frustration. These factors lead to user dissatisfaction with the legacy LMS (Chen & Keng, 2019; Xu, Wang, Tai, Lin., 2021).

Pull Effect

The pull effect is associated with the attractiveness of the new system that encourages users to switch. This attraction may stem from superior features, ease of use, technological compatibility with users' needs, higher user satisfaction, and enhanced motivational or experiential elements. In a gamified LMS, pull factors may include features aligned with students' learning needs and goal orientations, such as leaderboards, challenges, and adaptive reward systems (Alarifi, n.d.; Pramana, 2018).

Mooring Effect

The mooring effect refers to factors that inhibit or moderate the switching process, often related to psychological, social, or habitual barriers. These may include emotional attachment to the current system, loyalty to the institution providing it, or entrenched learning habits. The mooring effect helps explain why users may remain with an existing system despite the availability of better alternatives (Lisana, 2023; Pahnila, Siponen, Zheng., 2011).

The PPM model offers a comprehensive framework for explaining the dynamics of switching intention and has been widely applied in various domains, including banking, telecommunications, and online education. In this study, the model is used to evaluate how perceptions of the existing LMS, perceptions of the new gamified LMS, and psychological resistance influence students' intention to switch.

2.5 Previous Studies

Previous studies have extensively explored the integration of technology in education, particularly using Learning Management Systems (LMS), gamification approaches, and technology adoption models such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Push-Pull-Mooring (PPM) framework for analyzing switching behavior. In digital education contexts, gamification is frequently employed to enhance students' motivation and engagement, while PPM is applied to explain users' transition from one system to another based on push forces, pull attractions, and mooring inhibitors.

The review of 27 relevant prior studies (summarized in Table 1) reveals several key trends and divergences:

Table 1: State of the Art Research on LMS, Gamification, and PPM

No.	Year	Author	Research Focus	Method
A1	2021	(Manzano-León *et al.*, 2021)	Gamification in Education	Literature Review
A2	2020	(Smiderle *et al.*, 2020)	Gamification in Education	Empirical Study
A3	2020	(Dichev, Dicheva and Irwin, 2020)	Gamification in Education	Systematic Review
A4	2023	(Khaldi, Bouzidi and Nader, 2023)	Gamification in e-learning	Literature Review
A5	2022	(Limantara, Meyliana, Gaol, Prabowo., 2022)	Design Gamification in LMS	Model Development
A6	2019	(Lolo, Pratama, Mufarih, Wang., 2019)	Gamification in LMS	Empirical Study
A7	2022	(Limantara, Meyliana, Gaol, Prabowo., 2022)	Gamification in education	Systematic Review
A8	2023	(Alarifi, no date)	Switching Intention with PPM in online learning systems	Structural Equation Modeling
A9	2023	(Lisana, 2023)	Switching Intention with PPM in Mobile Learning	Quantitative Survey
A10	2022	(Wang and Shin, 2022)	Usage Intention with TAM & PPM in metaverse education application platform	Model Integration (TAM & PPM)
A11	2018	(Chen and Keng, 2019)	PPM, explores users intention english learning platform	Survey & SEM
A12	2021	(Xu, Wang, Tai, Lin., 2021)	Switching Behaviour Online Learning Platform with PPM	SEM Analysis
A13	2021	(Raharjo, Handayani and Putra, 2021)	Designing a Gamification of E-learning Applications	Design Research
A14	2020	(Facey-Shaw, Specht, van Rosmalen, Bartley, Bryan., 2020)	Badges affect intrinsic motivation	Experimental
A15	2019	(Karmanova, Chernova and Dokolin, 2019)	Gamification in e-learning technology	Literature Review
A16	2019	(Sriratnasari, Wang and Kaburuan, 2019)	Gamification framework in LMS	Framework Design
A17	2020	(Moreira, Ferreira, Escudero, Pereira, Durao., 2020)	Teaching & learning with gamification	Case Study

No.	Year	Author	Research Focus	Method
A18	2022	(Zhao, Playfoot, De Nicola, Guarino, Bratu, Di Salvadore, Muntean., 2022)	Gamification framework for STEM	Framework Development
A19	2018	(Chen, Huang, Gribbins, Swan., 2018)	Gamified online course	Course Evaluation
A20	2022	(Venter, 2022)	Influence of gamification element in online learning platform	Quantitative Study
A21	2023	(Shayan, Rondinelli, Zaanen, Atzmueller., 2023)	Analysis User Acceptance LMS	Survey Analysis
A22	2020	(Wicaksono, Cholily T, Juliani N, Asrini T, Wahyuni R., 2020)	Analysisis Feature LMS	Feature Analysis
A23	2023	(Modirrousta-Galian, Higham and Seabrooke, 2023)	Effects of inductive & gamification	Mixed Methods
A24	2020	(Panagiotarou, Stamatiou, Pierrakeas, Kameas., 2020)	Gamification e-learning acceptance with TAM	TAM Analysis
A25	2019	(Klock, Gasparini and Pimenta, 2019)	Quantitative & qualitative analysis: gamification for e-learning	Quantitative & Qualitative
A26	2020	(Sanjaya, Ferdianto and Titan, 2020)	Developing gamification mobile application	App Development
A27	2018	(Pramana, 2018)	Adoption Mobile learning with UTAUT & TAM	UTAUT & TAM Analysis

- **Gamification and Motivation (LMS):** Studies confirm that gamification elements (points, badges, leaderboards) positively affect student motivation and engagement (**A1, A2, A3**). However, a critical line of inquiry highlights that gamification's effectiveness is often **context-dependent** and heavily influenced by individual psychological characteristics, suggesting that a one-size-fits-all approach may fail or even demotivate certain learners (**A4, A7**). This divergence underscores the need to align system design with deeper user traits.
- **Switching Intention (PPM):** The PPM model has proven robust in explaining technology migration across various domains, including online learning systems (**A8, A9, A12**). **Alarifi (A8)** and Xu, Wang, Tai, Lin, **(A12)** consistently find that the perceived quality of the new system (Pull) and dissatisfaction with the old one (Push) are significant drivers. However, studies applying PPM in educational technology often overlook the complexity of the *system itself*. For instance, **Wang & Shin (A10)** integrated TAM and PPM but focused on a general metaverse platform, not a personalized, motivation-driven LMS. This indicates that while the mechanism of switching is understood, the content/design factors (like adaptive gamification) driving the Pull remain largely generic.
- **The Goal Orientation-Gamification Gap:** Research on the design and development of gamified LMS exists (**A5, A6, A16**), alongside studies focusing on the importance of aligning gamification with students' goal orientation (e.g., mastery vs. performance) to maximize persistence and satisfaction (**A14, Setyoadi & Patmanthara**). **Facey-Shaw (A14)**, for example, demonstrated that badges affect intrinsic motivation, which is directly relevant to mastery orientation. However, these two streams—the design/effectiveness of personalized LMS and the analysis of switching behavior (PPM)—have yet to be synthesized. Most PPM studies on e-learning focus on perceived ease of use and usefulness (TAM factors) as Pull effects, rather than deep motivational alignment.

To date, there is a notable lack of research that holistically integrates a personalized gamified LMS design based on students' goal orientation with a rigorous measurement of switching intention using the Push-Pull-Mooring (PPM) model.

This study aims to fill this critical knowledge gap by offering an empirical analysis of how the push factors of the traditional LMS, the motivation-aligned attractiveness (Pull) of a new gamified system, and personal inhibitors (Mooring) influence students' intention to switch. By explicitly classifying and accommodating six types of achievement goal orientations in the LMS prototype, this research moves beyond generic Pull factors and provides a deep, empirically-tested understanding of motivational alignment as a primary driver of technology adoption and migration in higher education.

3. Theoretical Model and Hypotheses Development

This study adopts the Push-Pull-Mooring (PPM) framework to examine the factors influencing students' switching intention from a conventional LMS to a gamified LMS that has been personalized based on their achievement goal orientation types. Each construct in the model is developed from prior literature and adapted to the context of digital learning.

3.1 Push Effect

The push effect represents negative conditions that drive users to leave their current system. In this study, the push effect includes two main constructs:

- Service Quality: Adapted from (*Journal of Management Information Systems*, 2003), this measures students' perceptions of the service quality of the legacy LMS, including system reliability, access speed, and information accuracy.
- Learning Comfort: Adapted from (Lu and Wung, 2020), this refers to students' comfort in using the traditional LMS, including interface design, navigation ease, and interaction usability.

Hypothesis 1 (H1): The Push Effect (perceived discomfort and low service quality of the previous LMS) has a significant positive influence on students' intention to switch to a new LMS.

3.2 Pull Effect

The pull effect reflects the attractiveness of the new system that encourages users to make a switch. In this study, the pull effect includes the following constructs:

- Motivation: Referencing (Afacan Adanır and Muhametjanova, 2021), this measures the ability of the new gamified LMS to foster student motivation through gamification features.
- Challenge: Adapted from (Al-Hunaiyyan, Alhajri, Al-Sharhan, AlGhannam., 2021), this measures the extent to which the new system provides academic challenges that drive engagement.
- Perceived Ease of Use: Derived from (Pramana, 2018) and rooted in the TAM model, this assesses how easy the new LMS is to use.
- Task-Technology Fit: Based on (Alyoussef, 2021), this measures how well the LMS features align with students' learning needs.
- Satisfaction: Adapted from (Chao, 2019), this measures user satisfaction with the experience of using the new LMS.

Hypothesis 2 (H2): The Pull Effect (positive perception of the new LMS features and user experience) has a significant positive influence on students' intention to switch from the old LMS.

3.3 Mooring Effect

The mooring effect serves as a moderating variable that can either strengthen or weaken the relationship between push/pull effects and switching intention. The mooring constructs in this study include:

- Affective Commitment: Adapted from (Xu, Wang, Tai, Lin., 2021), this measures students' emotional attachment to the existing LMS.
- Habit: Adapted from (Pahnila, Siponen and Zheng, 2011), this reflects students' habitual use of the old LMS formed through routine behavior.

Hypothesis 3 (H3): The mooring effect moderates the relationship between pull effect and switching intention, such that higher mooring weakens the influence of pull on switching intention.

Hypothesis 4 (H4): The mooring effect moderates the relationship between push effect and switching intention, such that higher mooring weakens the influence of push on switching intention.

3.4 Switching Intention

Switching intention refers to students' intent to abandon the legacy LMS and adopt the new gamified LMS. This construct serves as the dependent variable, influenced by push and pull factors and moderated by the mooring effect.

Hypothesis 5 (H5): The mooring effect has a significant influence on students' switching intention toward the gamified LMS.

Figure 1 illustrates the conceptual model employed in this study. The model integrates the Push Effect, Pull Effect, and Mooring Effect constructs based on the Push-Pull-Mooring (PPM) framework, which has been adapted to the context of switching intention toward a gamified Learning Management System (LMS).

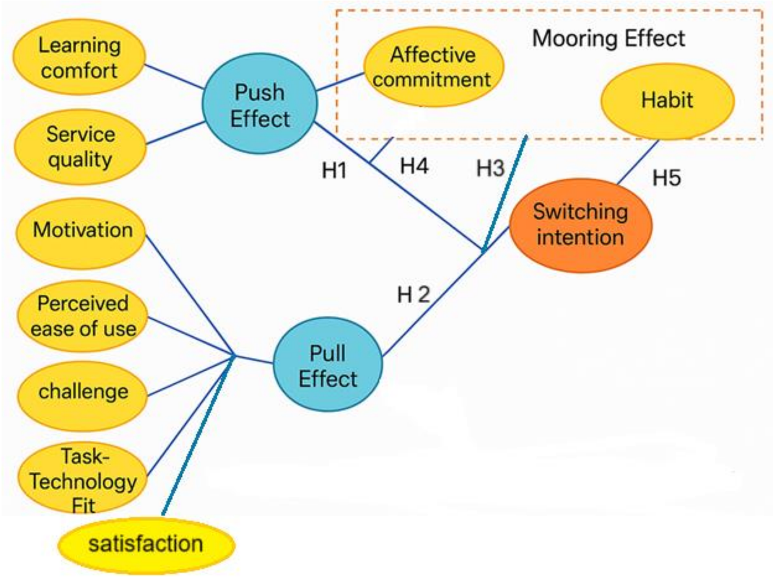


Figure 1: The PPM-Based Research Framework

4. Research Methodology

4.1 Population and Sampling

The target population for this study consisted of university students across various institutions in Indonesia who had prior experience using traditional Learning Management Systems (LMS). The sampling technique employed was non-probability sampling, specifically convenience sampling or purposive sampling, by inviting students who were willing to participate in evaluating the new LMS prototype. This approach was pragmatic given the two-stage data collection process and the need to access a large and diverse group of students for the large-scale survey.

The total sample size for Phase Two (the large-scale survey using the PPM questionnaire) was 1,054 university students from multiple institutions across Indonesia.

4.2 Sample Descriptive Statistics and LMS Usage Details

To ensure clarity on the sample characteristics and the context of data collection, the following descriptive statistics and LMS usage details were recorded:

- Academic Year : Primarily 2nd to 4th year students (e.g., 65% were in their 3rd year)
- Degree Program : Students from various study programs, including Information Technology, Business, and Education.
- Age Range : 18–24 years old (Mean Age: 20.5 years)
- Institutions : Students from Universities across Indonesia

4.3 LMS Usage Details

The 1,054 students in Phase Two were granted access to the gamified LMS prototype, Learning Nova.

- **Mode of Access:** The LMS was a web-based platform, accessible via standard web browsers on personal computers and mobile devices.
- **Subjects/Content:** Participants interacted with course content, primarily centered around an **"Introduction to ICT"** course , which included modules, assignments, pre-tests, and quizzes.

- **Duration of Use:** Participants were given a defined period, which was a minimum of one session of interaction with the personalized features (including completing a pre-test, module, and challenge) before completing the PPM questionnaire. This interaction was necessary for them to fully experience the personalized gamification elements, such as the Challenge and Leaderboard features, that were adapted based on their six achievement goal orientations. The time spent was sufficient for them to form a perception of the new system's Pull factors and their switching intention.

4.4 Research Type and Approach

This study is a quantitative research employing an explanatory approach, aiming to measure and analyze the influence of Push, Pull, and Mooring factors on students' switching intention toward a gamified Learning Management System (LMS). The LMS evaluated in this study was developed based on gamification principles and segmentation of students' motivational orientation types. Data analysis was conducted using multiple linear regression with the assistance of SPSS.

4.5 Research Framework

Figure 2 illustrates the conceptual logic flow of this study. Traditional LMS platforms have demonstrated negative impacts on students' engagement and learning motivation. Improvements have been attempted through gamified LMS designs; however, not all gamification approaches have shown significant effects on enhancing motivation and learning outcomes.

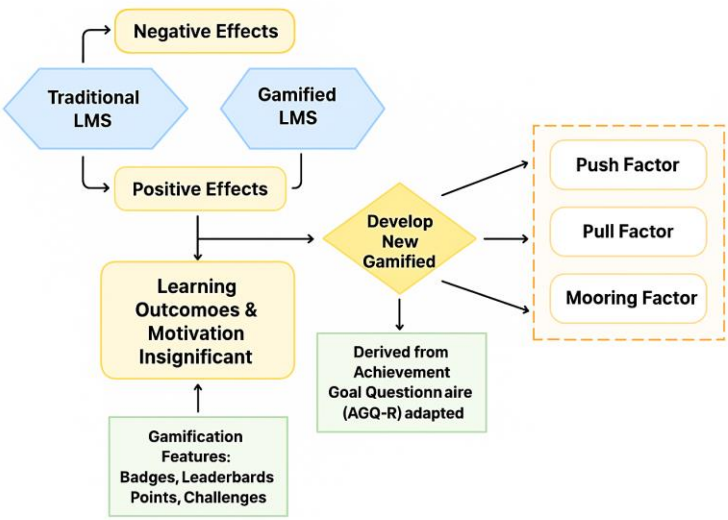


Figure 2: Research Framework

Therefore, this study proposes a gamified LMS design personalized according to users' goal orientation types, as identified through a modified version of the Achievement Goal Questionnaire-Revised (AGQ-R). Gamification elements—such as badges, leaderboards, and challenges—were adjusted based on students' motivational orientation profiles.

The primary focus of this research is not on learning outcomes, but on users' switching intention toward the new LMS. To evaluate this, the Push-Pull-Mooring (PPM) framework is employed as an evaluative model to measure the extent to which push, pull, and mooring factors influence students' decisions to switch from the traditional LMS to the new gamified system.

4.6 Research Procedure

The study was conducted in two main phases:

- **Phase One (Goal Orientation Classification):** Involved 150 initial participants. They completed a modified version of the Achievement Goal Questionnaire-Revised (AGQ-R) to identify their goal orientation types (e.g., Super Achiever, Mastery-Intrinsic). The results formed the basis for the personalized features of the LMS prototype.

- **Phase Two (PPM Survey):** Involved 1,054 university students. These students were invited to **interact** with the gamified LMS prototype (Learning Nova) and subsequently completed the Push-Pull-Mooring (PPM) questionnaire to measure push, pull, and mooring effects in the context of switching intention toward the new LMS. The questionnaire was administered immediately after their interaction to capture responses reflecting their actual experience with the system.

4.7 Research Instruments

The instruments used in this study include:

- AGQ-R (Achievement Goal Questionnaire–Revised): This instrument was used to identify and classify students into six types of achievement goal orientations: mastery-intrinsic, mastery-extrinsic (a newly defined variant), mastery ex-in, performance-only, super-achiever, and non-achiever. The classification process was conducted prior to students interacting with the LMS prototype, serving as the basis for interpreting user responses to the system.
- PPM Questionnaire (Push-Pull-Mooring): This instrument was employed to measure students' perceptions of the gamified LMS based on the three core constructs of the PPM model: Push Effect (factors driving students away from the old LMS), Pull Effect (attractiveness of the new LMS), and Mooring Effect (inhibitors or barriers to switching). The questionnaire was administered after students used the LMS prototype to ensure that their responses reflected their actual learning experiences with the system.

4.8 Design and Implementation of the Gamified LMS Prototype

The Learning Management System (LMS) prototype developed in this study is named Learning Nova—an online learning platform based on gamification principles, designed to adapt to students' achievement goal orientation types. System personalization was implemented based on students' motivational classification results, obtained from responses to a modified version of the Achievement Goal Questionnaire-Revised (AGQ-R).

Home Page and Student Type Classification

When users first access the system, they are presented with the landing page shown in Figure 3, which displays six types of motivational goal orientations: Super Achiever, Mastery Intrinsic, Mastery Extrinsic, Mastery Ex-In, Performance Only, and Non Achiever.

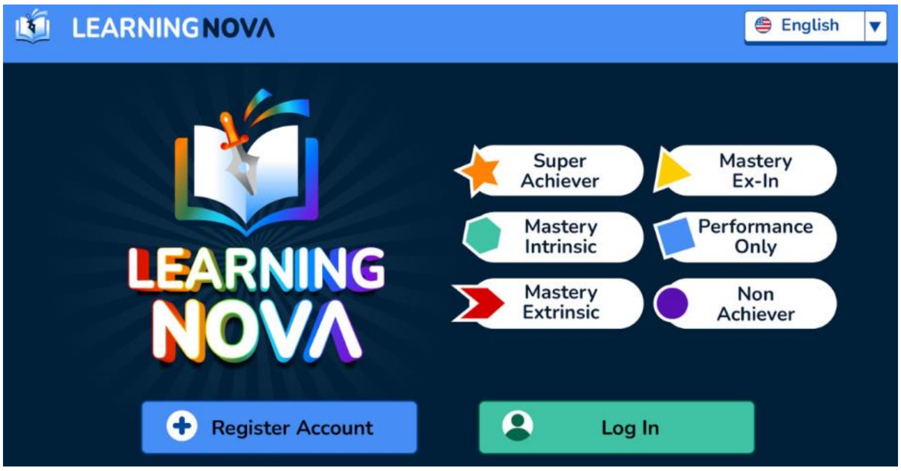


Figure 3: LearningNova Landing Page

Before entering the main learning system, students are required to complete the AGQ-R questionnaire, as shown in Figure 4. This questionnaire consists of several Likert-scale items designed to identify students' dominant motivational goal orientation. Based on the responses, the system automatically classifies each student into one of six orientation types. The LMS interface and gamification features are then personalized accordingly.

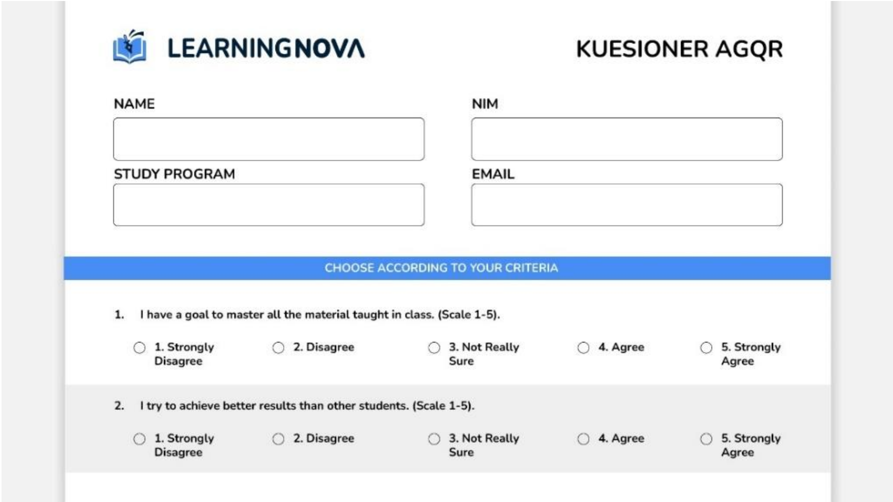


Figure.4: AGQ-R Questionnaire Page

Homepage Display and Learning Navigation

After completing the AGQ-R questionnaire and the gamification preference input, the system automatically classifies the user's motivational orientation, as illustrated in Figure 5. In this example, the user is identified as belonging to the Super Achiever type.

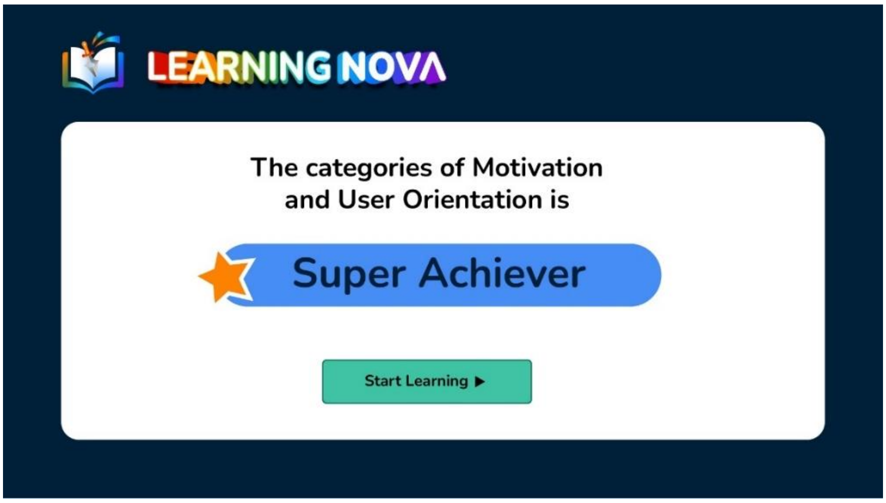


Figure 5: Questionnaire Result Page (Super-Achiever)

Figure 6 shows the homepage interface, which includes a personalized welcome message at the top of the screen, current announcements, and the My Class menu displaying active courses along with their completion progress.

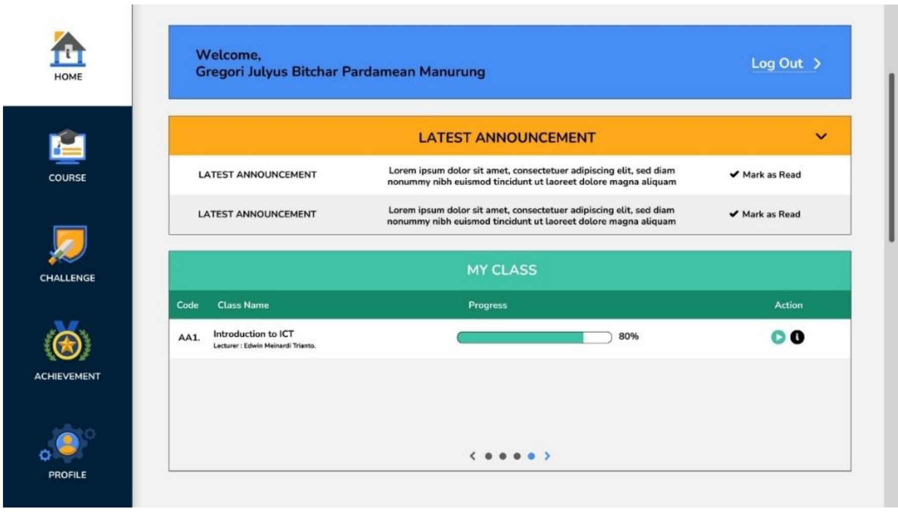


Figure 6: Homepage Interface

A visual progress bar is prominently featured to serve as a motivational prompt, encouraging users to complete their courses up to 100%. An action button is also provided to continue learning—aligned with the Super Achiever type, which tends to pursue all challenges to the maximum extent

Class Features and Assignment Submission

As shown in Figure 7, this page displays downloadable learning materials—such as Material_Midterm—along with information on assignment deadlines.

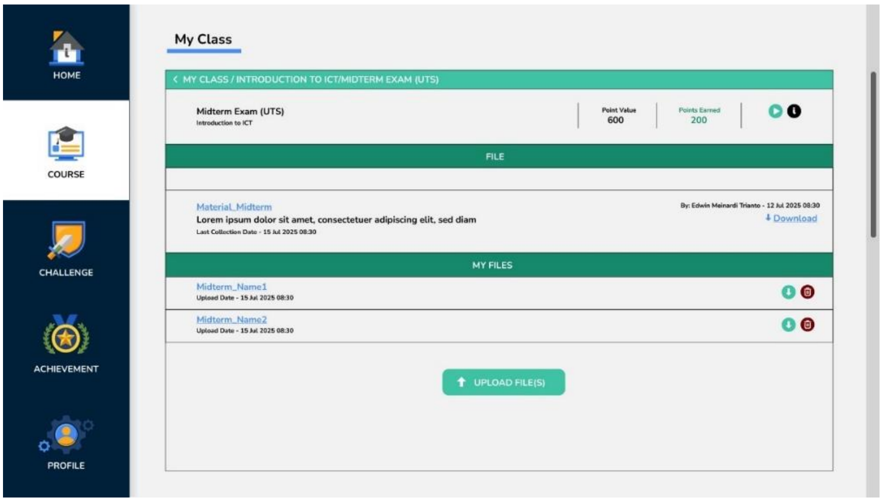


Figure 7: Course Menu Page – Assignment Submission and Points

This interface reflects characteristics typical of Super Achiever students, as it provides clear targets and enables them to monitor their progress in completing assigned tasks.

Figure 8 presents the structure of course content and student progress in the Introduction to ICT course. Each row displays a topic/module along with its completion indicators and associated assessments.

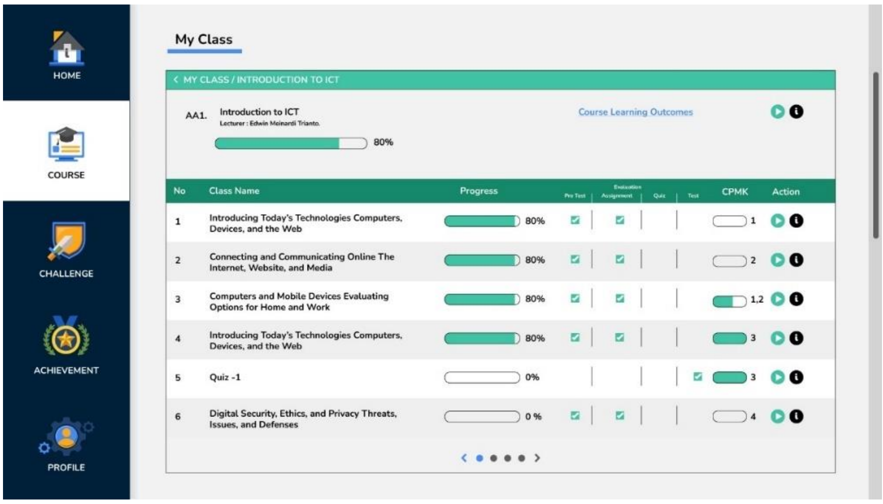


Figure 8: Course Menu Page – Class List and Module Progress

This layout aligns with the characteristics of Super Achiever students, as it provides a systematic and measurable structure—ideal for learners with strong goal-oriented and high-achievement tendencies.

Challenges and Interactive Gamification

The Challenge menu, as illustrated in Figures 9 and 10, displays a series of learning-based challenges. Figure 9 shows the challenge dashboard, which presents a list of learning activities or missions that users are required to complete.

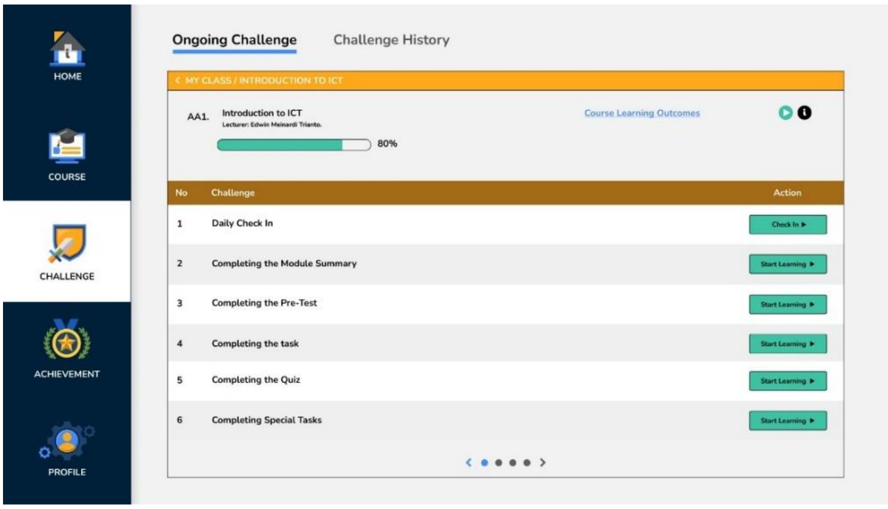


Figure 9: Ongoing Challenge Page

This page is specifically customized for users with the Super Achiever motivation type, who are typically competitive, goal-driven, and motivated by maximum achievement.

The purpose of this page is to enhance learning engagement and motivation through clearly structured academic and daily challenges. It provides incentives in the form of points, progress tracking, and badges, encouraging consistent and performance-oriented learning behavior.

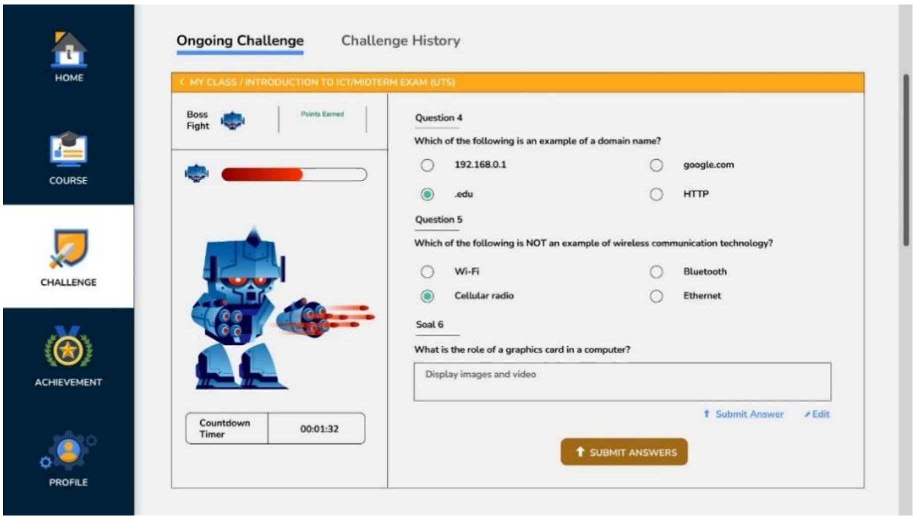


Figure 10: Challenge Page – Active Challenge (Boss Fight)

In the Learning Nova LMS, users with the Super Achiever orientation type are presented with a challenge called Boss Fight, which simulates a final exam or decisive task using game-based visual elements, as shown in Figure 10. This page features key elements such as a boss character representing the ultimate learning challenge, a health bar that decreases with each correct answer, a countdown timer to test both speed and accuracy, and progressively advancing multiple-choice questions. This feature aligns with the Super Achiever student profile, as it transforms the final evaluation process into a more stimulating and psychologically satisfying experience. It creates a sense of competition against the system, framing the final exam as a heroic mission to be conquered.

Leaderboard

As shown in Figure 11, the leaderboard system ranks users based on cumulative performance across various learning components, including level and rank (1st, 2nd, 3rd, etc.), student ID, name and study program, and scores from different activities such as assignments, pretests, module completion, content unlocking, and boss fights.

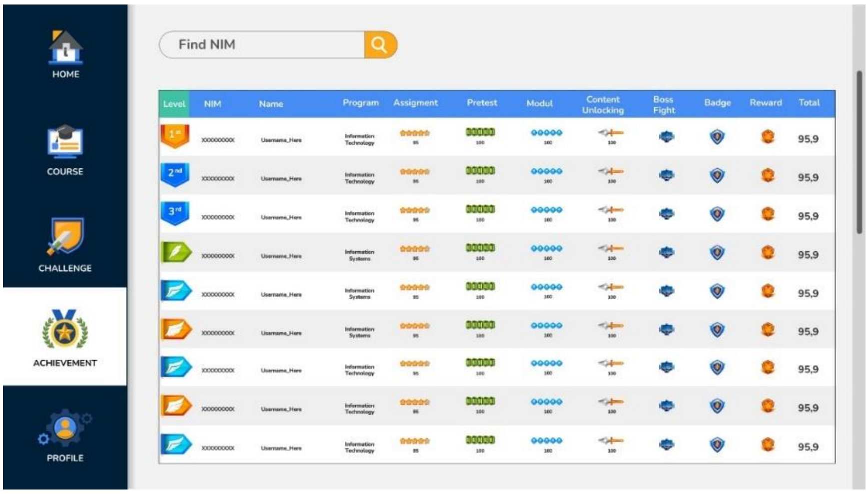


Figure 11: Leaderboard

Users with the Super Achiever orientation are highly driven by ranking systems and recognition of achievement. It also includes visual feedback in the form of badges and rewards. This leaderboard is particularly relevant for Super Achiever users, as it enhances motivation through healthy competition, provides clear feedback regarding one's relative standing among peers, and encourages students to strive for high scores and complete all components to maintain or improve their position.

The core feature of Learning Nova is its adaptive gamification based on students' achievement goal orientations. The design aims to move beyond generic Pull factors and focus on deep motivational alignment.

5. Preliminary Analysis

A preliminary analysis was conducted to ensure that all research instruments possessed acceptable levels of construct validity and internal reliability before hypothesis testing. This analysis includes validity and reliability tests for two main categories of instruments:

- The modified AGQ-R instrument used to classify students' motivational orientation types.
- The Push-Pull-Mooring (PPM) model instrument used to measure switching behavior.

The AGQ-R instrument was used to classify students into six motivational goal orientation types: Mastery-Intrinsic, Mastery-Extrinsic, Mastery Ex-In, Performance-Only, Super-Achiever, and Non-Achiever. A total of 150 students participated in the initial classification phase before accessing the gamified LMS prototype. The validity test of the motivational orientation instrument showed that all 19 items had a correlation coefficient (r-calculated) greater than the r-table value, ranging from 0.249 to 0.577, thus confirming that all items were valid.

- The reliability test was conducted using Cronbach's Alpha, which yielded a value of 0.769, indicating good internal consistency and reliability. Further analysis, by removing each item one by one, showed Cronbach's Alpha values remained stable within the range of 0.752 to 0.764, all exceeding the 0.70 threshold (George & Mallery, 2003), confirming that the instrument has reliable internal consistency.
- In the next phase, a total of 1,054 students from various universities across Indonesia were granted access to use the gamified LMS prototype and subsequently completed the PPM model questionnaire. This instrument measured the three main constructs of the Push-Pull-Mooring model (Push, Pull, and Mooring Effects), as well as Switching Intention.
- The validity test was conducted by comparing each item's item-total correlation with the r-table value, using degrees of freedom (df = N – 2 = 1052) and a significance level of 0.05, resulting in r-table = 0.062. An item was considered valid if its correlation value exceeded 0.062.

As a fundamental step in ensuring the accuracy of this study's measurement, the comprehensive results of the validity test for the Push-Pull-Mooring (PPM) model instrument, which was designed to evaluate the gamified Learning Management System (LMS), are presented in detail in Table 2 below.

Table 2: Validity Test Results of the Instrument for Evaluating the Gamified LMS Model Using the Push-Pull-Mooring (PPM) Framework

Indicator	Pearson Correlation	r_{table}	Description
X1	0.481	0.062	Valid
X2	0.339	0.062	Valid
X3	0.268	0.062	Valid
X4	0.245	0.062	Valid
X5	0.521	0.062	Valid
X6	0.210	0.062	Valid
X7	0.334	0.062	Valid
X8	0.319	0.062	Valid
X9	0.344	0.062	Valid
X10	0.381	0.062	Valid
X11	0.386	0.062	Valid
X12	0.303	0.062	Valid
X13	0.219	0.062	Valid
X14	0.476	0.062	Valid
X15	0.212	0.062	Valid
X16	0.418	0.062	Valid
X17	0.522	0.062	Valid
X18	0.455	0.062	Valid
X19	0.343	0.062	Valid

Indicator	Pearson Correlation	r_table	Description
X20	0.435	0.062	Valid
X21	0.390	0.062	Valid
X22	0.429	0.062	Valid
X23	0.521	0.062	Valid
X24	0.599	0.062	Valid
X25	0.442	0.062	Valid
X26	0.442	0.062	Valid
X27	0.449	0.062	Valid
X28	0.440	0.062	Valid
X29	0.443	0.062	Valid

Based on the calculation results, all items showed correlation coefficient values (r-calculated) greater than 0.062, indicating that all items are valid and suitable for use in measurement. Following the validity test, a reliability test was conducted on the instrument used to evaluate the gamified LMS model using the PPM framework.

The results of the reliability test for the instrument used to evaluate the gamified LMS model employing the Push-Pull-Mooring framework are presented in Table 3.

Table 3: Reliability Test Results of the Instrument for Evaluating the Gamified LMS Model Using the PPM Framework

Indicator	Cronbach's Alpha	r_table	Description
X1	0.794	0.062	Reliable
X2	0.800	0.062	Reliable
X3	0.802	0.062	Reliable
X4	0.803	0.062	Reliable
X5	0.792	0.062	Reliable
X6	0.809	0.062	Reliable
X7	0.800	0.062	Reliable
X8	0.801	0.062	Reliable
X9	0.799	0.062	Reliable
X10	0.799	0.062	Reliable
X11	0.799	0.062	Reliable
X12	0.806	0.062	Reliable
X13	0.804	0.062	Reliable
X14	0.794	0.062	Reliable
X15	0.804	0.062	Reliable
X16	0.797	0.062	Reliable
X17	0.792	0.062	Reliable
X18	0.795	0.062	Reliable
X19	0.800	0.062	Reliable
X20	0.796	0.062	Reliable
X21	0.798	0.062	Reliable
X22	0.796	0.062	Reliable
X23	0.792	0.062	Reliable
X24	0.788	0.062	Reliable
X25	0.796	0.062	Reliable

Indicator	Cronbach's Alpha	r_{table}	Description
X26	0.796	0.062	Reliable
X27	0.795	0.062	Reliable
X28	0.796	0.062	Reliable
X29	0.796	0.062	Reliable

After confirming item-level validity, construct-level reliability and validity were calculated to ensure internal consistency and independence among latent variables. For this purpose, Cronbach's Alpha values for each main construct (Push Effect, Pull Effect, Mooring Effect, and Switching Intention) were calculated from the mean of their constituent items. All alpha values must exceed the accepted threshold to demonstrate good construct reliability.

Furthermore, to review simple discriminant validity, inter-construct correlations (Pearson Correlation) were examined. Inter-construct correlation values lower than the square root of the Average Variance Extracted (AVE) (if AVE is calculated, or at least < 0.90) can serve as an initial indication of discriminant validity.

The results of the construct reliability analysis, specifically the values for Cronbach's Alpha, are detailed in Table 4.

Table 4: Construct Reliability Results (Cronbach's Alpha)

Construct	Item Used	Cronbach's Alpha	Description
Push Effect	Service Quality, Learning Comfort	0.88	Reliable
Pull Efect	Motivation, Challenge, Perceived Ease Of Use, Task Technology Fit, Satisfaction	0.81	Reliable
Mooring Effect	Habit, Affective, Commitment	0.84	Reliable
Switching Intentions	5 Statement	0.89	Reliable

The results indicate that all constructs have Cronbach's Alpha values exceeding the 0.70 threshold, confirming strong internal reliability at the construct level.

The reliability test was conducted using Cronbach's Alpha. A commonly accepted threshold for reliability is a value above 0.7; however, values between 0.6 and 0.7 may still be considered acceptable in exploratory research (Nunnally & Bernstein, 1994). Based on the reliability analysis of 29 items, the resulting Cronbach's Alpha values ranged from 0.788 to 0.809. All items also had item-total correlation coefficients (indicated as 'Pearson Correlation' in Table 2) greater than the r-table value of 0.062, which primarily confirms their validity. The high Cronbach's Alpha values demonstrate strong internal consistency for the overall instrument."

6. Result and Discussion

This chapter presents the empirical results of testing the Push-Pull-Mooring (PPM) conceptual model to evaluate the influence of various factors on students' Switching Intention in transitioning to a gamified LMS. The evaluation was conducted using a multiple linear regression approach with the help of SPSS software. This approach was chosen over structural equation modeling (SEM) techniques, as no specialized software such as AMOS or SmartPLS was used.

According to (Hair, 2010), multiple linear regression can be used to test theoretical models when constructs are measured directly (without latent indicators) and the aim is to evaluate causal relationships between variables. Similarly, (Ghozali, 2018) affirms that multiple linear regression remains a relevant analytical tool in quantitative research for testing the significance and direction of relationships between independent and dependent variables simultaneously. Therefore, this method is considered appropriate for examining both direct and moderating relationships among variables within the PPM model.

6.1 Test Data

A total of 1,054 students from various universities in Indonesia participated in the study. All respondents had used the gamified LMS prototype and completed a Likert-scale-based questionnaire. The questionnaire included the following constructs:

- Push Effect: Service Quality, Learning Comfort
- Pull Effect: Motivation, Challenge, Ease of Use, Task-Technology Fit, Satisfaction
- Mooring Effect: Habit, Affective Commitment
- Switching Intention: 5 separate statements

The selection of variables within each construct (push, pull, and mooring) was grounded in a literature review and conceptual analysis as outlined in the chapter Theoretical Model and Hypotheses Development. Each indicator was adapted from previously validated studies and contextualized for use within a gamified LMS environment. Using this approach, the PPM model in this study was systematically developed to identify key factors influencing students' intention to switch from a traditional LMS to a gamified LMS.

6.2 Analysis Technique

Data analysis was carried out in four regression stages, each designed to test different aspects of the PPM model. The regression models employed for hypothesis testing, which were designed to analyze different aspects of the PPM framework across four stages, are outlined in Table 5.

Table 5: Regression Models

Model	Variabel Independent	Variabel Dependent
H1 & H2	Push_Avg, Pull_Avg	Switching_Avg
H3	Mooring_Avg, Push_Avg, Mooring_Push	Switching_Avg
H4	Mooring_Avg, Pull_Avg, Mooring_Pull	Switching_Avg
H5	Mooring_Avg	Switching_Avg

Each construct was measured using several validated indicators. For the purpose of regression analysis, the mean score of all items within each construct was calculated and labeled as follows:

- Push_Avg: The average of all indicators under the Push Effect construct (Service Quality and Learning Comfort).
- Pull_Avg: The average of all indicators under the Pull Effect construct (Motivation, Challenge, Ease of Use, Task-Technology Fit, and Satisfaction).
- Mooring_Avg: The average of indicators for Habit and Affective Commitment under the Mooring Effect construct.
- Switching_Avg: The average of five statements measuring Switching Intention.

Moderation interactions were also calculated by multiplying the relevant construct means, resulting in two interaction terms:

- Mooring_Push = Mooring_Avg × Push_Avg
- Mooring_Pull = Mooring_Avg × Pull_Avg

This technique follows the moderated regression approach as outlined by Aiken & West (1991) and is commonly used in studies testing interaction effects among constructs.

For the moderation regression analysis (testing H3 and H4), a mean-centering procedure was applied to the Pull_Avg, Push_Avg, and Mooring_Avg variables before calculating the interaction terms Mooring_Pull and Mooring_Push. Centering was performed to reduce multicollinearity that might arise from high correlations between the main independent variables and the interaction terms.

6.3 Test Results for H1 and H2: The Effects of Push and Pull on Switching Intention

To examine the effects of Push Effect and Pull Effect on Switching Intention, a multiple linear regression analysis was conducted using SPSS. The purpose of this test was to evaluate the extent to which these two constructs can explain students' intention to switch to a gamified LMS.

- Hypothesis 1 (H1) posits that the Push Effect has a significant positive influence on Switching Intention.
- Hypothesis 2 (H2) tests whether the Pull Effect also significantly influences Switching Intention.

The results of the multiple linear regression analysis, which tested the direct effects of the Push and Pull Effects on Switching Intention (H1 and H2), are presented in Table 6.

Table 6: Regression Results for H1 and H2

Variable	B Regression Coef.	Std. Error	Beta	t	Sig. (p.value)	Description
Push_Avg	0.675	0.046	0.369	14.643	< 0.001	Signifikan (H1)
Pull_Avg	0.960	0.050	0.485	19.238	< 0.001	Signifikan (H2)

The analysis results show that both independent variables have a statistically significant influence on the dependent variable. Pull_Avg yielded a regression coefficient of 0.960 ($p < 0.001$), while Push_Avg produced a coefficient of 0.675 ($p < 0.001$). The coefficient of determination (R^2) reached 0.599, indicating that approximately 59.9% of the variance in Switching Intention can be explained by the combined effects of these two factors. This finding is further supported by an F-statistic of 784.152 ($p < 0.001$), confirming that the overall regression model is statistically significant.

Accordingly, both Hypothesis 1 (H1) and Hypothesis 2 (H2) are supported. These findings confirm that both positive perceptions of the new LMS features (Pull Effect) and discomfort with the old system (Push Effect) play important roles in influencing students' intention to switch to a gamified LMS.

6.4 Hypothesis Testing H3: Mooring as a Moderator of Pull Effect

Hypothesis 3 (H3) aims to test whether the Mooring Effect acts as a moderating variable in the relationship between Pull Effect and Switching Intention. To examine this, a multiple linear regression analysis was conducted involving three predictor variables: Pull_Avg, Mooring_Avg, and the interaction term Mooring_Pull (the product of Mooring_Avg and Pull_Avg).

The results of the regression analysis conducted to test Hypothesis 3 (H3), specifically examining the moderating role of the Mooring Effect on the relationship between Pull Effect and Switching Intention, are detailed in Table 7.

Table 7: Regression Results for Hypothesis H3

Variable	B Regression Coef.	Std. Error	Beta	t	Sig. (p.value)	Description
Pull_Avg	0.609	0.193	0.308	3.164	0.002	Signifikan
Mooring_Avg	0.289	0.203	0.250	1.419	0.156	Not Signifikan
Mooring_Pull	0.065	0.051	0.314	1.281	0.200	Not Signifikan

The regression results show that Pull_Avg still has a significant influence on Switching Intention ($B = 0.609$, $p = 0.002$). However, both Mooring_Avg ($p = 0.156$) and the interaction term Mooring_Pull ($p = 0.200$) do not exhibit statistically significant effects. Although the model's R^2 value reached 0.658 and the overall model was significant ($F = 672.823$, $p < 0.001$), the non-significant interaction term indicates that the Mooring Effect does not moderate the relationship between Pull Effect and Switching Intention.

Therefore, Hypothesis 3 (H3) is rejected. This implies that while Pull Effect has a direct impact, the strength of this relationship is neither enhanced nor diminished by students' emotional attachment or habitual use of the previous system.

6.5 Hypothesis Testing H4: Mooring as a Moderator of Push Effect

Hypothesis 4 (H4) tests the role of the Mooring Effect as a moderator in the relationship between Push Effect and Switching Intention. The regression model includes three predictors: Push_Avg, Mooring_Avg, and the interaction term Mooring_Push (the product of Mooring and Push constructs).

The detailed findings of the regression analysis used to test Hypothesis 4 (H4), specifically regarding the potential moderating effect of the Mooring construct on the Push Effect and Switching Intention relationship, are presented in Table 8.

Table 8: Regression Results for Hypothesis H4

Variable	B Regression Coef.	Std. Error	Beta	t	Sig. (p.value)	Description
Push_Avg	1.026	0.229	0.561	4.489	< 0.001	Signifikan
Mooring_Avg	0.916	0.228	0.793	4.016	< 0.001	Signifikan
Mooring_Push	–0.078	0.057	–0.390	–1.377	0.169	Not Signifikan

The regression results indicate that both Push_Avg (B = 1.026, $p < 0.001$) and Mooring_Avg (B = 0.916, $p < 0.001$) have a significant effect on Switching Intention. However, the interaction term Mooring_Push has a negative but statistically non-significant coefficient (B = –0.078, p = 0.169). The R^2 value of 0.650 indicates that 65.0% of the variation in Switching Intention is explained by the three variables, but the absence of a significant interaction effect confirms no moderation.

As a result, Hypothesis 4 (H4) is rejected. This finding suggests that students' emotional attachment or habitual use of the previous system does not strengthen or weaken the impact of negative perceptions toward the old LMS on their intention to switch to a new system.

The rejection of Hypothesis 3 (H3) and Hypothesis 4 (H4) indicates that while the restraint factor (Mooring Effect) has a significant direct influence, it does not moderate the relationship between the drive (Push) and attraction (Pull) factors and switching intention. This moderation failure can be attributed to two potential factors. First, the strength of the Pull Effect—driven by motivationally aligned gamification features—may be exceedingly strong, effectively overriding the inertia of existing habits and emotional commitment (Mooring) independently. In other words, the emotional and functional benefits of the new system were compelling enough to detach users without merely weakening or strengthening the Push/Pull effects. Second, the Mooring construct in this study focused on habits and affective commitment. Future studies might consider a more specific dimension of Mooring, such such as perceived switching costs or social norms, which may exhibit a clearer moderating effect.

Recommendation for In-Depth Analysis (Goal-Type): Since the LMS prototype was adaptively designed based on six goal orientations, future analysis could extend the model testing using multi-group analysis to explore differences. For instance, does the Pull Effect (feature attraction) have a stronger impact on the Super Achiever group compared to the Non-Achiever group, who might be more sensitive to the Push Effect (discomfort with the old LMS). This testing will provide a more nuanced understanding of which factor is most relevant for each motivational profile.

6.6 Hypothesis Testing H5: Direct Effect of Mooring on Switching Intention

Hypothesis 5 (H5) tests the direct effect of the Mooring Effect on Switching Intention using a simple linear regression. The analysis shows that Mooring_Avg has a significant effect on Switching Intention, with a regression coefficient of 0.850 ($p < 0.001$). A high t-value of 35.286 and an R^2 of 0.542 indicate that 54.2% of the variation in Switching Intention is explained by the Mooring Effect.

The final regression stage, which tested Hypothesis 5 (H5) regarding the moderating influence of the Mooring Effect on the relationship between the Pull Effect and Switching Intention, yielded the results presented in Table 9.

Table 9: Regression Results for Hypothesis H5

Variable	B Regression Coef.	Std. Error	Beta	t	Sig. (p.value)	Description
Mooring_Avg	0.850	0.024	0.736	35.286	< 0.001	Signifikan

Therefore, Hypothesis 5 (H5) is supported. This finding demonstrates that although the Mooring Effect does not function as a moderator in the relationship between Push and Pull effects and Switching Intention, it still exerts a strong direct influence on users' intention to switch. This indicates that even when students are emotionally attached to the previous LMS, they are still willing to transition to a new LMS—provided that the new system delivers a more enjoyable or emotionally satisfying learning experience.

The finding that the Mooring Effect acts as a direct predictor rather than a moderator suggests that existing habits and emotional attachments, while influential, do not alter the *degree* to which negative experiences (push) or positive new features (pull) drive switching. Instead, these mooring factors independently contribute to the decision-making process. This might be because the emotional incentives from a new, more satisfying system are strong enough to overcome the inherent inertia of existing habits and attachments, directly impacting the willingness to switch regardless of the perceived 'push' or 'pull' strength."

6.7 Basic Regression Assumption Checks

Before hypothesis testing (H1–H5), assumption checks were conducted to ensure the data's suitability for the linear regression model. The assumptions examined included residual normality, linearity, homoscedasticity, and the absence of multicollinearity.

Specifically, the issue of multicollinearity was tested using the Variance Inflation Factor (VIF). The VIF values for all predictor variables (including the centered interaction terms) in each regression model were below the threshold of 10 (e.g., below 5), indicating that multicollinearity was not a significant concern in the model. This check is crucial following the creation of the interaction terms (Mooring_Pull and Mooring_Push) to ensure a valid interpretation of the coefficients.

7. Conclusion

This chapter provides a comprehensive summary of the research findings, derived from the empirical testing of the Push-Pull-Mooring (PPM) model using data collected from 1,054 students regarding their intention to switch from a conventional LMS to a newly designed gamified LMS prototype. The primary objective was to determine the key motivational factors driving this Switching Intention.

Based on the results of the multiple linear regression analysis, the study confirms that the intention to switch is significantly influenced by all three PPM constructs as direct predictors:

- **Pull Effect (Dominant Factor):** The Pull Effect, representing students' attraction to the new gamified system, proved to be the most dominant factor. Positive perceptions regarding motivation, challenge, ease of use, and user satisfaction significantly contributed to the willingness to adopt the new LMS.
- Push Effect (Significant Factor): Dissatisfaction with the previous conventional LMS (the Push Effect), related to poor service quality and low learning comfort, also had a significant positive influence on Switching Intention.
- Mooring Effect (Direct Predictor): While the Mooring Effect (emotional attachment to the old system) was rejected as a moderating variable for the Push and Pull relationships (Hypotheses H3 and H4), its direct relationship with Switching Intention was statistically significant. This finding is crucial: even when students retained emotional ties or habit to the old LMS, the meaningful and relevant learning experience offered by the new system was sufficient to overcome this inertia and maintain a strong intention to switch.

Practical Implications of this study suggest that the development of gamified LMS must not only focus on designing engaging and motivating features (Pull Effect) but also proactively address student dissatisfaction with existing systems (Push Effect) and directly acknowledge underlying personal habits and emotional ties (Mooring Effect). For example, developers can integrate features that explicitly help users migrate data from the old system or provide transitional support to ease habit change.

Practical Examples of Applying Goal Profiles in Onboarding: Onboarding strategies and feature design should be tailored to motivational profiles:

- **Mastery-Intrinsic:** Provide quick access to in-depth content and exploration challenges without an immediate focus on rankings, emphasizing the intrinsic value of learning.
- **Performance-Only:** Prominently place leaderboards and reward/recognition notifications on the homepage to trigger competition-based motivation.
- **Non-Achiever:** Use simple progress bars and daily small achievement visualizations to reduce anxiety and gradually build positive momentum.

8. Future Research

Despite these robust findings, this study is subject to several methodological limitations that temper the generalizability of the conclusions:

- **Context and Sampling:** The data collection was limited to a specific student population and a prototype system. The generalizability of these results to other educational levels, different cultural contexts, or fully deployed commercial LMS platforms may be limited.
- **Intention vs. Behavior:** This research measured Switching Intention, which is a proxy for actual adoption. There can be a significant gap between what an individual intends to do and their eventual switching behavior when faced with real-world institutional or cost-related barriers.
- **Possible Common-Method Bias (CMB):** As all data was collected through self-reported surveys from a single source at one point in time, there is a possibility of Common-Method Bias. This could potentially inflate the observed correlations among the PPM constructs.

To build upon this work and address the current limitations, the following future research steps are recommended:

- **Longitudinal and Behavioral Data:** Future studies should adopt a longitudinal research design to track students after the gamified LMS is fully deployed, validating the findings by measuring actual adoption behavior and continued usage over time, thereby bridging the intention-behavior gap.
- **Richer Mooring Factors:** The Mooring construct should be expanded to include a richer set of factors beyond emotional attachment. This includes exploring concrete switching costs (e.g., effort to learn a new interface, institutional policies, data migration difficulty) and perceived risk factors associated with changing systems.
- **Tests by Goal Type:** The practical implication regarding motivational profiles should be empirically tested. Future research should segment the sample based on established student goal types (e.g., mastery-intrinsic vs. performance-only) and test whether the influence of Push and Pull factors on switching intention varies significantly across these different profiles.

AI Statement: The authors employed AI tools for the purposes of paraphrasing and proofreading assistance

Ethics Statement: All subjects gave their informed consent for inclusion before they participated in the study

References

Afacan Adanır, G. and Muhametjanova, G. (2021) “University students’ acceptance of mobile learning: A comparative study in Turkey and Kyrgyzstan,” *Education and Information Technologies*, 26(5), pp. 6163–6181. Available at: https://doi.org/10.1007/s10639-021-10620-1.

Alarifi, S.H. (no date) *Examining the Factors Affecting Students’ Switching Intention to Online Learning Systems during COVID-19 in Saudi Arabia*.

Al-Hunaiyyan, A. *et al.* (2021) “Factors Influencing the Acceptance and Adoption of Online Learning in Response to the COVID-19 Pandemic,” *International Journal of Web-Based Learning and Teaching Technologies*, 16(6), pp. 1–16. Available at: https://doi.org/10.4018/IJWLTT.20211101.oa5.

Almeida, C., Kalinowski, M. and Feijó, B. (2021) “A Systematic Mapping of Negative Effects of Gamification in Education/Learning Systems,” in *2021 47th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, pp. 17–24. Available at: https://doi.org/10.1109/SEAA53835.2021.00011.

Alyoussef, I.Y. (2021) “E-Learning Acceptance: The Role of Task–Technology Fit as Sustainability in Higher Education,” *Sustainability*, 13(11), p. 6450. Available at: https://doi.org/10.3390/su13116450.

Antonaci, A., Klemke, R. and Specht, M. (2019) “The effects of gamification in online learning environments: A systematic literature review,” *Informatics*, 6(3). Available at: https://doi.org/10.3390/informatics6030032.

Bansal, H.S. (2005) “‘Migrating’ to New Service Providers: Toward a Unifying Framework of Consumers’ Switching Behaviors,” *Journal of the Academy of Marketing Science*, 33(1), pp. 96–115. Available at: https://doi.org/10.1177/0092070304267928.

Brian Chen, C.C. *et al.* (2018) “Gamify online courses with tools built into your learning management system (Lms) to enhance self-determined and active learning,” *Online Learning Journal*, 22(3), pp. 41–54. Available at: https://doi.org/10.24059/olj.v22i3.1466.

Cao, W. *et al.* (2020) “The psychological impact of the COVID-19 epidemic on college students in China,” *Psychiatry Research*, 287, p. 112934. Available at: https://doi.org/10.1016/j.psychres.2020.112934.

Chao, C.M. (2019) “Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model,” *Frontiers in Psychology*, 10(JULY). Available at: https://doi.org/10.3389/fpsyg.2019.01652.

Chen, Y.-H. and Keng, C.-J. (2019) “Utilizing the Push-Pull-Mooring-Habit framework to explore users’ intention to switch from offline to online real-person English learning platform,” *Internet Research*, 29(1), pp. 167–193. Available at: https://doi.org/10.1108/IntR-09-2017-0343.

Dichev, C., Dicheva, D. and Irwin, K. (2020) “Gamifying learning for learners,” *International Journal of Educational Technology in Higher Education*, 17(1), p. 54. Available at: https://doi.org/10.1186/s41239-020-00231-0.

Elliot, A.J. and Church, M.A. (1997) *A Hierarchical Model of Approach and Avoidance Achievement Motivation*, *Journal of Personality and Social Psychology Copyright*. American Psychological Association, Inc.

Facey-Shaw, L. *et al.* (2020) “Do Badges Affect Intrinsic Motivation in Introductory Programming Students?,” *Simulation and Gaming*, 51(1), pp. 33–54. Available at: https://doi.org/10.1177/1046878119884996.

Fang, K., Li, L. and Wu, Y. (2023) “Research on student engagement in distance learning in sustainability science to design an online intelligent assessment system,” *Frontiers in Psychology*, 14. Available at: https://doi.org/10.3389/fpsyg.2023.1282386.

Felea, M. *et al.* (2018) “E-LEARNING IN HIGHER EDUCATION: EXPLORATORY SURVEY AMONG ROMANIAN STUDENTS,” in *14th International Conference eLearning and Software for Education*. Carol I National Defence University Publishing House, pp. 157–162. Available at: https://doi.org/10.12753/2066-026x-18-237.

Galih Wasis Wicaksono, st *et al.* (2020) *Analysis of Learning Management System Features based on Indonesian Higher Education National Standards using the Feature-Oriented Domain Analysis*, *2020 8th International Conference on Information and Communication Technology (ICoICT)*.

Hakim Firdaus, L. and Hendradjaya, B. (no date) "DESAIN GAMIFIKASI ADAPTIF UNTUK LEARNING MANAGEMENT SYSTEM MENGGUNAKAN GAMING ACHIEVEMENT GOAL," 15(2).

Hakulinen, L. and Auvinen, T. (2014) "The Effect of Gamification on Students with Different Achievement Goal Orientations," in *2014 International Conference on Teaching and Learning in Computing and Engineering*. IEEE, pp. 9–16. Available at: https://doi.org/10.1109/LaTiCE.2014.10.

Hamari, J., Koivisto, J. and Sarsa, H. (2014) "Does gamification work? - A literature review of empirical studies on gamification," in *Proceedings of the Annual Hawaii International Conference on System Sciences*. IEEE Computer Society, pp. 3025–3034. Available at: https://doi.org/10.1109/HICSS.2014.377.

Hidayat, W.N. *et al.* (2021) "Gamified Mobile Learning For Digital Business Model Course," in *2021 3rd International Conference on Research and Academic Community Services (ICRACOS)*, pp. 290–295. Available at: https://doi.org/10.1109/ICRACOS53680.2021.9702057.

Hou, A.C.Y. *et al.* (2011) "'Migrating to a new virtual world': Exploring MMORPG switching through human migration theory," *Computers in Human Behavior*, 27(5), pp. 1892–1903. Available at: https://doi.org/10.1016/j.chb.2011.04.013.

Journal of Management Information Systems (2003) "The DeLone and McLean Model of Information Systems Success: A Ten-Year Update," 19(4), pp. 9–30. Available at: https://doi.org/10.1080/07421222.2003.11045748.

Karmanova, E., Chernova, E. V and Dokolin, A. (2019) "Modeling Knowledge Assessment with Gamification Technology on E-Learning Platform," *2019 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon)*, pp. 1–6. Available at: https://api.semanticscholar.org/CorpusID:209458509.

Khaldi, A., Bouzidi, R. and Nader, F. (2023) "Gamification of e-learning in higher education: a systematic literature review," *Smart Learning Environments*. Springer. Available at: https://doi.org/10.1186/s40561-023-00227-z.

Khan, A., Ahmad, F.H. and Malik, M.M. (2017) "Use of digital game based learning and gamification in secondary school science: The effect on student engagement, learning and gender difference," *Education and Information Technologies*, 22(6), pp. 2767–2804. Available at: https://doi.org/10.1007/s10639-017-9622-1.

Klock, A.C.T., Gasparini, I. and Pimenta, M.S. (2019) "User-Centered Gamification for E-Learning Systems: A Quantitative and Qualitative Analysis of its Application," *Interacting with Computers*, 31(5), pp. 425–445. Available at: https://doi.org/10.1093/iwc/iwz028.

Lim, L.T.S. *et al.* (2022) "Assessing the effect of the COVID-19 pandemic, shift to online learning, and social media use on the mental health of college students in the Philippines: A mixed-method study protocol," *PLOS ONE*, 17(5), pp. e0267555-. Available at: https://doi.org/10.1371/journal.pone.0267555.

Limantara, N. *et al.* (2022) "Factors Influencing the Implementation of Gamification for Learning in Information Systems Education," *International Journal of Emerging Technologies in Learning*, 17(8), pp. 32–41. Available at: https://doi.org/10.3991/ijet.v17i08.29777.

Lin, C.L. *et al.* (2021) "Factors Influence Students' Switching Behavior to Online Learning under COVID-19 Pandemic: A Push–Pull–Mooring Model Perspective," *Asia-Pacific Education Researcher*, 30(3), pp. 229–245. Available at: https://doi.org/10.1007/s40299-021-00570-0.

Lisana, L. (2023) "Factors affecting university students switching intention to mobile learning: a push-pull-mooring theory perspective," Education and Information Technologies, 28(5), pp. 5341–5361. Available at: https://doi.org/10.1007/s10639-022-11410-z.

Lolo, S. *et al.* (2019) "An Analysis of the Gamification Use in Learning Management System," in *2019 International Conference of Computer Science and Information Technology (ICoSNIKOM)*. IEEE, pp. 1–8. Available at: https://doi.org/10.1109/ICoSNIKOM48755.2019.9111496.

Lu, H.-P. and Wung, Y.-S. (2020) "Applying Transaction Cost Theory and Push-Pull-Mooring Model to Investigate Mobile Payment Switching Behaviors with Well-Established Traditional Financial Infrastructure," *Journal of Theoretical and Applied Electronic Commerce Research*, 16(2), pp. 1–21. Available at: https://doi.org/10.4067/S0718-18762021000200102.

Manzano-León, A. *et al.* (2021) "Between level up and game over: A systematic literature review of gamification in education," *Sustainability (Switzerland)*, 13(4), pp. 1–14. Available at: https://doi.org/10.3390/su13042247.

Meskhi, B., Ponomareva, S. and Ugnich, E. (2019) "E-learning in higher inclusive education: needs, opportunities and limitations," *International Journal of Educational Management*, 33(3), pp. 424–437. Available at: https://doi.org/10.1108/IJEM-09-2018-0282.

Modirrousta-Galian, A., Higham, P.A. and Seabrooke, T. (2023) "Effects of inductive learning and gamification on news veracity discernment.," *Journal of Experimental Psychology: Applied*, 29(3), pp. 599–619. Available at: https://doi.org/10.1037/xap0000458.

Moreira, F. *et al.* (2020) "Teaching and learning Modelling and Specification based on gamification," in *2020 15th Iberian Conference on Information Systems and Technologies (CISTI)*, pp. 1–6. Available at: https://doi.org/10.23919/CISTI49556.2020.9140829.

Nguyen, N.-T. (2021) "A study on satisfaction of users towards learning management system at International University – Vietnam National University HCMC," *Asia Pacific Management Review*, 26(4), pp. 186–196. Available at: https://doi.org/10.1016/j.apmrv.2021.02.001.

Pahnila, S., Siponen, M. and Zheng, X. (2011) "Integrating Habit into UTAUT: The Chinese eBay Case," *Pacific Asia Journal of the Association for Information Systems*, pp. 1–30. Available at: https://doi.org/10.17705/1pais.03201.

Panagiotarou, A. *et al.* (2020) "Gamification acceptance for learners with different E-skills," *International Journal of Learning, Teaching and Educational Research*, 19(2), pp. 263–278. Available at: https://doi.org/10.26803/IJLTER.19.2.16.

Patmanthara, S. *et al.* (2024) "Implementation of Problem-based Learning Models Using E-Modules in Software and Game Development Courses to Improve Student Learning Outcomes in Vocational High Schools," in, pp. 649–655. Available at: https://doi.org/10.2991/978-2-38476-198-2_90.

Pramana, E. (2018) "Determinants of the Adoption of Mobile Learning Systems among University Students in Indonesia," *Journal of Information Technology Education: Research*, 17, pp. 365–398. Available at: https://doi.org/10.28945/4119.

Raharjo, S.R., Handayani, P.W. and Putra, P.O.H. (2021) "Active Student Learning through Gamification in a Learning Management System," *The Electronic Journal of e-Learning*, 19(6), pp. 601–613. Available at: www.ejel.org.

Rau, M. *et al.* (2019) "Impact of Motivational Factors on the Learning Process in the Use of Learning Management Systems: An Empirical Study Based on Learners' Experiences," in C. Stephanidis (ed.) *HCI International 2019 - Posters*. Cham: Springer International Publishing, pp. 278–283.

Robson, K. *et al.* (2015) "Is it all a game? Understanding the principles of gamification," *Business Horizons*, 58(4), pp. 411–420. Available at: https://doi.org/https://doi.org/10.1016/j.bushor.2015.03.006.

Saleem, A.N., Noori, N.M. and Ozdamli, F. (2022) "Gamification Applications in E-learning: A Literature Review," *Technology, Knowledge and Learning*, 27(1), pp. 139–159. Available at: https://doi.org/10.1007/s10758-020-09487-x.

Sanjaya, L.S., Ferdianto and Titan (2020) "Development of Gamification Mobile Application for Students," in *2020 International Conference on Information Management and Technology (ICIMTech)*, pp. 605–608. Available at: https://doi.org/10.1109/ICIMTech50083.2020.9211283.

Septian Ferdiansyah, D., Patmanthara, S. and Suswanto, H. (no date) "A new decade for social changes Evaluation of Technological Pedagogical Content Knowledge (TPACK) Teachers of SMK Negeri 6 Malang (Case Study of Electrical Power Installation Engineering and Autotronic Engineering)," 27, p. 2022. Available at: www.techniumscience.com.

Setyoadi, E.T. and Patmanthara, S. (2024) "Students' goal orientation and gamification in learning for academic performance: A systematic literature review." Available at: https://doi.org/10.22219/raden.v4i1.

Shayan, P. *et al.* (2023) "Multi-Level Analysis of Learning Management Systems' User Acceptance Exemplified in Two System Case Studies," *Data*, 8(3), p. 45. Available at: https://doi.org/10.3390/data8030045.

Smiderle, R. *et al.* (2020) "The impact of gamification on students' learning, engagement and behavior based on their personality traits," *Smart Learning Environments*, 7(1). Available at: https://doi.org/10.1186/s40561-019-0098-x.

Soraya, D.U. *et al.* (2024) "Problem Based Learning Media 'Learn Web Dev' for Vocational Student," in, pp. 1165–1171. Available at: https://doi.org/10.2991/978-2-38476-198-2_165.

Sriratnasari, S.R., Wang, G. and Kaburuan, E.R. (2019) "Applying Innovative Learning Management System (LMS) with Gamification Framework," in *2019 International Seminar on Application for Technology of Information and Communication (iSemantic)*. IEEE, pp. 569–573. Available at: https://doi.org/10.1109/ISEMANTIC.2019.8884295.

Venter, M. (2022) "Online programming learning platform: The influence of gamification elements," in *2022 IEEE IFEES World Engineering Education Forum - Global Engineering Deans Council (WEEF-GEDC)*, pp. 1–6. Available at: https://doi.org/10.1109/WEEF-GEDC54384.2022.9996263.

Wang, G. and Shin, C. (2022) "Influencing Factors of Usage Intention of Metaverse Education Application Platform: Empirical Evidence Based on PPM and TAM Models," *Sustainability (Switzerland)*, 14(24). Available at: https://doi.org/10.3390/su142417037.

Xu, H. *et al.* (2021) "Empirical study on the factors affecting user switching behavior of online learning platform based on push-pull-mooring theory," *Sustainability (Switzerland)*, 13(13). Available at: https://doi.org/10.3390/su13137087.

Xue, E., Li, J. and Xu, L. (2022) "Online education action for defeating COVID-19 in China: An analysis of the system, mechanism and mode," *Educational Philosophy and Theory*, 54(6), pp. 799–811. Available at: https://doi.org/10.1080/00131857.2020.1821188.

Yuen, A.H.K., Cheng, M. and Chan, F.H.F. (2019) "Student satisfaction with learning management systems: A growth model of belief and use," *British Journal of Educational Technology*, 50(5), pp. 2520–2535. Available at: https://doi.org/https://doi.org/10.1111/bjet.12830.

Yusril Firmansyah, M., Patmanthara, S. and Gatot Sutapa, Y. (2022) "Creative Problem-Solving Learning Media to Improve Students Learning Outcomes in Basic Graphic Design Subject," *Letters in Information Technology Education (LITE)*, 5(1), pp. 12–17.

Zhao, D. *et al.* (2022) "An Innovative Multi-Layer Gamification Framework for Improved STEM Learning Experience," *IEEE Access*, 10, pp. 3879–3889. Available at: https://doi.org/10.1109/ACCESS.2021.3139729.

Evaluation of an AI-Based Feedback System for Enhancing Self-Regulated Learning in Digital Education Platforms

Maxot Rakhmetov[1], Aigul Sadvakassova[2], Galiya Saltanova[1], Bayan Kuanbayeva[3] and Galiya Zhusupkalieva[3]

[1]Department of Computer Science, Faculty of Physics, Mathematics and Information Technology, Khalel Dosmukhamedov Atyrau University, Kazakhstan

[2]Department of Computer Science, Faculty of Information Technology, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan

[3]Department of Physics and Technical Disciplines, Faculty of Physics, Mathematics and Information Technology, Khalel Dosmukhamedov Atyrau University, Kazakhstan

m.rahmetov@asu.edu.kz
sadvakassova_ak_1@enu.kz (corresponding author)
g.saltanova@asu.edu.kz
b.kuanbaeva@asu.edu.kz
g.zhusupkalieva@asu.edu.kz

https://doi.org/10.34190/ejel.23.4.4150

Abstract: The development of self-regulated learning (SRL) skills, including the ability to plan, monitor and reflect, is increasingly recognised as essential for academic success in online learning environments. Despite this, most digital learning platforms continue to provide limited feedback, typically focused on task outcomes rather than learning processes. This study investigates the effectiveness of an artificial intelligence-based feedback system integrated into a standard online course platform. The system delivers adaptive, process-oriented feedback by analysing anonymised engagement summaries and short reflective inputs, aiming to promote self-regulated learning strategies without requiring additional instructor involvement or manual input for feedback generation. A quasi-experimental study was conducted with 180 undergraduate students enrolled in a fully online course. Participants were pseudo-randomly assigned by an automated allocation script to an experimental group (n = 90) receiving AI-based adaptive feedback or a control group (n = 90) with standard LMS features. The system employed behavioural indicators (e.g., time-on-task, quiz activity and content engagement) and natural language analysis of reflective entries to generate personalised prompts related to goal-setting (including time management), effort regulation and metacognitive reflection. Data sources included post-course surveys, aggregated system interaction records, academic performance data and open-ended student feedback on the system's perceived effectiveness and usability. Students who received adaptive feedback exhibited significantly stronger engagement with SRL behaviours, including earlier task initiation, increased use of optional learning resources and greater consistency in study routines. Qualitative responses indicated that participants found the feedback clear, timely, actionable and supportive of their cognitive and motivational processes. In contrast, control group participants primarily relied on grade-based feedback and exhibited fewer strategic adjustments during the course. The findings suggest that a lightweight, AI-driven feedback mechanism can be effectively integrated into online course platforms to support SRL at scale. This study demonstrates how adaptive AI feedback can meaningfully influence academic outcomes, planning behaviour and engagement with feedback in digital learning environments.

Keywords: Self-regulated learning, Adaptive feedback, Learning analytics, Digital education, Motivation and reflection, Artificial intelligence in education

1. Introduction

Self-regulated learning (SRL) refers to students' ability to plan, monitor and reflect on their learning processes. These skills are essential for success in digital education, where students work independently with minimal guidance (Zimmerman, 2000). Yet most LMSs lack integrated SRL support, offering static, outcome-based feedback (e.g., grades/correctness) without guiding strategy adjustment (Tsai, Whitelock-Wainwright and Gašević, 2020). This limited model undermines SRL, reducing engagement and increasing procrastination (Wolters and Brady, 2021).

Artificial intelligence (AI) offers new opportunities to address these challenges by providing real-time, individualised support that encourages self-directed learning. By analysing engagement indicators, AI-driven systems can deliver timely prompts that foster planning, monitoring and reflection (Cavalcanti et al., 2021; Lim

Cite this article: Rakhmetov, M. et al. 2025. "Evaluation of an AI-Based Feedback System for Enhancing Self-Regulated Learning in Digital Education Platforms", *Electronic Journal of e-Learning*, 23(4), pp 126-141, https://doi.org/10.34190/ejel.23.4.4150

et al., 2023). Unlike correctness-based feedback, AI can promote deeper learning by supporting self-regulation. AI-based feedback can operate autonomously, offering consistent, equitable and adaptive guidance at scale (Mejeh, Sarbach and Hascher, 2024). Despite substantial AI-in-education research, many tools target performance rather than underlying SRL mechanisms and address isolated elements (e.g., planning or reflection) instead of the full cycle. Integration into standard LMSs also remains limited. Hence, scalable, interpretable systems are needed to deliver process-oriented feedback across SRL phases with minimal manual input.

To address this gap, the present study focuses on four key SRL components: planning, monitoring, reflection and effort regulation, which together capture the core cognitive, metacognitive and motivational processes of effective independent study. Time management is treated as a behavioural aspect of planning, reflecting students' ability to organise study schedules and control pacing. These components align with Zimmerman's (2000) cyclical model of forethought, performance and reflection. They can also be reliably observed through digital engagement data. Broader SRL frameworks such as those by Pintrich (2000) and Panadero (2017) include motivational and contextual factors, but these are more difficult to capture through learning system data. The selected components therefore provide a balanced and measurable representation of SRL within digital contexts. Planning and effort regulation correspond to forethought and strategic control, monitoring captures ongoing metacognitive awareness, and reflection represents post-task evaluation and adaptation. These frameworks continue to guide current AI-supported SRL research where Zimmerman's and Pintrich's models remain central (van der Graaf et al., 2023; Heikkinen et al., 2025). Building on this theoretical foundation, the present study introduces an AI-powered feedback system designed to operationalise these SRL components within a digital learning environment.

To implement this approach, the system was integrated into a standard online learning platform to support all major SRL phases. It analyses patterns of student engagement and reflective input to generate personalised prompts aimed at fostering planning, time management and reflection. It adapts feedback dynamically based on individual learning behaviours, offering continuous and accessible support throughout the course.

Based on the identified gaps, the study addresses three research questions (RQs) focusing on the effects and perceptions of AI-based feedback for SRL:

RQ1: To what extent does AI-based feedback improve students' self-regulated learning (SRL) behaviours compared to standard platform feedback?

RQ2: Which components of SRL (planning, monitoring, reflection or effort regulation) benefit most from the use of adaptive feedback?

RQ3: How do students perceive the feedback in terms of usefulness, clarity and motivation?

The main goal is to evaluate the effects of adaptive AI-based feedback on students' SRL and academic engagement in online education. The study also examines how feedback clarity, usefulness and motivational value influence students' learning experience.

2. Literature Review

The integration of artificial intelligence into digital education has opened new avenues for supporting self-regulated learning. This literature review synthesises research on self-regulation frameworks, feedback models, AI applications in education and existing gaps to justify the need for intelligent feedback systems (Wong et al., 2018; Crompton and Burke, 2023).

2.1 Self-Regulated Learning Frameworks

Self-regulated learning refers to students' proactive management of their cognitive, metacognitive and motivational processes to achieve learning goals (Zimmerman, 2000). Zimmerman's cyclical model of SRL outlines three phases: forethought (goal-setting, planning), performance (monitoring, strategy use) and self-reflection (evaluation, attribution). Each phase involves distinct strategies, from task analysis to self-assessment (Zimmerman and Moylan, 2009). Similarly, Pintrich's model emphasises four areas: cognition, motivation, behaviour and context, highlighting the interplay of metacognitive and motivational factors (Pintrich, 2000).

These skills are particularly crucial in online learning environments, where students face greater autonomy and fewer external cues (Wolters and Brady, 2021). This autonomy often makes consistent engagement difficult (Broadbent and Poon, 2015). Effective self-regulation strongly predicts academic achievement, yet many students struggle without external support (Panadero, 2017). Traditional digital platforms often fail to provide the scaffolding needed to nurture these abilities, delivering feedback that is static and outcome-focused rather than process-oriented (Tsai, Whitelock-Wainwright and Gašević, 2020; Jansen et al., 2020).

In the context of this study, cognitive and metacognitive regulation are represented by monitoring and reflection. Monitoring captures learners' ongoing awareness of their cognitive strategies and progress while reflection involves the evaluation and adaptation of those strategies after task completion. Together, these processes explain how students regulate learning. In addition, effort regulation is conceptualised as the motivational and volitional dimension of SRL, capturing learners' persistence and ability to sustain engagement when tasks become demanding.

Intelligent tools such as virtual mentors and planning aids have shown promise in activating strategic behaviours by prompting students to reflect, plan or adjust their learning goals (Jones and Castellano, 2018; Karaoğlan Yılmaz, Olpak and Yılmaz, 2018). The present study is conceptually grounded in Zimmerman's cyclical model, complemented by Pintrich's motivational perspective. Planning and effort regulation operationalise forethought, monitoring operationalises performance and reflection captures post-task evaluation and adaptation.

2.2 Feedback Models in Education

Feedback plays a key role in shaping students' cognitive and metacognitive development (Hattie and Timperley, 2007). According to their model, it operates at four levels: task (correctness), process (strategies), self-regulation (metacognitive guidance) and self (motivation). Process- and self-regulation–level feedback are most effective for promoting SRL, as they foster strategic thinking and self-evaluation (Lui and Andrade, 2022). Lui and Andrade's (2022) model further explains that learners process feedback through cognitive, metacognitive and motivational mechanisms, stressing that it should align with students' goals and readiness to support meaningful learning.

Narciss (2013) expanded the understanding of formative feedback through the Interactive Tutoring Feedback (ITF) model, which conceptualises feedback as a multidimensional instructional activity. The model highlights cognitive, diagnostic and motivational functions, emphasising feedback loops that foster self-regulation. Building on this, Panadero and Lipnevich (2022) proposed the MISCA model (Message, Implementation, Student, Context, Agents), integrating cognitive, affective and contextual factors to explain how feedback is perceived, processed and acted upon. Effectiveness depends on message content and learner engagement. Together, these frameworks show that feedback should target process and self-regulation levels rather than task accuracy alone.

In digital education feedback often remains limited to correctness or grading with little personalisation or SRL support (Cavalcanti et al., 2021; Garcia, Falkner and Vivian, 2018). This persists despite improved delivery technologies (Carless and Boud, 2018) and is especially evident in asynchronous formats with minimal instructor input (Araka et al., 2020). AI therefore offers dynamic, process-oriented feedback that supports SRL (Deeva et al., 2021). AI-driven feedback requires flexible, secure platforms ensuring privacy and scalability. For example, a custom distance learning system in Kazakhstan was developed to enhance control over functionality, protection and local adaptation (Rakhmetov et al., 2024).

In general, AI-driven feedback agents, especially those incorporating natural language processing (NLP), have shown potential in promoting student autonomy by offering clear, timely and non-judgemental guidance on performance and self-regulation (Fleckenstein, Liebenow and Meyer, 2023; Karaoğlan Yılmaz and Yılmaz, 2020). However, effectiveness depends on student trust and perceived relevance (Ranalli, 2021), making tone, timing and transparency crucial design factors.

2.3 AI Applications in Education

Artificial intelligence technologies, including learning analytics, adaptive systems and conversational agents, increasingly shape digital education through personalised, real-time feedback (Hooshyar, Pedaste and Yang, 2020; Crompton and Burke, 2023). Dashboards show behaviours such as quiz frequency or time-on-task (Tsai, Whitelock-Wainwright and Gašević, 2020) but they often lack actionable support for strategy adjustment (Cukurova, Kent and Luckin, 2019).

More interactive AI systems, such as chatbots or analytics-based tutors, show promise for supporting SRL processes like planning and reflection (Lim et al., 2023; Glick, Miedijensky and Zhang, 2024). AI-driven planning nudges and real-time feedback loops reduce procrastination and promote more consistent study behaviour (Heikkinen et al., 2025; Moubayed et al., 2020). Many tools focus on performance and are hard to integrate into LMS environments (Molenaar, 2022).

Advances in natural language processing (NLP) and large language models (LLMs) have broadened AI feedback capabilities. GPT-4–based systems providing tiered feedback improve students' reflection and planning in programming courses (Nguyen and Allan, 2024; Somasundaram, Mohamed Junaid and Mangadu, 2020), while NLP-based writing assessment tools enhance student revision and metacognitive awareness (Fleckenstein, Liebenow and Meyer, 2023). Yet full-cycle SRL support remains rare (van der Graaf et al., 2023), with reflection and motivation still under-supported.

This gap highlights the limited focus on metacognitive scaffolding (Azevedo and Gašević, 2019) and the need for more interpretable and context-sensitive feedback mechanisms (Rosé et al., 2019). AI is also used to maintain academic integrity through proctoring technologies monitoring user behaviour and biometric data (Sakhipov, Omirzak and Fedenko, 2025), but such systems raise privacy, stress and transparency concerns.

2.4 Gaps in Existing AI-Supported SRL Tools and Comparative Overview

Despite growing interest in artificial intelligence to support self-regulated learning, several key limitations persist in current systems. Many existing tools focus narrowly on one phase of SRL, such as planning, monitoring or reflection, without supporting the full cycle in an integrated way (van der Graaf et al., 2023; Wong et al., 2018). Feedback also tends to emphasise performance outcomes (e.g., quiz scores) rather than developing strategies such as goal-setting, time management or metacognitive reflection (Cavalcanti et al., 2021; Glick, Miedijensky and Zhang, 2024).

A second gap is integration: many tutoring systems operate as external add-ons, limiting scalability (Järvelä, Nguyen and Hadwin, 2023; Crompton and Burke, 2023). Although behavioural profiling through clustering and trace data is increasingly common (Moubayed et al., 2020), embedding such insight into adaptive feedback within learning platforms remains rare (Bergdahl et al., 2024).

A third limitation relates to the depth of feedback. Few systems provide process- or self-regulation-level guidance (Narciss, 2013; Panadero and Lipnevich, 2022), focusing instead on task correctness or performance metrics. Consequently, learners receive limited support for sustained self-regulation. Another challenge is perception: AI feedback, though objective, may seem less authentic (Zhang et al., 2025; Ranalli, 2021). Students report increased motivation but also concern about reduced human interaction (Fan et al., 2025; Djokic et al., 2024).

To address these gaps, this study introduces a lightweight, scalable AI feedback system that supports all SRL phases within a single LMS-integrated framework. Using K-means clustering and rule-based NLP, it delivers timely, interpretable feedback without complex infrastructure. Table 1 compares selected prior systems by SRL components, AI techniques, data sources and integration levels.

Table 1: Comparison of AI-Based SRL Support Systems

System	SRL Phase(s) Supported	Data Source	AI Method	Feedback Type	Platform Integration
CourseMIRROR (Menekse et al., 2025)	Reflection	Reflective texts	Rule-based NLP	Post-lecture prompts	Mobile app
Chatbot-SRL (Lee, Hwang and Chen, 2025)	Reflection	Chat interactions	Rule-based chatbot	Real-time chat prompts	LMS / website
GPT Tutor (Sun et al., 2025)	Planning, Monitoring, Reflection	Code + interaction logs	LLM (GPT-3.5)	Multi-level real-time feedback	Coding platform
Virtual Mentors (Glick, Miedijensky and Zhang, 2024)	All SRL phases	Planning tool usage	AI virtual agents	Interactive training modules	MS Planner
This Study	All SRL phases	Platform logs + short reflections	K-means clustering + rule-based NLP	Adaptive in-course prompts + dashboard	Native LMS integration

2.5 Synthesis and Conceptual Focus

The reviewed literature reveals persistent limitations: incomplete SRL coverage, weak integration and limited metacognitive feedback. To address these issues, this study focuses on four interconnected components of SRL: planning, monitoring, reflection and effort regulation. Within this framework, time management represents a behavioural aspect of planning, reflecting how students regulate pacing and task scheduling. These elements align with major SRL models (Zimmerman, 2000; Pintrich, 2000; Panadero, 2017).

The components inform both the analytical framework and the AI-based feedback design. Planning and effort regulation represent forethought and strategic control, monitoring reflects active metacognitive awareness during task performance, and reflection involves post-task evaluation and adaptation. The system operationalises these processes within one digital environment, providing adaptive feedback across SRL phases and ensuring theoretical coherence throughout the study.

3. Materials and Methods

This study employed a quasi-experimental design to evaluate the effectiveness of an AI-driven feedback system in enhancing self-regulated learning behaviours.

3.1 Participants and Context

This 10-week study was conducted at Khalel Dosmukhamedov Atyrau University in a fully online, self-paced course using a plugin-compatible learning management system (LMS) with integrated activity logging. A total of 180 undergraduate students took part voluntarily. They were pseudo-randomly assigned to an experimental group (n = 90) receiving AI-based adaptive feedback or a control group (n = 90) with standard LMS features such as grades and brief instructor comments.

All participants completed the same materials independently without synchronous instruction. Instructor involvement was limited to uploading materials and routine grading; AI feedback did not involve instructor input. Baseline equivalence was established via a brief self-report on prior online learning experience (Schunk and Greene, 2017). No demographic data were collected. Participation was voluntary and anonymous; informed consent was obtained during course registration on the platform, where users agreed to the use of anonymised data for research purposes.

3.2 AI Feedback System

The artificial intelligence-based feedback system functions as an autonomous plugin within the institutional LMS. It operates independently of the platform infrastructure and provides adaptive, data-informed feedback that supports students' self-regulated learning. The system delivers personalised and timely guidance that strengthens core SRL processes without direct instructor involvement. The overall workflow is presented in Figure 1.

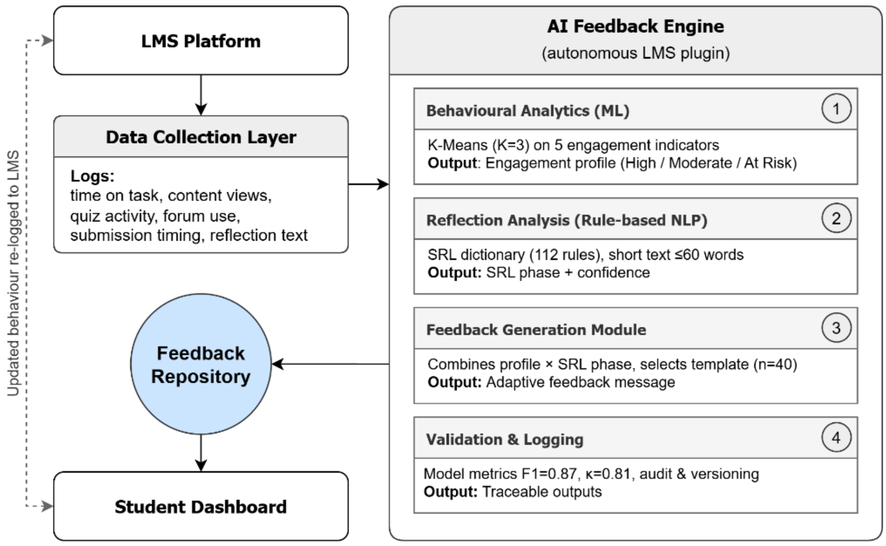


Figure 1: Workflow of the AI-Based Feedback System

The system employs a modular pipeline that combines behavioural analytics, rule-based natural language processing (NLP) and adaptive feedback generation. The data layer consolidates five behavioural indicators, including time-on-task, content interaction, quiz activity, forum participation and submission timing, together with short reflective statements written by students. All processing uses anonymised data within the institution to ensure privacy and compliance.

The behavioural analytics module applies K-means clustering (k = 3) to produce engagement profiles labelled high, moderate and at-risk. Cluster validity was checked with elbow and silhouette criteria. These profiles inform feedback tone, frequency and content. The NLP component analyses short reflections for SRL phase detection. A word limit standardises input and preserves rule precision, since longer texts reduce classification reliability. Reflections are pre-processed and lexically matched to the validated SRL lexicon, then assigned a phase using weighted scoring and confidence estimation; low-confidence results trigger a neutral planning prompt. Representative patterns and implementation parameters are listed in Table 2.

Table 2: Representative Lexical Rules and Implementation Details

Item	Examples / Parameters
Lexical patterns	plan, goal, schedule, check, track, realised, improve, difficult
SRL phases	planning, monitoring, reflection, effort regulation
Lexicon size	112 patterns
Message templates	40 short templates (e.g. “Set one concrete goal for the next 30 minutes”)
Reflection limit	up to 60 words
Clustering	K-means, 3 clusters (high, moderate, at-risk)
Cluster features	time-on-task, quiz activity, content interaction, forum posts, submission timing
NLP scoring	weighted lexical score; confidence threshold 0.6

The feedback module combines each learner’s engagement profile with the detected SRL phase to select one of 40 templates. Tone and frequency adapt to the profile, with rate-limiting to prevent redundancy. All actions are logged with version identifiers for the SRL lexicon, message library and configuration to ensure traceability.

Validated feedback is cached for fast retrieval and delivered in the LMS interface; a dashboard visualises engagement and feedback history. Each interaction updates the record, closing the loop and enabling ongoing refinement aligned with the forethought–performance–reflection cycle. The system functions as an evolving process, not a static recommender, while maintaining interpretability, transparency and reproducibility through explicit rules, validation metrics and documented procedures that support replication.

3.3 Study Design

The study used a quasi-experimental design with pseudo-random assignment to experimental and control groups. Both completed the same 10-week online course. The instructor uploaded materials, graded manually assessed tasks and provided brief comments. The experimental group (n = 90) received adaptive, system-generated feedback with personalised prompts and dashboards; the control group (n = 90) had standard LMS features. Feedback and engagement data were collected in anonymised, aggregated form. A mixed-methods design compared SRL scores, assignment behaviours and performance, and analysed post-course surveys on clarity, usefulness and motivation. Figure 2 summarises the study design and data sources.

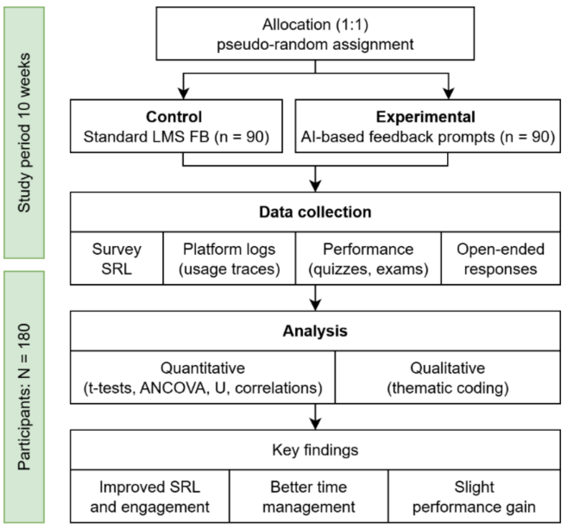


Figure 2: Overview of the Study Design and Data Collection Process

3.4 Analysis Methods

A multi-method analytical framework was adopted to explore the research questions, combining survey data, behavioural logs, academic performance and open-ended responses.

3.4.1 Quantitative analysis

Quantitative data included post-course survey responses and anonymised interaction logs collected via the system's internal dashboard, which summarised engagement behaviours. SRL was measured using adapted subscales from the Motivated Strategies for Learning Questionnaire (MSLQ) (Dent and Koenka, 2016), covering planning, monitoring, reflection and effort regulation. All items were rated on a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree), and composite scores were computed for each construct. Missing values affecting fewer than 5% of cases were handled using mean substitution at the subscale level.

Independent-samples t-tests were used to compare SRL scores, quiz engagement and submission timing between groups. Normality was assessed using Shapiro–Wilk tests; when violated, Mann–Whitney U tests were applied.

In the experimental group, Pearson correlations were used to examine associations between system engagement (e.g., number of feedback prompt responses and dashboard visits) and SRL outcomes. These analyses complemented the between-group comparisons and informed the interpretation of behavioural engagement patterns.

3.4.2 Qualitative analysis

To explore students' experiences with the feedback system, open-ended survey responses were analysed using thematic analysis following Braun and Clarke's (2006) approach. Responses from the experimental group were inductively coded in NVivo to identify recurring themes, including planning, motivation, reflection and perceptions of system value. Two researchers coded the data independently; discrepancies were discussed and resolved to ensure reliability. Responses from the control group were reviewed in parallel to provide contrast and contextualise typical engagement with standard platform feedback. This analysis addressed RQ3 by capturing students' perceptions of the adaptive system's clarity, usefulness and motivational impact (Panadero and Lipnevich, 2022; Ryan and Deci, 2020).

A summary of the main measures and analysis methods used across the study is presented in Table 3, including comparisons of SRL constructs, behavioural indicators, performance outcomes and thematic coding of open-ended responses.

Table 3: Measures and Analysis Methods

Measure	Data Source	Analysis Method
SRL Behaviour Score	MSLQ survey	t-test (Exp vs Ctrl)
Effort Regulation Score		
Submission lead time	System dashboard	Mann–Whitney U
Course performance	LMS gradebook	ANCOVA (covariate: prior GPA)
Prompt responses	Feedback system logs	Correlation (SRL score)
Dashboard views		Correlation (effort score)
Open-ended survey responses	System dashboard aggregates	Thematic analysis (NVivo)

4. Results and Findings

4.1 Quantitative Results

4.1.1 SRL Survey outcomes

Students who received AI-generated prompts showed significantly stronger SRL behaviours than those with standard LMS feedback, particularly in planning and reflection (Table 4).

Table 4: Outcomes for Experimental and Control Groups

Measure	Experimental (M ± SD)	Control (M ± SD)	Test (p-value)	Cohen's d
SRL Behaviour Score (1–7)	5.68 ± 0.52	5.22 ± 0.58	t = 6.47 (p < .001)	0.84
Planning subscale (1–7)	5.85 ± 0.57	5.35 ± 0.65	t = 6.34 (p < .001)	0.82
Reflection subscale (1–7)	5.62 ± 0.64	5.15 ± 0.70	t = 5.43 (p < .001)	0.70
Monitoring subscale (1–7)	5.48 ± 0.60	5.28 ± 0.62	t = 2.54 (p = .012)	0.33
Effort Regulation Score (1–7)	5.80 ± 0.62	5.45 ± 0.68	t = 4.17 (p < .001)	0.54
Exam Score (%)	82.1 ± 9.2	79.3 ± 9.8	F = 3.82 (p = .053)	–
Practice Quizzes (per week)	4.5 ± 1.7	2.9 ± 1.4	t = 7.96 (p < .001)	1.03
Submission Lead Time (hrs)	10.1 ± 9.8	3.8 ± 5.4	U = 672 (p < .001)	–
Late Submissions (number of students)	4	7	–	–

Figure 3 presents a radar chart comparing mean self-regulated learning subscale scores between experimental and control groups. The experimental group outperformed the control group across all dimensions, with the most pronounced differences observed in planning and reflection. Notably, the smaller margin in monitoring suggests that while students became better at planning and evaluating their learning, real-time self-checking remained more difficult to support through asynchronous prompts. The similarity in effort regulation between groups, though still favouring the experimental group, may reflect broader motivational traits less sensitive to system feedback. These profiles illustrate how AI-based feedback influences specific SRL capacities.

Figure 3: SRL Subscale Profiles for Experimental and Control Groups

4.1.2 Learning performance

While exam performance differences between groups were small, students in the experimental group showed a slight advantage. Quiz performance remained comparable across groups. However, students who received adaptive prompts took more optional quizzes, suggesting a stronger focus on mastery.

Controlling for prior GPA, ANCOVA yielded a group effect on Exam Score, $F(1, 177) = 3.82$, $p = .053$, partial $\eta^2 = .021$ (adjusted means: experimental = 81.8%, control = 79.6%). The covariate GPA was significant, $F(1, 177) = 28.94$, $p < .001$. The interaction between Group and GPA was not significant.

4.1.3 Behavioural log analysis

Dashboard data revealed clear differences in learning behaviours. Students receiving adaptive feedback completed more optional quizzes, revisited content more often and spent more time within the LMS platform. These students also submitted assignments significantly earlier than peers in the control group, indicating improved planning and reduced procrastination.

Engagement with the system was consistently high: most students interacted regularly with the personalised dashboard and responded to feedback prompts. Moderate positive correlations were observed between prompt engagement and SRL scores, as well as between engagement and final quiz performance, suggesting that students who engaged more frequently tended to demonstrate stronger self-regulated learning behaviours and slightly higher academic outcomes (Table 5).

Within the experimental group, correlation analysis indicated a modest but clear relationship between prompt usage and SRL scores. As shown in Figure 4, students who responded to a greater number of system prompts generally achieved higher SRL scores. Those who engaged more frequently also tended to report improved planning and reflective thinking, suggesting a deeper adoption of metacognitive strategies.

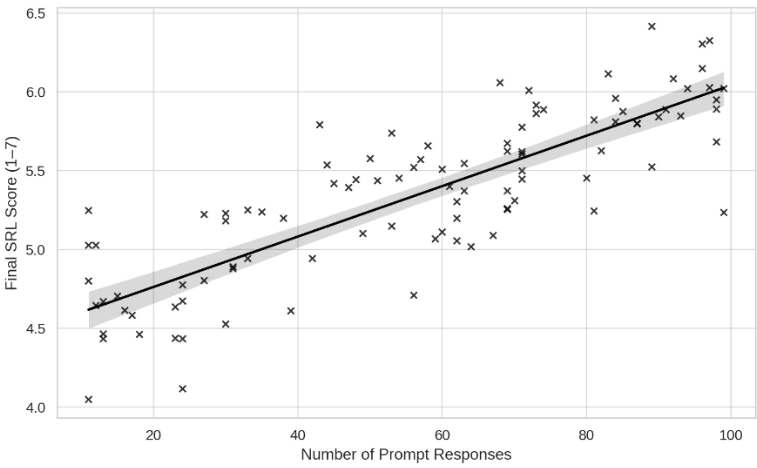


Figure 4: Scatter Plot Showing the Correlation Between Prompt Responses and SRL Score

As shown in Table 5, the number of prompt responses and dashboard views was moderately correlated with SRL behaviour and effort regulation scores. Notably, students who reported stronger learning habits also performed better on the final quiz. These results suggest that consistent engagement supports more effective study strategies.

Table 5: Correlations Between System Engagement, Learning Behaviours and Academic Outcomes

Variable	1.	2.	3.	4.	5.
1. Prompt Responses	1				
2. Dashboard Views	.44**	1			
3. SRL Behaviour Score	.48**	.36*	1		
4. Effort Regulation Score	.40**	.42**	.57**	1	
5. Final Quiz Score (%)	.32*	.28	.45**	.46**	1

Note: * p < .05, ** p < .01. N = 90 (experimental group only).

Figure 5 shows that students receiving improved feedback submitted assignments earlier and more consistently than those in the control group, suggesting better time management and stronger effort regulation. These behaviours indicate more proactive pacing and sustained engagement throughout the course. Students in the experimental group also had fewer late submissions (4 vs. 7), with an average of 540 feedback interactions over 10 weeks and 68% of prompts being viewed or answered.

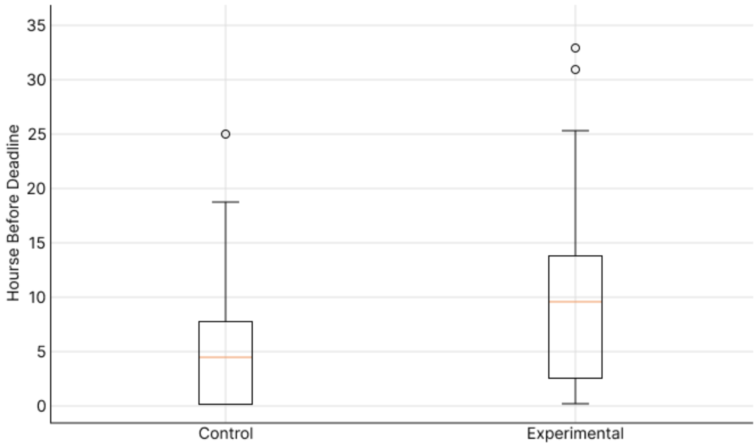


Figure 5: Boxplot of Assignment Submission Lead Time (Experimental vs. Control)

4.2 Qualitative Results

4.2.1 Student perceptions of the feedback system (experimental group)

Thematic analysis of open-ended responses from the experimental group revealed five primary themes. Improved planning and organisational strategies were the most commonly cited benefits, reported by 68% of students. Enhanced reflection and self-awareness were noted by 55% of respondents, with students indicating that the AI feedback system helped them identify learning gaps and adjust study strategies. Increased motivation and reduced anxiety were reported by 38% of students, who valued the regular, supportive prompts. Preferences for system features, particularly the personalised dashboard and feedback visualisation, were mentioned by 35% of participants. At the same time, 20% of students noted limitations, such as repetitive prompts and a lack of gamification features.

4.2.2 Comparison to control group

Engagement levels with the educational platform varied notably between the experimental and control groups (Figure 6). In the experimental group, 38.3% of students reported regular use of the platform, 28.3% used it occasionally and 33.3% minimally. In the control group, only 20% reported regular use, while 55% used it minimally. The question referred to general engagement with the learning platform and course materials, not the feedback tool specifically. However, students in the experimental group noted that the integrated feedback system increased their motivation to log in more frequently and engage with additional resources and tasks.

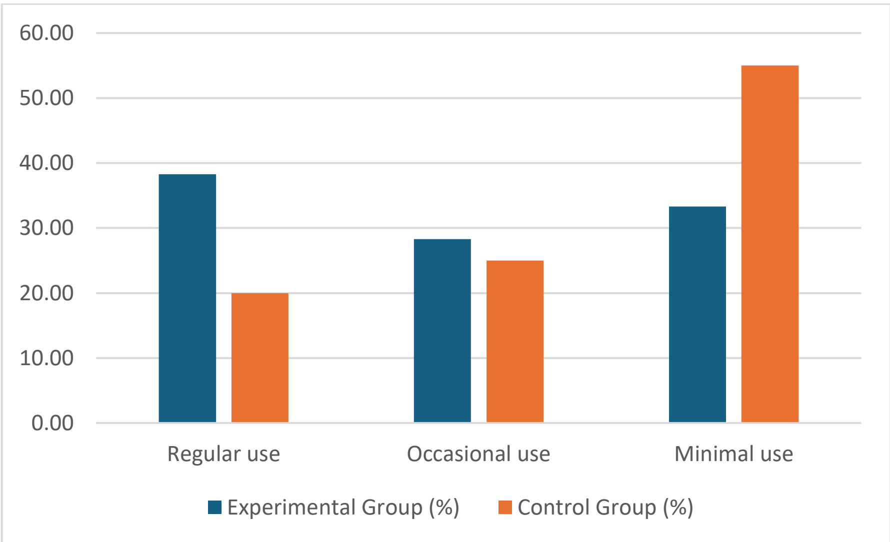


Figure 6: Student Engagement with the Learning Platform (Self-Reported Use Levels)

Analysis of control group responses indicated predominantly passive engagement with feedback. Approximately 70% of students reported primarily checking grades, and 45% read instructor comments without significant subsequent adjustment to their study behaviours. Only 15% of control group participants reported any proactive strategy modification in response to feedback. Several students explicitly expressed a need for more structured, timely and actionable feedback, highlighting the comparative value of the advanced feedback system for supporting self-regulated learning processes.

4.3 Integration of Quantitative and Qualitative Findings

Findings from both quantitative and qualitative analyses were largely consistent. Significant improvements in planning and reflection ($p < .001$) observed in survey data corresponded with behavioural indicators such as earlier task initiation and more frequent use of optional learning resources, reinforcing student reports of enhanced organisation and metacognitive awareness. A smaller but statistically significant gain in monitoring ($p = .012$) mirrored qualitative feedback indicating that students found real-time self-checking more difficult to sustain, even with support. Although the difference in exam performance between groups did not reach conventional significance ($p = .053$), qualitative responses suggested increased perceived preparedness and long-term strategic adjustment.

4.4 Summary of Key Findings by Research Questions

RQ1: Students who received adaptive AI-based feedback demonstrated significantly stronger self-regulated learning behaviours than those with standard LMS feedback ($p < .001$). This included higher scores on planning, reflection and effort regulation, as well as more proactive engagement with optional course components. These results support prior research on the effectiveness of structured, process-oriented support for fostering SRL in online environments.

RQ2: The most substantial improvements were observed in planning and reflection ($p < .001$), consistent across both survey responses and behavioural indicators (e.g., earlier submissions, more consistent engagement). Monitoring gains were present but smaller ($p = .012$), likely due to the inherent challenge of supporting real-time self-checking through asynchronous prompts. These patterns reflect the system's strength in promoting forethought and reflection over in-the-moment regulation.

RQ3: Most students in the experimental group rated the AI feedback as helpful and motivating. In open-ended responses, 68% cited improvements in planning, 55% in reflection and 38% reported reduced anxiety. Students frequently praised the dashboard's clarity, visual design and the supportive tone of the feedback. In contrast, students in the control group described their engagement with feedback as largely passive, with limited strategic response to grades or instructor comments.

Overall, the AI system effectively enhanced students' SRL-related behaviours, especially in planning and time management. While exam score differences were modest, the behavioural and perceptual changes observed suggest that more substantial performance gains could emerge over longer periods of use.

5. Discussion

This study examined the effects of an adaptive feedback system in a fully online course. Findings showed improved SRL, especially in planning, reflection and effort regulation, and students perceived the system as useful, clear and motivating. This section interprets these results, situates them within the literature, proposes an educational model for AI-supported SRL, addresses limitations and outlines implications for practice and future research, contributing to the design of scalable, empathetic AI tools for digital education.

5.1 Enhancing Planning and Reflection through AI Feedback

The AI-based system strengthened self-regulated learning, especially planning, reflection and effort regulation (Glick, Miedijensky and Zhang, 2024; Wong et al., 2018). These gains align with existing research emphasising the value of process-oriented feedback for deepening cognitive and metacognitive engagement (Hattie and Timperley, 2007). Unlike standard platform feedback, the tool supported all key phases of the learning cycle (forethought, performance and reflection) following Zimmerman's model.

Planning improvements appeared in earlier submissions, indicating prompts fostered goal-setting and time management (Heikkinen et al., 2025), and habits consolidated over time, consistent with effects of structured guidance (Bannert, Reimann and Sonnenberg, 2014). Reflection improved as prompts encouraged students to evaluate their learning and adjust strategies, mirroring the effects of effective formative feedback (Lui and Andrade, 2022).

Monitoring gains were smaller, likely due to limits of asynchronous prompts in supporting real-time checks (Lim et al., 2023). These findings highlight the need for more interactive or embedded supports, such as in-task quizzes, to enhance self-monitoring during learning. Although academic performance gains were modest, students who demonstrated stronger SRL behaviours also tended to perform slightly better, suggesting a potential indirect effect. Students' qualitative feedback supported the interpretation of the system as a helpful virtual coach that promoted self-awareness and sustained motivation through clear and consistent guidance (Karaoğlan Yılmaz and Yılmaz, 2020).

5.2 Metacognitive and Motivational Dimensions

The AI-supported tool also helped improve students' motivation by supporting both their thinking and emotional engagement with learning. Students reported higher motivation, less anxiety and better effort management, likely because the feedback felt supportive and non- judgemental (Ryan and Deci, 2020). This aligns with work linking motivation and metacognition (Efklides, 2011). Students who interacted more with the system also showed stronger gains in self-regulation, suggesting that how helpful and well-worded the feedback felt was important (Panadero and Lipnevich, 2022). Some students, however, noted repetitive messages, indicating a need for greater variety and personalisation.

5.3 Proposed Educational Model

Figure 7 presents the educational model that summarises how AI-driven feedback supports SRL. It integrates student characteristics and behavioural data into adaptive mechanisms using clustering and lightweight NLP to generate tailored prompts across all self-regulated learning phases: forethought, performance and reflection. It also represents a continuous-improvement loop, where behavioural and reflective inputs inform subsequent feedback cycles, sustaining alignment between learner behaviour and adaptive guidance.

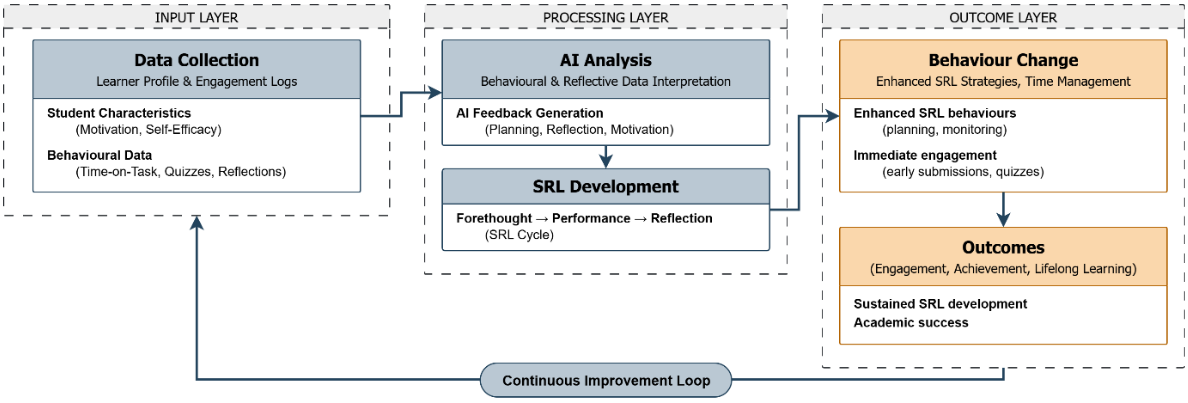


Figure 7: Educational Model for AI-Supported Self-Regulated Learning in an LMS

Through iterative interaction with AI-generated feedback, students progressively refine their planning, monitoring and time management strategies. These behavioural adaptations foster short-term engagement and long-term SRL development. Overall, the model positions AI as a scalable and data-informed mechanism that personalises learning support while maintaining theoretical coherence and system simplicity.

5.4 Connections to Prior Research

The findings of this study extend Zimmerman's cyclical model of self-regulated learning by demonstrating how adaptive AI feedback can operationalise the forethought, performance and reflection phases within an online environment. The empirical evidence supports the view that process-oriented prompts grounded in SRL theory can effectively foster metacognitive engagement and motivational regulation. Consistent with Zimmerman's model, the system supported all phases of SRL (planning, performance and reflection) aligning with evidence that structured, timely prompts can foster metacognitive engagement (Hattie and Timperley, 2007; Panadero, 2017). The results echo prior studies demonstrating the value of adaptive scaffolding in promoting learner autonomy and reducing procrastination (Lim et al., 2023; Heikkinen et al., 2025). Additionally, the positive student perceptions support previous findings on the motivational benefits of non-judgemental, personalised AI feedback (Karaoğlan Yılmaz and Yılmaz, 2020). Unlike earlier systems focused solely on performance metrics, this study highlights the value of integrating behavioural clustering with NLP to deliver lightweight, process-oriented support. This approach directly addresses known limitations in current digital platforms (Cavalcanti et al., 2021; van der Graaf et al., 2023). Together, these results affirm the promise of AI as a scalable tool for fostering effective, student-centred learning strategies in digital education.

5.5 Limitations

While this study provides valuable insights, several limitations must be acknowledged. First, because the study wasn't fully randomised, differences in motivation or engagement might still have affected the results. Second, the sample was limited to 180 participants enrolled in a fully online learning course, which limits how broadly the findings can be applied across other disciplines, educational levels or institutional settings. Third, the 10-week study period may not have been long enough to observe the full development of self-regulated learning habits or their sustained impact on academic performance. Fourth, although effective for individual regulation, the system's logic was static and lacked advanced methods such as semantic personalisation or reinforcement learning for deeper adaptability. Finally, the research addressed only individual learning processes and did not consider socially shared regulation, an important factor in collaborative online learning that merits further exploration.

5.6 Practical Implications

The findings suggest several actionable strategies for improving online learning within educational institutions. Instructors can support students by embedding simple prompts for planning and reflection directly into course materials, particularly in courses with limited real-time teacher interaction. This can help students develop better learning organisation and monitor their progress more effectively. Feedback should be delivered in a supportive, non-judgemental tone, as students responded positively to the coaching style perceived in the AI feedback prompts. Small interactive elements such as quizzes or check-ins can help students assess understanding. Learning platforms can use basic behavioural indicators, like quiz attempts or login patterns, to automatically identify students who may need support and deliver timely prompts. Lightweight systems of this kind are especially useful for large-scale deployment, since they demand little computational power and fit easily into existing learning platforms without major technical upgrades (Fischer et al., 2020). Such systems are feasible even for universities with limited infrastructure or staff.

5.7 Future Research Directions

Building on these findings, future research should explore whether improvements in self-regulated learning are sustained over time and lead to lasting academic benefits. It is also important to examine the applicability of the system across various disciplines, educational levels and institutional contexts to assess its generalisability. Enhancing the system with more advanced natural language processing techniques such as semantic analysis or reinforcement learning could support deeper and more flexible personalisation. In addition, expanding the feedback design to support socially shared regulation of learning (SSRL) may increase the system's effectiveness in collaborative and group-based learning environments.

6. Conclusion

This study evaluated the impact of an AI-driven feedback system embedded in a learning management platform on students' self-regulated learning in a fully online course. The findings show that adaptive, process-oriented feedback significantly improved students' planning, reflection and time management compared with standard platform feedback. Students who received AI-generated prompts-initiated tasks earlier, engaged more frequently with optional resources and reported greater motivation and self-awareness. Gains in monitoring were smaller but positive, suggesting the need for additional in-task scaffolds to strengthen real-time regulation.

The study also extends theoretical understanding of how adaptive AI feedback operationalises self-regulation across cognitive, metacognitive and motivational dimensions. The proposed educational model links engagement analytics with rule-based natural language analysis to deliver transparent and pedagogically meaningful feedback across all SRL phases. This approach provides a practical balance between adaptability, ethical data use and system simplicity, making it suitable for institutional adoption. Practically, the results suggest that integrating such AI tools within existing LMS environments can help educators support learner autonomy without increasing workload. Institutions may use similar approaches to improve equity of feedback and enable early intervention in large online cohorts. Future research should examine the long-term effects of adaptive feedback on sustained SRL behaviours, extend testing across disciplines and explore the inclusion of socially shared regulation features. Overall, the study provides empirical evidence that interpretable AI systems can act as effective and scalable supports for developing independent learning skills, bridging the gap between learning analytics research and real-world educational practice.

AI Statement: During the preparation of this manuscript, the authors used Grammarly to enhance readability and language.

Ethics Statement: Ethical approval was not required for this minimal-risk study, which used anonymised platform logs and voluntary post-course surveys without collection of personally identifying or sensitive data; all participants provided informed consent for the use of anonymised data.

Funding: This work was financially supported by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (grant AP25796073, 2025–2027).

References

Araka, E., Maina, E., Gitonga, R. and Oboko, R., 2020. Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—systematic review (2008–2018). *Research and Practice in Technology Enhanced Learning*, 15(1), p.6. https://doi.org/10.1186/s41039-020-00129-5

Azevedo, R. and Gašević, D., 2019. Analyzing multimodal multichannel data about self-regulated learning with advanced learning technologies: Issues and challenges. *Computers in Human Behavior*, 96, pp.207–210. https://doi.org/10.1016/j.chb.2019.03.025

Bannert, M., Reimann, P. and Sonnenberg, C., 2014. Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and Learning*, 9(2), pp.161–185. https://doi.org/10.1007/s11409-013-9107-6

Bergdahl, N., Bond, M., Sjöberg, J., Dougherty, M. and Oxley, E., 2024. Unpacking student engagement in higher education learning analytics: A systematic review. *International Journal of Educational Technology in Higher Education*, 21(1), p.63. https://doi.org/10.1186/s41239-024-00493-y

Braun, V. and Clarke, V., 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), pp.77–101. https://doi.org/10.1191/1478088706qp063oa

Broadbent, J. and Poon, W.L., 2015. Self-regulated learning strategies and academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, 27, pp.1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Carless, D. and Boud, D., 2018. The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education*, 43(8), pp.1315–1325. https://doi.org/10.1080/02602938.2018.1463354

Cavalcanti, A.P., Barbosa, A., Carvalho, R., Freitas, F., Tsai, Y.-S., Gašević, D. and Mello, R.F., 2021. Automatic feedback in online learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence*, 2, p.100027. https://doi.org/10.1016/j.caeai.2021.100027

Crompton, H. and Burke, D., 2023. Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, 20, p.22. https://doi.org/10.1186/s41239-023-00392-8

Cukurova, M., Kent, C. and Luckin, R., 2019. Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. *British Journal of Educational Technology*, 50(6), pp.3032–3046. https://doi.org/10.1111/bjet.12829

Deeva, G., Bogdanova, D., Serral, E., Snoeck, M. and De Weerdt, J., 2021. A review of automated feedback systems for learners: Classification framework, challenges and opportunities. *Computers & Education*, 162, p.104094. https://doi.org/10.1016/j.compedu.2020.104094

Dent, A.L. and Koenka, A.C., 2016. The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. *Educational Psychology Review*, 28(3), pp.425–474. https://doi.org/10.1007/s10648-015-9320-8

Djokic, I., Milicevic, N., Djokic, N., Malcic, B. and Kalas, B., 2024. Students' perceptions of the use of artificial intelligence in educational services. *Amfiteatru Economic*, 26(65), pp.294–310. https://doi.org/10.24818/EA/2024/65/294

Efklides, A., 2011. Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist*, 46(1), pp.6–25. https://doi.org/10.1080/00461520.2011.538645

Fan, G., Liu, D., Zhang, R. and Pan, L., 2025. The impact of AI-assisted pair programming on student motivation, programming anxiety, collaborative learning, and programming performance: A comparative study with traditional pair programming and individual approaches. *International Journal of STEM Education*, 12(1), p.16. https://doi.org/10.1186/s40594-025-00537-3

Fischer, C., Pardos, Z.A., Baker, R.S., Williams, J.J., Smyth, P., Yu, R., Slater, S., Baker, R. and Warschauer, M., 2020. Mining big data in education: Affordances and challenges. *Review of Research in Education*, 44(1), pp.130–160. https://doi.org/10.3102/0091732X20903304

Fleckenstein, J., Liebenow, L.W. and Meyer, J., 2023. Automated feedback and writing: A multi-level meta-analysis of effects on students' performance. *Frontiers in Artificial Intelligence*, 6, 1162454. https://doi.org/10.3389/frai.2023.1162454

Garcia, R., Falkner, K. and Vivian, R., 2018. Systematic literature review: Self-Regulated Learning strategies using e-learning tools for Computer Science. *Computers & Education*, 123, pp.150–163. https://doi.org/10.1016/j.compedu.2018.05.006

Glick, D., Miedijensky, S. and Zhang, H., 2024. Examining the effect of AI-powered virtual-human training on STEM majors' self-regulated learning behavior. *Frontiers in Education*, 9, 1465207. https://doi.org/10.3389/feduc.2024.1465207

Hattie, J. and Timperley, H., 2007. The power of feedback. *Review of Educational Research*, 77(1), pp.81–112. https://doi.org/10.3102/003465430298487

Heikkinen, S., Saqr, M., Malmberg, J. and Tedre, M., 2025. A longitudinal study of interplay between student engagement and self-regulation. *International Journal of Educational Technology in Higher Education*, 22(1), p.21. https://doi.org/10.1186/s41239-025-00523-3

Hooshyar, D., Pedaste, M. and Yang, Y., 2020. Mining educational data to predict students' performance through procrastination behavior. *Entropy*, 22(1), p.12. https://doi.org/10.3390/e22010012

Jansen, R.S., van Leeuwen, A., Janssen, J., Conijn, R. and Kester, L., 2020. Supporting learners' self-regulated learning in Massive Open Online Courses. *Computers & Education*, 146, p.103771. https://doi.org/10.1016/j.compedu.2019.103771

Järvelä, S., Nguyen, A. and Hadwin, A., 2023. Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology*, 54(4), pp.1057–1076. https://doi.org/10.1111/bjet.13325

Jones, A. and Castellano, G., 2018. Adaptive robotic tutors that support self-regulated learning: A longer-term investigation with primary school children. *International Journal of Social Robotics*, 10(3), pp.357–370. https://doi.org/10.1007/s12369-017-0458-z

Karaoğlan Yılmaz, F.G. and Yılmaz, R., 2020. Learning analytics as a metacognitive tool to influence learner transactional distance and motivation in online learning environments. *Innovations in Education and Teaching International*, 58(5), pp.575–585. https://doi.org/10.1080/14703297.2020.1794928

Karaoğlan Yılmaz, F.G., Olpak, Y.Z. and Yılmaz, R., 2018. The effect of the metacognitive support via pedagogical agent on self-regulation skills. *Journal of Educational Computing Research*, 56(2), pp.159–180. https://doi.org/10.1177/0735633117707696

Lee, Y.F., Hwang, G.J. and Chen, P.Y., 2025. Technology-based interactive guidance to promote learning performance and self-regulation: A chatbot-assisted self-regulated learning approach. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-025-10478-x

Lim, L., Bannert, M., van der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., Rakovic, M., Molenaar, I., Moore, J. and Gašević, D., 2023. Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior*, 139, p.107547. https://doi.org/10.1016/j.chb.2022.107547

Lui, A.M. and Andrade, H.L., 2022. The next black box of formative assessment: A model of the internal mechanisms of feedback processing. *Frontiers in Education*, 7, 751548. https://doi.org/10.3389/feduc.2022.751548

Menekse, M., Putra, A.S., Kim, J., Butt, A.A., McDaniel, M., Davidesco, I., Cadieux, M., Kim, J. and Litman, D., 2025. Enhancing student reflections with natural language processing based scaffolding: A quasi-experimental study in a large lecture course. *Computers and Education: Artificial Intelligence*, 8, Article 100397. https://doi.org/10.1016/j.caeai.2025.100397

Mejeh, M., Sarbach, L. and Hascher, T., 2024. Effects of adaptive feedback through a digital tool – a mixed-methods study on the course of self-regulated learning. Education and Information Technologies, 29, pp.1–43. https://doi.org/10.1007/s10639-024-12510-8

Molenaar, I., 2022. The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning. *Computers and Education: Artificial Intelligence*, 3, p.100070. https://doi.org/10.1016/j.caeai.2022.100070

Moubayed, A., Injadat, M., Shami, A. and Lutfiyya, H., 2020. Student Engagement Level in an e-Learning Environment: Clustering Using K-means. *American Journal of Distance Education*, 34(2), pp.137–156. https://doi.org/10.1080/08923647.2020.1696140

Narciss, S., 2013. Designing and evaluating tutoring feedback strategies for digital learning environments on the basis of the Interactive Tutoring Feedback Model. *Digital Education Review*, 23, pp.7–26. Available at: https://revistes.ub.edu/index.php/der/article/view/11284 [Accessed 10 November 2025].

Nguyen, H. and Allan, V., 2024. Using GPT-4 to provide tiered, formative code feedback. In: *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1 (SIGCSE 2024)*. Portland, OR, USA: Association for Computing Machinery, pp.958–964. https://doi.org/10.1145/3626252.3630960

Panadero, E., 2017. A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, 8, 422. https://doi.org/10.3389/fpsyg.2017.00422

Panadero, E. and Lipnevich, A.A., 2022. A review of feedback models and typologies: Towards an integrative model of feedback elements. *Educational Research Review*, 35, p.100416. https://doi.org/10.1016/j.edurev.2021.100416

Pintrich, P.R., 2000. Chapter 14 – The role of goal orientation in self-regulated learning. In: M. Boekaerts, P.R. Pintrich and M. Zeidner, eds. *Handbook of Self-Regulation*. San Diego: Academic Press, pp.451–502. https://doi.org/10.1016/B978-012109890-2/50043-3

Rakhmetov, M., Kuanbayeva, B., Saltanova, G., Zhusupkalieva, G. and Abdykerimova, E., 2024. Improving the training on creating a distance learning platform in higher education: Evaluating their results. *Frontiers in Education*, 9, 1372002. https://doi.org/10.3389/feduc.2024.1372002

Ranalli, J., 2021. L2 student engagement with automated feedback on writing: Potential for learning and issues of trust. *Journal of Second Language Writing*, 52, p.100816. https://doi.org/10.1016/j.jslw.2021.100816

Rosé, C.P., McLaughlin, E.A., Liu, R. and Koedinger, K.R., 2019. Explanatory learner models: Why machine learning (alone) is not the answer. *British Journal of Educational Technology*, 50(6), pp.2943–2958. https://doi.org/10.1111/bjet.12858

Ryan, R.M. and Deci, E.L., 2020. Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, 61, p.101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Sakhipov, A., Omirzak, I. and Fedenko, A., 2025. Beyond face recognition: A multi-layered approach to academic integrity in online exams. *Electronic Journal of e-Learning*, 23(1), pp.81–95. https://doi.org/10.34190/ejel.23.1.3896

Schunk, D.H. and Greene, J.A., 2017. Historical, contemporary, and future perspectives on self-regulated learning and performance. In: D.H. Schunk and J.A. Greene, eds. *Handbook of Self-Regulation of Learning and Performance*. 2nd ed. Routledge, pp.1–15. https://doi.org/10.4324/9781315697048-1

Somasundaram, M., Mohamed Junaid, K.A. and Mangadu, S., 2020. Artificial Intelligence (AI) enabled Intelligent Quality Management System (IQMS) for personalized learning path. *Procedia Computer Science*, 172, pp.438–442. https://doi.org/10.1016/j.procs.2020.05.096

Sun, D., Xu, P., Zhang, J., Liu, R. and Zhang, J., 2025. How self-regulated learning is affected by feedback based on large language models: Data-driven sustainable development in computer programming learning. *Electronics*, 14(1), p.194. https://doi.org/10.3390/electronics14010194

Tsai, Y.-S., Whitelock-Wainwright, A. and Gašević, D., 2020. The privacy paradox and its implications for learning analytics. In: *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge (LAK '20)*. Frankfurt, Germany: Association for Computing Machinery, pp.230–239. https://doi.org/10.1145/3375462.3375536

van der Graaf, J., Raković, M., Fan, Y., Lim, L., Singh, S., Bannert, M., Gašević, D. and Molenaar, I., 2023. How to design and evaluate personalized scaffolds for self-regulated learning. *Metacognition and Learning*, 18(3), pp.783–810. https://doi.org/10.1007/s11409-023-09361-y

Wong, J., Baars, M., Davis, D., Van Der Zee, T., Houben, G.J. and Paas, F., 2018. Supporting self-regulated learning in online learning environments and MOOCs: A systematic review. *International Journal of Human–Computer Interaction*, 35(4–5), pp.356–373. https://doi.org/10.1080/10447318.2018.1543084

Wolters, C.A. and Brady, A.C., 2021. College students' time management: A self-regulated learning perspective. *Educational Psychology Review*, 33(4), pp.1319–1351. https://doi.org/10.1007/s10648-020-09519-z

Zhang, A., Gao, Y., Suraworachet, W., Nazaretsky, T. and Cukurova, M., 2025. Evaluating trust in AI, human, and co-produced feedback among undergraduate students. *arXiv preprint*. Available at: https://arxiv.org/abs/2504.10961 [Accessed 25 April 2025].

Zimmerman, B.J., 2000. Chapter 2 – Attaining self-regulation: A social cognitive perspective. In: M. Boekaerts, P.R. Pintrich and M. Zeidner, eds. *Handbook of Self-Regulation*. San Diego: Academic Press, pp.13–39. https://doi.org/10.1016/B978-012109890-2/50031-7

Zimmerman, B.J. and Moylan, A., 2009. Self-regulation: Where metacognition and motivation intersect. In: D.J. Hacker, J. Dunlosky and A.C. Graesser, eds. *Handbook of Metacognition in Education*. New York: Routledge, pp.299–315. Available at: https://www.taylorfrancis.com/chapters/edit/10.4324/9780203876428-23/self-regulation-barry-zimmerman-adam-moylan [Accessed 10 November 2025].

What Makes an Online Exam an Exam? Student Perspectives on Assessment Practices at a Major Online University in the Pre-Gen AI era

Maria Aristeidou[1], Simon Cross[1], Klaus-Dieter Rossade[2], Carlton Wood[3], Terri Rees[1] and Patrizia Paci[3]

[1]Institute of Educational Technology, The Open University, Milton Keynes, UK
[2]Faculty of Wellbeing, Education and Language Studies, The Open University, Milton Keynes, UK
[3]Faculty of Science, Technology, Engineering and Mathematics, The Open University, Milton Keynes, UK

maria.aristeidou@open.ac.uk (corresponding author)
simon.j.cross@open.ac.uk
klaus-dieter.rossade@open.ac.uk
carlton.wood@open.ac.uk
terri.rees@open.ac.uk
patrizia.paci@open.ac.uk

https://doi.org/10.34190/ejel.23.4.4456

Abstract: Several universities are evaluating the feasibility of adopting permanent online exam programmes, emphasising the need to assess their decisions and allocate appropriate resources to develop sustainable exam systems. Existing literature on online exams has primarily focused on closed-ended exam formats with immediate feedback, often overlooking other exam types and, importantly, the experiences of distance-learning students. Moreover, most studies concentrate on the perspectives of on-campus students, leaving a gap in understanding for students studying remotely. This study addresses this gap by examining distance-learning students' experiences as they transition from traditional in-person exams to uninvigilated remote online open-book/open-web (OBOW) exams, prior to the widespread adoption of generative artificial intelligence (GenAI). Thus, the study captures student experiences and institutional practices in a pre-GenAI landscape, unaffected by AI-generated content. As part of a larger project involving 562 distance-learning students, we conducted semi-structured interviews with 30 participants three years after the outbreak of the Covid-19 pandemic. Thematic analysis focused on three main areas: (a) students' considerations regarding the place and time of taking remote online exams; (b) their understanding of the changing nature of exams in the online context; and (c) reflections on controlling the exam environment, with particular focus on invigilation and exam integrity issues and challenges faced by students. Key findings indicate that students valued greater flexibility, control, and accessibility in remote online exams but expressed anxiety regarding technology reliability. Unexpectedly, gender differences emerged in perceptions of cheating and exam integrity, with female students emphasising personal learning value and male students expressing greater concern about cheating opportunities. Additionally, confusion existed among students regarding what qualifies as an exam under new flexible formats. These findings contribute to the theoretical understanding of online assessment by highlighting the complex interplay of authenticity, trust, fairness, and learner autonomy. They also point to practical challenges and opportunities in designing equitable, flexible, and sustainable assessment models for higher education. The study's contributions include illuminating the underexplored perspectives of distance learners in OBOW contexts and pre-GenAI environments, informing policy and pedagogy as universities continue to adapt assessment in increasingly online and hybrid landscapes. These insights guide the development of institutional practices that balance technology, pedagogy, and student-centred design to enhance fairness and student confidence.

Keywords: Higher education, Online assessment, Remote online exams, Distance learning, Student experience

1. Introduction

The role, status and method of conducting examinations in Higher Education (HE) have been scrutinised following the Covid-19 pandemic with heightened attention to access, inclusivity, integrity, authorship, and authenticity in assessment. The move to remote, online formats has prompted universities globally to reassess assessment structures, often resulting in a spectrum of solutions that blend formative and summative elements (Heil and Ifenthaler, 2023). While online exams can offer a viable alternative to in-person assessment (Werhner, 2018; Peytcheva-Forsyth and Aleksieva, 2021; Spiegel and Nivette, 2023), recent systematic reviews highlight that effective implementation depends on the synthesis of technology, pedagogical design, and student-centred

Cite this article: Aristeidou, M. et al. 2025. "What Makes an Online Exam an Exam? Student Perspectives on Assessment Practices at a Major Online University in the Pre-Gen AI era", *Electronic Journal of e-Learning*, 23(4), pp 142-154, https://doi.org/10.34190/ejel.23.4.4456

adaptation (Heil and Ifenthaler, 2023; Tahir et al., 2025). Such developments also prompt deeper discussion about the ontological boundaries of 'exam' – as conventions once rooted in control and invigilation are being replaced by practices that value flexibility and accessibility (Aristeidou et al., 2024). This 'exam' discussion prompts further exploration of the examination's place concerning accreditation, pedagogy, and location and delineates the boundary between exam and 'not-exam'.

The literature on 'online exams' (which can include both digital exams taken in person and remotely) often defines the boundary between exams and 'not-exam' based on the levels of process control, knowledge access, and methods of oversight (Heil and Ifenthaler, 2023). Central themes include the permitted time window, resource accessibility, and structure of invigilation – including emerging forms of digital proctoring (Han, Nikou and Ayele, 2024). However, a noticeable gap persists in examining transitions experienced by distance learners – particularly as most recent scholarship and practice remain focused on on-campus, closed-book formats or digital assessment in hybrid contexts (Aristeidou et al., 2024). This study addresses that gap by foregrounding the experiences of distance-learning students as they navigate the shift from in-person, invigilated exams to uninvigilated OBOW remote online formats at scale. We use 'remote online exam' to refer to end-of-course summative activities (described in the methodology section) that, in a face-to-face context, would be described as an 'exam' conducted remotely (on paper or digitally) and submitted online. This is not a fixed definition but rather one that research, such as this study, needs to refine further by examining the variety of assessment tasks and activities that meet this broad description.

Building on this conceptual framing, this study is guided by the following primary research question:

> *"What are the perceptions and experiences of distance-learning students regarding the transition to uninvigilated Open Book Open Web (OBOW) remote online exams at The Open University?"*

1.1 Remote Online Exams

Emerging studies suggest that distance learning students often express favourable attitudes towards online exams taking place remotely, citing effectiveness, reliability, and accessbitility (Ilgaz and Afacan Adanır, 2020; Aristeidou et al., 2024). Yet, recent reviews reveal that positive acceptance is not universally distributed, with students who report disabilities, mental health concerns or lack of requisite technology facing persistent barriers (Heil and Ifenthaler, 2023; Aristeidou et al., 2024). Recent cluster analysis confirms that factors such as assessment competency, workspace satisfaction and tailored support are critical for reducing anxiety and enhancing satisfaction in online assessment environments (Aristeidou et al., 2024).

Contemporary research also highlights the pedagogical potential of remote exams: closed-ended formats can encourage feedback and reflection (Whitelock, 2006; Dermo, 2009; Dreher, Reiners and Dreher, 2011; Hodgson and Pang, 2011; Spector et al., 2016). OBOW approaches specifically foster higher-order skills by inviting practical application of knowledge in authentic contexts and reducing academic dishonesty (Williams and Wong, 2009; Slack and Priestley, 2023; Spiegel and Nivette, 2023). This design paradigm supports academic integrity by shifting away from rote memorisation toward real-world problem-solving while simultaneously boosting student confidence.

Despite the positive student attitudes and pedagogical potential, significant challenges remain. Technical issues, such as inconsistent internet access and device reliability, disproportionately impact many students, particularly those who are less technologically confident (James, 2016; Topuz and Kinshuk, 2021). Older students, for example, often exhibit greater hesitancy toward new exam technologies, although repeated exposure may improve acceptance (Froehlich et al., 2023). Supportive preparation and familiarisation with exam platforms are essential for equity.

Additionally, technological innovations sometimes exacerbate exam stress, with features like visible countdown timers and privacy concerns contributing to anxiety (Choi, Song, and Zaman, 2020; Novick et al., 2022). The stigma of suspicion toward 'cheating' fosters distrust among students and faculty, undermining engagement (Lee and Fanguy, 2022). Further, individual factors such as gender and discipline shape stress experiences, demanding student-centred approaches prioritising well-being (Elsalem et al., 2020; St-Onge et al., 2022).

Moreover, trust and integrity remain central challenges. Issues with verifying identities and preventing misconduct are persistent concerns (Muzaffar et al., 2021). The cost-effectiveness and ethical acceptability of digital proctoring, as well as the reliability of anti-plagiarism software, remain under scrutiny (QAA, 2021). Notably, student trust in academic misconduct deterrents remains low, with less than 20% confidence reported in some studies (Peytcheva-Forsyth and Aleksieva, 2021). Accordingly, a well-structured assessment design that is sensitive to these challenges—such as tool selection, question design, and robust monitoring—is critical (St-Onge, 2022).

A critical gap persists in understanding and addressing the needs of underrepresented student groups in online exam settings, including distance learners, students with disabilities, older learners, and those with caregiving responsibilities or limited technology access (Heil and Ifenthaler, 2023; Aristeidou et al., 2024). Importantly, comparative data from The Open University confirm that these inequities persist in both acceptance and experience among these groups (Aristeidou et al., 2024), underscoring that progress in equitable assessment remains incomplete.

This growing body of evidence increasingly situates these disparities within the wider contexts of assessment authenticity, inclusivity, and student well-being. Consequently, emerging best practices advocate for formative assessment opportunities, transparent communication, and empowerment of learner choice as essential strategies to reduce anxiety and foster engagement (Rossade et al., 2022; JISC, 2025). Thus, effective online exam design must strike a thoughtful balance between technological capability and ethical, inclusive, pedagogically sound principles to support all learners equitably.

Reflecting these themes in practice, comparative studies at The Open University where this study took place reveal little change in revision patterns across most metrics relative to the pre-pandemic era, including learning benefits, enjoyment, and institutional support. However, students reported feeling less anxious during online exam revision and expressed higher satisfaction with the exam environment despite acknowledging associated challenges (Aristeidou et al., 2024). Furthermore, prior research at the same institution also highlights an interconnection between factors such as assessment competencies and acceptance of invigilation approaches, particularly noting that certain groups—those with disabilities, caregiving responsibilities, mental health concerns, or limited technology access—exhibit lower acceptance of online exams (Aristeidou et al., 2024) These findings reinforce the critical importance of bolstering student preparation, confidence, and assessment skills as foundational to advancing equitable and effective online assessment.

1.2 Research Purpose

Motivated by a need to understand how distance-learning students perceive recent trends away from in-person exams and towards remote online exams, this study focuses on the student experience at one large European distance-teaching university during a period of major adjustment and trialling various un-invigilated online exam formats. The study examines key dimensions of this change, including the impact on student well-being and associated concerns. This represents an early study into distance learning university students' narratives about transitioning from a fixed in-person format to OBOW remote online exams. The nature of OBOW will vary across an institution, so it is important to gather a range of views from across disciplines and specific implementations. This work raises questions for and contributes to ongoing research on the boundaries between traditional exams and alternative assessment methods.

2. Methodology

2.1 Context and Settings

The Open University where the study took place has a tradition of distance learning at scale centred around independent learning using course materials via virtual learning environments (VLE) supplemented by tutor support, online tutorials, and small tutorial group interaction. Until 2020, assessments usually included continuous summative (with formative feedforward) online assessments and final summative assessments, which were either face-to-face exams or other coursework submitted online. Approximately 24% of courses end in exams involving over 20,000 learners annually. In response to, and since 2020, in-person exams were replaced with remote OBOW online exams.

The types of questions included in OBOW exams at The Open University vary across discipline areas, schools, courses and levels of study (Cross et al., 2023). These types range from equations and numerical workings through short answer responses and multiple-choice questions to longer essay or report-style responses. Similarly, the time window when students must start and finish OBOW exams varies from one to seven days. The time permitted to complete the exam varies, similar to conventional exams. Literature indicates that both the exam type (e.g., Novick et al., 2022) and the nature of the submission window and time permitted (e.g., Mumtaz et al., 2022) can significantly impact student perceptions. Variants in each format may offer distinct advantages and drawbacks.

The variations of the OBOW implemented by The Open University constitute a longer-term trend of replacing traditional in-person timed exams with alternatives. Courses that still concluded with an in-person exam are those where academic colleagues responsible for designing and approving assessment determined that an exam was still required or preferred over an alternative end-of-model assessment. All OBOW online remote exams were uninvigilated.

Recent research (Domínguez-Figaredo, Gil-Jaurena and Morentin-Encina, 2022) demonstrates that rapid transitions to online assessment in distance learning universities can significantly affect student performance and perceptions, highlighting challenges and opportunities directly relevant to this study.

It is important to highlight that this study was conducted before the widespread adoption of generative artificial intelligence (GenAI) tools, which have recently emerged as significant factors in shaping online assessments. The exam formats and student experiences reported here, therefore, reflect a pre-GenAI academic environment. Subsequent research will need to explore how the availability of AI-generated content and assistance affects notions of exam integrity, academic honesty, and assessment design.

2.2 Study Design and Sampling

We conducted an embedded mixed-method design (Creswell and Clark, 2018), primarily using qualitative data (interviews) supplemented by quantitative data (surveys). Survey responses contributed to participant selection for interviews. The survey from which interview participants were recruited was administered to a random university-wide sample of students between 24 February and 22 March 2023 and received 562 responses. This included students of any year and faculty at The Open University and those with no prior experience taking exams at the university. Ethics exemption was obtained from the university ethics committee, and participation was voluntary.

Previous research suggests that age (Froehlich et al., 2023), gender, field of study (Elsalem et al., 2020), and disability (Ilgaz and Afacan Adanır, 2020) can significantly impact the online exam experience. Students were, therefore, invited for an interview using a purposive sampling approach intended to ensure the sample would be, as much as possible, representative of the university population across demographics (gender, faculty, age group and declared disability representation), student characteristics and academic performance, and would include students who have taken in-person exams, remote online exams, or both. This helped mitigate disciplinary bias as courses in some subject areas used exams more frequently than others. A sample of 30 people was selected for the interviews and deemed sufficient to provide a good range of learner perspectives. Five additional invitations were sent out to additional candidates/participants with the same characteristics to achieve sufficient representation due to non-responses. The 30 interview participants received thank-you vouchers for their time.

2.3 Data Collection

2.3.1 Survey

As part of the survey, students were presented with various potential online exam interaction options as reported in Cross et al. (2023). Students' responses were expected to be informed by their previous experience of online exams at The Open University or elsewhere, and their perception of the proposed future exam model that will include these interaction options. Students were also asked about their feelings towards taking online exams on a 3-point scale (positive, undecided, or negative feelings) and whether they would prefer online exams over their regular in-person exams (yes/no).

2.3.2 Semi-Structured interviews

The research team developed an interview guide to explore student experience with the current OBOW exam format and technology, and other potential remote online exam formats, as well as students' perceptions of invigilation, cheating, and remote online exam validity. The interview aspects derived from the research team's long-term experience with assessment, remote online exams research, the relevant literature, and as directors or members of the institution-wide assessment programme. Interviews were conducted in Microsoft Teams and audio-recorded for transcription purposes.

2.4 Participants

Thirty students participated in the interviews. Table 1 shows the key characteristics of the group. There were equal numbers of male and female students representing all age groups. Compared to the overall student population, there was an over-representation of students from STEM (53.3%) and FASS (30%). However, this may reflect the greater use of exams as end-of-module assessments in subjects within these faculties compared to FBL and WELS (where schools did not administer many online exams). The interview sample included seven students (23.3%) with a declared disability similar to the university average. Further information about each interview participant was used to interpret and contextualise interview comments, such as if the comment may have been influenced by the specific type of OBOW experienced.

Table 1: Student information (n = 30)

	n	%		n	%
Gender			Faculty		
Female	15	50%	STEM	16	53%
Male	15	50%	FASS	9	30%
Age group			WELS	3	10%
25 and under	2	6.7%	FBL	2	7%
26-35	8	26.6%	Declared disability		
36-45	8	26.6%	Yes	7	23.3%
46-55	5	16.7%	No	23	76.7%
56-65	3	10%			
66 and over	3	10%			

2.5 Data Analysis

Interviews were transcribed and imported into nVivo (Version 12) along with survey and demographic data relating to the participants. Thematic analysis (Braun and Clarke, 2006) was used to identify, analyse, and report patterns across the dataset whilst being sensitive to the interviewee's original words and meanings. Analysis followed a six-step approach. Two researchers (Authors A and E) became familiarised with the dataset (step 1) and each independently generated descriptive codes to summarise the data (step 2). The researchers compared codebooks and calculated inter-rater reliability (IRR) as 82% using the Miles et al. (2019) approach (dividing the number of times coders agreed by the total number of times coding was possible). This was considered acceptable. Differences were discussed and resolved through consensus, resulting in an agreed codebook with codes grouped into initial themes where possible. Initial themes were reviewed (step 4) and discussed with the research team to help validate groupings. In step 5, Authors A and B proposed theme names and definitions, which were discussed and agreed upon with the rest of the research team. Finally, findings were refined (step 6) and processed, ready for reporting in the data analysis. This included anonymising names. Each interview quote is followed by the participant's identifier (R1 – R30). The team revised steps four to six after receiving formal feedback from external reviewers. The final codebook can be found in Table 2:

Table 2: Interview Codebook - Interview themes, codes and description

Main themes	Codes	Description
Considering place and time	Convenience	Avoiding travel, time, and parking-related inconveniences
	Anxiety	Tackling mental health-related issues and in-person anxiety
	Accessibility	Benefits for people with mobility issues
	Flexibility	Taking the exam wherever and sometimes whenever they want
	Sustainability	Not travelling has no emission reduction
	Exam atmosphere	Replicating the experiential value and accomplishment feelings of in-person exams
	Technology concerns	Expressing concerns about poor broadband connection, equipment, failure in using hardware, or software issues
	Other commitments	Catering to childcare or employment commitments

Main themes	Codes	Description
Understanding the changing nature of the exam	Exam types	Commenting on the different exam types (e.g., multiple choice, open book) and their pros and cons.
	Authentic assessment	Discussing how the OBOW style exams resemble real-life situations and cultivate skills
	Comparisons with coursework	Spotting similarities and differences with coursework and discussing exam necessity
	Communication	Suggesting clearer instructions on the differences between the different exam types, formats and submission windows
Controlling the environment: invigilation and exam integrity	Cheating	Expressing different opinions about whether or why students would cheat (pointless or easy to cheat, differences between exam types, individual attitudes)
	Invigilation	Supporting or expressing doubts about different invigilation approaches, their effectiveness and their acceptance.
	Validity & worth of degree	Expressing concerns about a reduction in academic standards, devaluation of exams and issues with potential employers

3. Results

3.1 Online Exams Information

Interviewees said they had engaged in one or more assessment tasks during their OBOW remote online exam. This distribution of tasks was broadly as expected, given the nature of representation from each subject faculty/department (Table 3). When viewed across an institution, remote online exams comprise a variety of different combinations of assessment tasks.

Table 3: Online exam activities

Online exam activities	Interview participants	
	n	%
Equations or other numerical workings	18	60 %
Short answers (paragraph or less)	13	43.3%
Essay (more than a page)	13	43.3%
Long answers (more than a paragraph, less than a page)	11	36.7%
Multiple choice exams	10	33.3%
Producing visual output (drawings, photographs, diagrams)	5	16.7%
Self-reflection	2	6.7%
Producing audio output (recording or live)	1	3.3%
Translation	1	3.3%

The period in which students could complete their exams (the period between the start and end) varied. This, in part, reflected variability in subjects and assessment design decisions of course teams. The following table shows the submission windows for the exams taken by students – noting that a student may have taken more than one type of exam (Table 4).

Table 4: Submission windows

	Interview participants	
	n	%
7-day or more submission window	7	23.3%
3-day submission window	7	23.3%
24-hour submission window	9	30%
Timed exams – to be completed within 2-4.5 hours	12	40%

Twenty-three students (76.7%) reported having positive feelings towards taking online exams, five students (16.7%) had negative feelings, and two (6.7%) were undecided. Where relevant, the thematic analysis highlights when the submission window or assessment task type may help explain or contextualise participant comments.

3.2 Thematic Analysis

Three major themes in students' narratives about transitioning from in-person to remote online exams are discussed in this thematic analysis. The first theme unpacks participants' views on issues related to the place and time of exams. Place (i.e., home) and time (i.e., length of submission window, period available) are two key characteristics that differentiate remote online exams from in-person exams. The second theme focuses on the perception of change and, more specifically, the transition experience. The final theme related to participants' views about the exam process and, more specifically, issues associated with exam integrity. This theme was labelled 'control and trust' and refers to student attitudes towards assessment integrity.

3.2.1 Theme 1: Considering place and time

Most distance learning students participating in the study felt that remote online exams offered greater temporal flexibility in duration and starting times. The convenience of not having to travel (often significant distances) to an examination hall to sit exams emerged as one sub-theme. For example, students discussed how 'time-consuming' (R3) it is to travel hours away from home, and even those students more negatively disposed towards taking the online exam conceded how 'much more stressful' (R1) it can be to have to find the examination hall.

Participants with and without declared disabilities also felt that remote online exams could help support equity and inclusivity. Some mentioned how the remote online element could offer 'a lot of equity to students who have additional needs' (R10) and can be 'much more inclusive' (R19). A participant with declared disabilities spoke of the benefits for those with a range of declared disabilities:

> *"I think it's much more accessible for people with mobility issues who would struggle to get to an exam hall. I think it's much more accessible for people with mental health issues who would struggle with the stress of an exam." (R5).*

That such sentiment was quite widespread indicates an awareness of the variety of challenges some students encounter when taking exams. Perhaps this is partly because accessibility and an open approach to all are frequently made visible to students as part of the university's core mission.

Participants also considered that remote online exams could help offer greater choice about when an exam could start and the duration they were 'open.' This meant that when combined with the ability to sit the exam remotely at home, taking an exam could be better accommodated around other personal and work commitments. Even when of fixed limited duration, students saw value in exams that allow flexibility. Examples of perceived or experienced flexibility included having the choice to start at any time over a week, which could help cater for personal or work commitments such as childcare or employment or practical challenges, such as finding an uninterrupted exam environment or ensuring all necessary equipment is in place and working. In some cases, increased flexibility was necessary to accommodate the other demands of taking an exam remotely rather than in person:

> *"…it can be quite difficult if somebody needs to have three or four hours potentially uninterrupted at a really specific place and time at home. So, having that kind of flexibility where maybe it's over a few days, or even over a day, just having the flexibility of choosing a start time, I think that's really important." (R12)*

One significant issue for some students is a sense of anxiety in the use of technologies for remote online exam taking. Whilst all students regularly use an online portal to upload assessments and download feedback and grades during their course, this anxiety may be associated with the actual or perceived higher stakes associated with the assessment being 'an exam.' Concerns were sometimes subject-specific or related to the demands of a particular assessment task. For example, one STEM student taking an exam that involved scanning equations was concerned that a scanner malfunction might jeopardise their timed exam (R24). Another student highlighted worries about accidentally losing their work on the computer during timed exams (R11). Further anxieties related to software usability, such as having to 'send' a multiple-choice questionnaire without a 'save' option (R29), the possibility of uploading difficulties when writing and submitting an essay within 24 hours, and other software issues or unspecified technology failure (R30). One STEM student who was uneasy about taking timed exams felt that technology failure is a major stressor they cannot control:

"I can control how much revision I do or whether I've maybe done my best to understand the work, but something that's outside of my control like the technology is what stresses me." (R24)

Some respondents, particularly those who sat an OBOW remote essay exam, appear to particularly emphasise the value of traditional exam halls' physical environment and atmosphere (R8, R9, R13). They argued that while online exams offer flexibility, they cannot replicate the experiential value of an in-person setting. One respondent, undecided towards online exams, captured the sentiment:

"The absence of critical elements of the process, such as the environment, would make an online exam feel less like a real exam." (R8).

Adding to this point, another participant commented on the value of the exam hall setting:

"The space and concentration provided by a proper exam hall were valuable and may not be replicated at home." (R9)

In the interviews, students said that remote online exams let them feel 'in control of the environment' as 'there are no distractions at home' (R6). Lastly, one participant suggested that an unexpected benefit of remote online exams could be the carbon savings of not travelling to the exam centre (R4).

Overall, this theme explored the perceived benefits and challenges of sitting exams in a remote setting, with sub-themes such as convenience, anxiety, accessibility, flexibility, distractions, and other commitments, all of which were apparent in the interviews.

3.2.2 Theme 2: Transition and contrast

At The Open University, the transition from in-person to remote online exams was often accompanied by transitioning from one assessment style to another. This reflected the move from an invigilated exam to the OBOW format. In experiencing this transition, students were allowed to contrast one approach to an exam with another and, subsequently, to reflect on how they felt about the new format.

Overall, those interviewed were satisfied with the new OBOW approach to remote online exams. This was observed for both those positive about online exams and those who were more circumspect. Several participants felt that their OBOW remote online exams promoted a more authentic assessment approach by making the assessment activity more realistic and reflective of real-life situations. This was especially observed in those who were given between 1 and 7 days to complete the exam activity. Contrast was made between the artificial nature of in-person timed exams and work, with one participant noting 'in real life, you would never need to sit intensely in a hall for three hours and extract from your memory with no support, no internet, no reference material' (R10). Others noted the lack of pressure (R22), the benefit of having access to all their study materials (R2, R17), and that the assessment seemed to do better at assessing skills rather than memory (R16):

"[There was] the time pressure that makes you do the work, but without any of that sort of horrible anxiety of, oh, God, I've not revised this or that. It was within your power to sort of do reading simultaneously. It didn't feel like a test of raw learning. It felt like a test of research skill" (R22).

Students also noted the alignment between the types of assessment activity used in exams and their continuous assessment. For example, STEM students who sat short-timed multiple choice questions exams commented how much it helped that 'the format was similar to [their] coursework' (R18). Disciplines will differ with respect to preferred or more effective assessment activity type, but reflective comments from students with respect to how well it promoted prompted deeper engagement with tasks such as problem-solving (for example, in STEM context, multiple-choice format (R24)).

For some participants, more so for those accustomed to in-person exams, the contrast with remote online exams was not entirely positive. Reservations were expressed about the suitability of longer submission windows (24 hours or more) for specific question types, such as multiple-choice questionnaires, short-answer questions, and equations (R17). This crosscuts the theme of integrity and trust, which will be discussed later.

Of most note was the emerging theme of how and why the university referred to these as assessments exams. Interview transcripts of students from different faculties indicated some were puzzled by extended submission windows and how this compared (and materially differed) to their familiar coursework (R1, R10, R13, R15). A participant who took an essay "exam" with a 3-day window suggested that it could be replaced with a final assignment "I don't think it has to be an exam; it could have a more flexible format, it could be [having] the 72-hour window" (R13). This indicates that the student considered the format used to fall outside their conception of what an exam is, and a sense that alternatives to exams may work better. The students then said that they felt exams were only still being used because of a technological rather than a pedagogic imperative. They explained, "… [so] what this exam idea is, is [that] we have the technology, now we are going to use it, rather than we have technology, *how* could we use it, if we don't need exams, why are we having exams?" (R13, our emphasis).

Indeed, one participant specifically raised the question of what is and what is not an exam and suggested the university could be clearer on the differences between the in-person and online exams (R1). The ambiguity in definition and messaging may be complicated further by the specific, historically-routed terminology used by the university where 'end of module assessment' without capitals means something different with capitals (the form referring to the last assessment in the module, which usually contributes most the final module score and the latter to an assignment without specified time limit, due on a given date specified months in advance and considered distinctly 'not' an exam). Here, the shift to remote online exams disrupted existing terminologies and may have created confusion, especially for students transitioning to the new format and its consequences for question formats, study material access, and overall assessment approaches.

Overall, issues associated with this theme of transition and contrast included the changing nature and definition of the exam, responses and reactions to different remote online exam types, expressions of concern with the technology used, and comparison with other assessments encountered during the course (i.e., continuous assessment).

3.2.3 Theme 3: Control and trust: Invigilation, and exam integrity

The third theme that emerged strongly during the interviews and is discussed in this paper is control and trust. Most comments coded to this theme related to exam integrity, cheating and the capacity of OBOW remote online exams to adequately control for this. Some participants, otherwise generally positive about online exams, expressed cynicism that all students would follow the rules and a firm belief that students would cheat if given the opportunity. It is worth noting that participant reflections on exam control, trust, and integrity occurred before generative AI tools were widely accessible to students. The emergence of GenAI may significantly impact these themes by introducing new dynamics in potential academic misconduct and necessitating innovative assessment designs to uphold integrity.

Our analysis indicates that most comments related to this sub-theme were made by male students. A (male) STEM student who took timed multiple choice and equation exams felt that 'the greater the opportunity [to cheat], the greater likelihood of cheating' (R27, Male, aged 40). Similarly, a FASS student who sat a 3-day essay exam believed that 'if you give people the chance, they will cheat' (R22, Male, aged 29). Additionally, three STEM participants with experience in multiple types of exams raised concerns about proxy exams, where someone might complete the exam on another student's behalf (R12, R26, R4, all males aged 39, 54 and 69). One participant who took a long answer and equation exam felt that whether cheating takes place depends on the nature of the exam (R18, Female, aged 30), as the following (male) FASS participant eloquently summarised the complexity by focusing on the individual:

> *'Whether you follow the rules and just take the maximum advantage you can of the situation or cross the line and breach the rules because you don't think you're going to get caught depends on you as an individual. But there's definitely more scope, isn't there?' (R15).*

In contrast, several respondents from different faculties (but all of whom took exams with submission windows of a day or more) appear to trust their fellow students not to cheat and even emphatically deny the possibility of cheating taking place. We observe that most comments relating to this sub-theme were made by female students. Students viewed cheating as pointless because their studies were 'all about [studying] for [their] own benefit' (R3, Female, aged 47), that 'they've invested in [them]selves' (R25, Female, aged 37) and that cheating would undermine the personal 'sense of achievement' (R13, Female, aged 56). It would appear that for the female participants interviewed in this study, the OBOW nature of the exams further eliminated the need for deception, as they were permitted to consult notes (R14) or use course materials (R17). Some even felt that certain subjects, like business case studies, were inherently resistant to cheating (R23), which brought up the notion of authentic assessment again.

The responses suggest that the issue of cheating in remote online exams is complex and may depend on various factors, including what students choose to emphasise and discuss in an interview context.

None of the remote online exams that students experienced in this study included forms of surveillance technology (e.g., online proctoring), so students could not comment on how such systems may have impacted their perception of control. However, many expressed views on online invigilation and the impact of its use or absence on degree validity.

Several respondents representing diverse faculties and experiences with online exams (both positive and negative perspectives) voiced strong opposition to the practice of browser blocking. They expressed significant concerns about access to personal computers (R13, R20), arguing that implementing the concept would be challenging and likely negatively impact the wider user experience (R27). Additionally, some respondents pointed out the ineffectiveness of browser blocking, citing the ease of accessing browsers through other devices (R7, R13, R28). Face and voice recognition was more positively viewed, although some doubted their effectiveness. For example, some respondents representing different discipline areas pointed out that cameras and voice recognition can be circumvented by those intent on cheating (R4, R14, R21), highlighting the need for additional measures to prevent cheating. Additionally, a respondent who sat timed exams and held overall negative views towards remote online exams pointed out that continuous invigilation measures would be impractical for exams with longer (i.e., a few hours) submission windows (R24).

Leading from this, despite generally positive attitudes towards remote online exams, some students (spanning faculties and exam types) expressed concerns about the potential impact on degree validity and worth (R14, R15). Respondents feared that reliance on remote online exams could weaken academic standards and potentially compromise exam integrity (R16). This is partly related to potential employer perceptions and the perceived need to uphold the robustness of academic qualifications.

4. Discussion

When encountering contrasting approaches to assessment, students will inevitably make comparisons and take a view of how well the new approach performs. This study aims to understand the reactions and experiences of distance learners as their university transitions from an in-person, timed exam format to a remote, online, and more flexible open-book exam approach. The analysis directly responds to the research question by showing how distance learners conceptualise and adapt to change in exam format, environment, and expectations.

One challenge in unpacking the student perspective is that moving from in-person to remote online exams involves several changes simultaneously. Students take the exam at home rather than in an exam centre; students take the exam (usually) online rather than only on paper; students must rely on technology for successful completion and submission rather than this being physically managed manually by an invigilator; students may have longer or a more flexible time window to start and end the exam, and students may be set different types of assessment task because of the change assessment format and time window (i.e. open-book assessment).

This study has identified several key elements of the student narrative associated with changing place and time. Overall, students were positive about the flexibility in space and time for remote online exams, although this was tempered by some anxiety over the risks associated with technology malfunction. They appreciated the flexibility in start time and the ability to sit the exam in an (uninterrupted) environment under their control. This supports the finding of Aristeidou et al. (2024), who found that for students at the same university as used in this study, the main difference between in-person and remote online exams was a perceived improvement in the physical environment of exam-taking. The benefits for those with caregiving responsibilities, those in paid employment, or those with disabilities were also mentioned. The latter appears to align with prior research on the benefits of online exams for students with accessibility needs (Ilgaz and Afacan Adanır, 2020).

Technology facilitated the process of taking remote online exams, but was viewed as a potential risk to success, generating anxiety similar to concerns reported in Topuz and Kinshuk (2021). These findings extend current literature by confirming that while distance learners tend to have high technological familiarity, perceptions of fairness and reliability remain closely tied to institutional support structures and technical dependability. Thus, familiarisation activities and mock-exam opportunities (Froehlich et al., 2023) are likely to reduce anxiety and reinforce student confidence in online assessment. However, unlike Heil and Ifenthaler (2023) and Tahir et al. (2025), who stress that the educational benefits of digital assessment depend on coherent pedagogical alignment and student preparedness, the participants in this study focused more on logistical flexibility and exam control than on pedagogical coherence. This suggests that implementation success, from the learner's point of view, may rely as much on perceived autonomy as on instructional soundness, underscoring the importance of aligning design intent with student experience.

A second challenge to interpretation has been that not all OBOW practices are identical. Our analysis offers a view of how students across faculties and variants experience the OBOW remote online exams differently. Benefits such as authenticity and reflection found in this study support previous conceptual arguments about open-book assessment (Hodgson and Pang, 2011). However, the findings also nuance these claims by showing that greater flexibility can blur students' perceptions of what constitutes an "exam," suggesting the need for more transparent communication and a clear definition of assessment purpose—an insight that advances understanding of assessment literacy in digital contexts. These challenges aside, our analysis has raised two additional findings of particular interest. First, moving to remote online exams can throw existing definitions of what an 'exam' is and what an exam 'is not' into sharp relief, echoing tensions reported in the current reassessment of high-stakes testing (Lee and Fanguy, 2022). It is beholden on educators to pay attention to defining and explaining the reason for continuing to use, or changing the use, of these terms and identifying points of student confusion. What defines an exam may include aspects that we discuss in this paper, such as the place and timing of the assessment. For example, our study indicates the greatest perceived distinguishing factor is time – between time-pressured exams and those with larger submission windows.

Second, female students appeared to talk about exam integrity differently than male students. Female students generally emphasised the value of the assessment for their personal learning. They, therefore, saw cheating as a wasted effort, while male students expressed greater concerns about potential cheating opportunities in remote exams. This was unexpected. Lee and Fanguy (2022) call for greater critical engagement in educational fairness discussions, and our findings could indicate these need to consider student demographics and prior experiences. Student attitudes towards remote invigilation – a phenomenon not experienced by the students interviewed – were more in line with previous work (e.g., Novick et al., 2022), as were general comments regarding concerns about academic standards.

In terms of implications, these findings highlight that online and OBOW exams require ongoing design review to maintain both perceived fairness and authenticity. Institutions should integrate training that helps students understand the rationale behind remote assessment models and supports equitable learner experiences. Programme leads and policymakers might also consider how different student groups interpret the purpose and value of these exams, ensuring design decisions balance flexibility with perceived rigour.

The present study focused exclusively on distance-learning students within a single university who were already writing and submitting continuous assessments remotely. While this may limit the transferability of some findings, more universities are now delivering teaching and assessment at a distance. This growing context enhances the relevance of the findings and their potential applicability to institutions transitioning to online or blended models. The modest interview sample and single-institution focus may limit generalisability, and the research pre-dates the widespread use of GenAI, a factor anticipated to reshape exam design and integrity. Nonetheless, the results provide a timely pre-GenAI benchmark against which future studies can measure the evolving impact of emerging tools.

The flexibility and convenience of remote online exams were frequently praised by participants, although coupled with concerns about technical difficulties and the authenticity of student work. These mixed perceptions underscore the complex balance institutions must strike between enabling accessibility and maintaining rigorous academic standards. The data and themes in this study thus extend existing findings by articulating how distance learners critically negotiate control, responsibility, and trust in remote assessments—a perspective underrepresented in the current literature.

Consequently, policymakers and educators must remain agile, continuously updating assessment frameworks to reflect emerging technologies and evolving capabilities of students. By explicitly linking student experiences to broader debates about authenticity, integrity, and accessibility, this study contributes to both theory and practice in rethinking high-stakes assessment in post-digital education.

5. Conclusion

This study interviewed thirty undergraduate distance learners who experienced a shift in exam format from in-person exams to remote online OBOW-style exams. Four findings of particular note are: First, students appreciated having a sense of control over their assessment, although in so doing, it also made the exam feel less like an exam. Future exam design may need to consider how to reconcile these points. Second, the positive perception of control was evident from comments about the type of remote online examinations – predominantly OBOW-style assessments offered in this study. Third, there were unexpected and tentative indications that perceptions of cheating and exam integrity may have a gendered dimension. This finding challenges existing assumptions and warrants further investigation due to its implications for the design of equitable and effective assessment. Fourth, students and institutions need clarity on the very definition of what is and is not an exam. Further research across different contexts could enhance the generalisability of these findings.

Recognising that this study was conducted before the widespread adoption of generative AI technologies, the findings describe student experiences in a pre-GenAI context, highlighting the importance of further research to understand how emerging AI tools may impact online exam design and integrity.

Overall, the insights by the participating distance learners contribute original perspectives to the ongoing discourse on assessment reform (Rossade et al., 2022; JISC, 2025), regardless of whether these are termed exams or not. The study advances knowledge by surfacing nuanced learner views, questioning prevailing assumptions, and offering practical implications for creating more inclusive, authentic, and trusted online assessment environments. Future research should build on these findings to expand understanding across diverse institutional contexts and examine the dynamic influence of technological change.

AI statement: No AI tools have been used in the development of this paper.

Ethics statement: 'Online exams' was considered a low-risk study that meets The Open University criteria for exemption from formal review (reference number: HREC/4262/Aristeidou), http://open.ac.uk/research/ethics/. All subjects gave their informed consent for inclusion before they participated in the study.

References

Aristeidou, A., Cross, S., Rossade, K.D., Wood, C., Rees, T. and Paci, P., 2024. Online exams in higher education: Exploring distance learning students' acceptance and satisfaction. *Journal of Computer Assisted Learning,* 40(1), pp. 342-359. https://doi.org/10.1111/jcal.12888

Braun, V. and Clarke, V., 2006. Using thematic analysis in psychology. *Qualitative research in psychology,* 3(2), pp. 77–101. https://doi.org/10.1191/1478088706qp063oa

Choi, B.-Y., Song, S. and Zaman, R., 2020. *Smart education: Opportunities and challenges induced by COVID-19 pandemic: a survey-based study*. In: 2020 IEEE International Smart Cities Conference ISC2. Piscataway, NJ, USA: IEEE, pp. 1–8. https://doi.org/10.1109/ISC251055.2020.9239063

Creswell, J. and Clark, V.L.P., 2018. *Designing and conducting mixed methods research*. 3rd ed. Sage.

Cross, S., Aristeidou, M., Rossade, K.D., Wood, C. and Brasher, A., 2023. The impact of online exams on the quality of distance learners' exam and exam revision experience: Perspectives from The Open University UK. *Online Learning,* 27(2), pp. 27-45. https://doi.org/10.24059/olj.v27i2.3761

Dermo, J., 2009. e-Assessment and the student learning experience: A survey of student perceptions of e-assessment. *British Journal of Educational Technology,* 40(2), pp. 203–214. https://doi.org/10.1111/j.1467-8535.2008.00915.X

Domínguez-Figaredo, D., Gil-Jaurena, I. and Morentin-Encina, J., 2022. The impact of rapid adoption of online assessment on students' performance and perceptions: Evidence from a distance learning university. *Electronic Journal of e-Learning,* 20(3), pp. 224-241. https://doi.org/10.34190/ejel.20.3.2399

Dreher, C., Reiners, T. and Dreher, H., 2011. Investigating factors affecting the uptake of automated assessment technology. *Journal of Information Technology Education: research*, 10(1), pp. 161–181. https://doi.org/10.28945/1492

Elsalem, L., Al-Azzam, N., Jum'ah, A.A., Obeidat, N., Sindiani, A.M. and Kheirallah, K.A., 2020. Stress and behavioral changes with remote E-exams during the Covid-19 pandemic: A cross-sectional study among undergraduates of medical sciences. *Annals of Medicine and Surgery*, 60, pp. 271–279. https://doi.org/10.1016/J.AMSU.2020.10.058

Froehlich, L., Sassenberg, K., Jonkmann, K., Scheiter, K. and Stürmer, S., 2023. Student diversity and e-exam acceptance in higher education. *Journal of Computer Assisted Learning,* 39(4), pp. 1196-1210. https://doi.org/10.1111/jcal.12794

Han, S., Nikou, S. and Yilma Ayele, W., 2024. Digital proctoring in higher education: a systematic literature review. *International Journal of Educational Management,* 38(1), pp. 265-285. https://doi.org/10.1108/IJEM-12-2022-0522

Heil, J. and Ifenthaler, D., 2023. Online assessment in higher education: A systematic review. *Online Learning,* 27(1), pp. 187-218. https://doi.org/10.24059/olj.v27i1.3398

Hodgson, P. and Pang, M.Y.C., 2011. Effective formative e-assessment of student learning: a study on a statistics course. *Assessment & Evaluation in Higher Education,* 37(2), pp. 215–225. https://doi.org/10.1080/02602938.2010.523818

Ilgaz, H. and Afacan Adanır, G., 2020. Providing online exams for online learners: Does it really matter for them? *Education and Information Technologies,* 25(2), pp. 1255–1269. https://doi.org/10.1007/S10639-019-10020-6/TABLES/9

James, R., 2016. Tertiary student attitudes to invigilated, online summative examinations. *International Journal of Educational Technology in Higher Education*, 13(1), pp. 1–13. https://doi.org/10.1186/S41239-016-0015-0/TABLES/3

JISC, 2025. *Trends in assessment in higher education: considerations for policy and practice: shaping the future of assessment practices in higher education*. Available at: https://www.jisc.ac.uk/reports/trends-in-assessment-in-higher-education-considerations-for-policy-and-practice (Accessed 14 October 2025).

Lee, K. and Fanguy, M., 2022. Online exam proctoring technologies: Educational innovation or deterioration? *British Journal of Educational Technology*, 53(3), pp. 475-490. https://doi.org/10.1111/bjet.13182

Mumtaz, S., Parahoo, S.K., Gupta, N. and Harvey, H.L., 2023. Tryst with the unknown: navigating an unplanned transition to online examinations. *Quality Assurance in Education,* 31(1), pp. 4-17. https://doi.org/10.1108/QAE-12-2021-0197

Muzaffar, A.W., Tahir, M., Anwar, M.W., Chaudry, Q., Mir, S.R. and Rasheed, Y., 2021. A systematic review of online exams solutions in e-learning: Techniques, tools, and global adoption. *IEEE Access,* 9, pp. 32689–32712. https://doi.org/10.1109/ACCESS.2021.3060192.

Novick, P.A., Lee, J., Wei, S., Mundorff, E.C., Santangelo, J.R. and Sonbuchner, T.M., 2022. Maximizing academic integrity while minimizing stress in the virtual classroom. *Journal of Microbiology & Biology Education,* 23(1), pp. e00292--21. https://doi.org/10.1128/jmbe.00292-21

Peytcheva-Forsyth, R. and Aleksieva, L., 2021. *Forced introduction of e-assessment during COVID-19 pandemic: How did the students feel about that? (Sofia University case)*. In: AIP Conference Proceedings. https://doi.org/10.1063/5.0041862.

Rossade, K-D., Janssen, J., Wood, C. and Ubachs, G. (eds.) 2022. *Designing online assessment: Solutions that are rigorous, trusted, flexible and scalable*. Maastricht, The Netherlands: European Association of Distance Teaching Universities (EADTU). https://doi.org/10.5281/zenodo.6563226. Available at: https://oro.open.ac.uk/87399/ (Accessed 14 October 2025).

Slack, H.R. and Priestley, M., 2023. Online learning and assessment during the Covid-19 pandemic: exploring the impact on undergraduate student well-being. *Assessment and Evaluation in Higher Education,* 48(3), pp. 333-349. https://doi.org/10.1080/02602938.2022.2076804

Spector, J.M. et al., 2016. Technology Enhanced Formative Assessment for 21st Century Learning. *Journal of Educational Technology & Society*, 19(3), pp. 58–71.

Spiegel, T. and Nivette, A., 2023. The relative impact of in-class closed-book versus take-home open-book examination type on academic performance, student knowledge retention and wellbeing. *Assessment and Evaluation in Higher Education,* 48(1), pp. 27-40. https://doi.org/10.1080/02602938.2021.2016607

St-Onge, C., Ouellet, K., Lakhal, S., Dubé, T. and Marceau, M., 2022. COVID-19 as the tipping point for integrating e-assessment in higher education practices. *British Journal of Educational Technology*, 53(2), pp. 349–366. https://doi.org/10.1111/bjet.13169

Tahir, M.H.M., Saputra, S., Othman, S., Shah, D.S.M., Sulaiman, S.H., Azhari, M.A. and Mohandas, E.S., 2025. Online assessment in higher education: A systematic literature review. *Multidisciplinary Reviews,* 9(1), 2026024. https://doi.org/10.31893/multirev.2026024

Topuz, A.C. and Kinshuk, 2021. A review of literature to understand student's perceptions regarding online assessments. In: Y. Wen et al., eds. *Expanding Global Horizons Through Technology Enhanced Language Learning*. Singapore: Springer Singapore, pp. 49–72. https://doi.org/10.1007/978-981-15-7579-2_4

Werhner, M.J., 2018. A comparison of the performance of online versus traditional on-campus Earth science students on identical exams. *Journal of Geoscience Education*, 58(5), pp. 310–312. doi: 10.5408/1.3559697

Whitelock, D., 2006. Electronic assessment: marking, monitoring and mediating learning. *International Journal of Learning Technology,* 2(2–3), p. 264. https://doi.org/10.1504/ijlt.2006.010620

Williams, J.B. and Wong, A., 2009. The efficacy of final examinations: A comparative study of closed-book, invigilated exams and open-book, open-web exams. *British Journal of Educational Technology*, 40(2), pp. 227-236. https://doi.org/10.1111/j.1467-8535.2008.00929.x

Low-Cost Simulations and Augmented Reality: Enhancing Practical Learning in e-Learning Environments

Tetty Setiawaty[1] and Gunadi Tjahjono[2]
[1]Department of Building Engineering Education, Faculty of Teacher Training and Education Universitas Nusa Cendana, Indonesia
[2]Department of Electrical Engineering Education, Faculty of Teacher Training and Education Universitas Nusa Cendana, Indonesia

tetty_setiawaty@staf.undana.ac.id (corresponding author)

https://doi.org/10.34190/ejel.22.3.4046

Abstract: This study aims to enhance engineering education by introducing a cost-effective simulation approach that combines cardboard prototyping and augmented reality (AR) as alternatives to traditional wood-based practice. The primary objective is to determine whether these tools can improve students' technical skills, work attitudes, and overall learning performance in woodworking design within a vocational education context. The study addresses a critical challenge in e-learning: providing interactive and tangible experiences without relying solely on digital devices or high-cost materials. The study comprised 76 second-semester students from a vocational engineering program, separated into Group A (conventional learning using wood) and Group B (simulation-based learning utilizing cardboard and AR integration). Both groups adhered to the Conceive–Design–Implement–Operate (CDIO) structure throughout their learning sessions. Quantitative data were gathered using structured observation rubrics that evaluated four primary indicators: technical execution, planning accuracy, collaboration, and professionalism. The findings indicate that Group B, which employed cardboard simulations augmented with AR overlays, attained an average performance score of 8607, in contrast to 7350 for Group A. Group B exhibited enhanced planning, lower error rates, and more robust work attitudes. Feedback obtained from reflection sheets corroborated pupils' enhanced comprehension of spatial concepts and safety protocols. This study advocates for e-learning methodologies by introducing a novel hybrid paradigm that integrates physical simulation with digital support via AR. It mitigates the shortcomings of entirely online or exclusively digital learning systems by incorporating physical, manipulable elements into the virtual learning experience. This method enables students to engage with tangible items while obtaining digital instruction, connecting cognitive design with physical implementation. This work enhances the e-learning sector by integrating accessible physical simulation with AR technology, presenting a practical model suitable for low-resource settings. It illustrates that practical, low-tech resources—when enhanced by smart digital integration—can yield quantifiable educational improvements and promote the cultivation of vital engineering skills.

Keywords: e-Learning, Cardboard simulation, CDIO method, Blended learning, Engineering education, Practical skills development, Digital learning integration

1. Introduction

Amidst global technological progress and changing industry demands, engineering education pedagogy is evolving to equip students for real-world difficulties more effectively (Forcael, Garcés and Lantada, 2023; Al-Zoubi *et al.*, 2024). This change is evident in frameworks like Conceive–Design–Implement–Operate (CDIO), which synchronize educational experiences with professional engineering methods (Tanveer and Usman, 2022; Lenin, Siva Kumar and Selvakumar, 2023). In vocational education, pedagogical approaches must be based on theoretical frameworks and practical, scalable, and economical methodologies (Kang, 2024; Younis, 2025). In light of these changes, incorporating simulations and active learning technologies is becoming progressively vital.

A significant issue in engineering education is the financial expense and safety limitations linked to conventional workshop-based teaching, particularly with wood, metal, or electrical materials (Sahoo, Saraf and Uchil, 2025). These issues are particularly salient in resource-constrained institutions. Simulation-based learning has been thoroughly examined, encompassing computer-based modeling and physical prototyping (Demirel, Ahmed and Duffy, 2022; Cascella *et al.*, 2023; Shahrezaei *et al.*, 2024; Sounthornwiboon, Sriprasertpap and Nilsook, 2025). Nonetheless, digital simulations frequently necessitate advanced gear and comprehensive training for educators and learners (Brunzini *et al.*, 2022; Weis *et al.*, 2024). Consequently, a hybrid strategy employing economical physical media emerges as a pertinent answer.

Cite this article: Setiawaty, T. and Tjahjono, G. 2025. "Low-Cost Simulations and Augmented Reality: Enhancing Practical Learning in e-Learning Environments", *The Electronic Journal of e-Learning, 23(4)* pp 155-175, https://doi.org/10.34190/ejel.22.3.4046

Despite extensive research on simulation and engineering pedagogy, scant attention has been afforded to cardboard prototyping as a simulation medium for engineering design within woodcraft education. Cardboard provides the benefits of being economical, lightweight, secure, and readily manipulable with basic tools (Sapienza *et al.*, 2022; Venkatesan *et al.*, 2023). These attributes are appropriate for introductory design training and quick prototyping, particularly in vocational settings.

This project tackles a significant pedagogical deficiency: enhancing student learning outcomes in wood-based design via simulation without dependence on expensive or hazardous materials. The subsequent research questions have been formulated:

- How does using cardboard-based simulation influence students' design performance and problem-solving in woodworking education?
- What differences in work attitude and craftsmanship can be observed between students using simulation-based tools and those applying direct wooden materials?
- To what extent does using simulation (cardboard) improve planning accuracy and professional behavior in workshop-based learning?

This research advances engineering education by showcasing an innovative, scalable simulation technique that uses cardboard as a substitute for timber components in vocational training. It also presents a preliminary AR integration to facilitate visual verification throughout the design phase. The proposed method seeks to connect digital learning with practical application, offering a cost-efficient, safe, and pedagogically robust option for developing technical skills.

2. Literature Review

The gap between theoretical knowledge and practical application is a well-known challenge in engineering education (Bühler, Jelinek and Nübel, 2022). Students often struggle to translate abstract design concepts into tangible, real-world products that meet professional standards (ElSayary, 2025). This disconnect can hinder their ability to effectively implement design ideas in practice, particularly in fields where hands-on skills are critical. Numerous studies have documented this issue, emphasizing the importance of developing teaching methodologies that allow students to bridge this gap more effectively (Resch and Schrittesser, 2023; Al-khresheh, 2024). While valuable for building foundational knowledge, traditional methods frequently fail when equipping students with the practical skills they need to succeed in the engineering industry (Malhotra, Massoudi and Jindal, 2023). As a result, there is a growing recognition of the need for educational strategies that balance theoretical instruction with experiential learning (Salinas-Navarro *et al.*, 2024), helping students to grasp the complexities of real-world engineering problems better.

One of the most widely explored solutions to this challenge has been using digital simulations, which provide students with virtual environments to interact with complex design tasks. These tools have improved students' understanding of engineering concepts by allowing them to visualize and manipulate models in a controlled setting—digital simulations, as highlighted by Rodríguez-Abitia et al. (2020), have become invaluable in helping students tackle complex engineering problems without the need for expensive physical materials. However, these tools come with significant financial and technical burdens. Many educational institutions, particularly those with limited resources, struggle to implement advanced simulation software due to the high acquisition, maintenance, and training costs required for both instructors and students. Additionally, the absence of physical interaction in these virtual environments can limit students' ability to develop crucial hands-on skills in disciplines like woodworking and mechanical engineering, where material properties and tactile feedback are essential for mastering practical techniques. Educators have sought more accessible, hands-on alternatives to supplement or replace digital tools.

2.1 The Role of Simulations in Engineering Education

Digital simulations have become essential in modern engineering education, providing students with immersive virtual environments to explore complex designs and engineering concepts. These simulations, as highlighted by Zhang et al. (2023), allow students to visualize and manipulate digital models of projects, offering insights into processes like construction, assembly, and systems operation. In fields like civil, mechanical, and electrical engineering, where theoretical knowledge is often abstract, simulations help bridge the gap by offering real-time feedback and experimentation. Students can engage in tasks such as stress testing, fluid flow analysis, or circuit design in ways that would be difficult or impossible in traditional classroom settings (Portillo *et al.*, 2025).

These tools allow for iterative testing, enabling students to modify their designs quickly and explore multiple scenarios without the risk and expense of physical materials.

However, digital simulations have notable limitations despite their benefits, especially regarding tactile and hands-on skills. As Ferguson et al. (2022) pointed out, the absence of physical interaction in virtual environments makes them less effective for skills like woodworking or mechanical engineering, where direct contact with materials is essential for mastering the craft. In fields requiring precise manual dexterity and material manipulation, such as carpentry or machining, the lack of haptic feedback can hinder the development of essential practical skills. Students may become adept at navigating digital environments but struggle when transitioning to real-world scenarios, where the physical properties of materials—such as weight, texture, and resistance—play a significant role in the success of a project.

In addition to their limitations in tactile learning, digital simulations often present challenges regarding accessibility and cost. As noted by Hippe et al. (2020), the financial investment required for advanced simulation software and the hardware needed to run these programs can be prohibitive for many educational institutions. The steep learning curve associated with these tools also requires significant time and resources for instructors and students to master the technology. This complexity, combined with the costs of purchasing and maintaining the necessary equipment, creates barriers to widespread adoption, particularly in resource-limited settings. These drawbacks highlight the need for alternative, more affordable simulation methods to complement or replace digital tools, especially in hands-on disciplines like woodworking.

2.2 CDIO Approach in Engineering Education

The Conceive, Design, Implement, Operate (CDIO) framework has gained recognition as a comprehensive methodology for enhancing engineering education by offering a structured approach that mimics real-world product development. By focusing on the complete lifecycle of a project, the CDIO model enables students to move beyond theoretical learning to practical application, fostering a deeper understanding of both design and implementation (Shuhaiber and Aldwairi, 2023). In the Conceive phase, students generate ideas and identify a project's needs, allowing them to develop problem-solving skills early on. During the Design phase, students create detailed plans and technical specifications, preparing them for the implementation phase, where they turn their designs into tangible products. The final operation phase involves testing and assessing the functionality and sustainability of their creations, ensuring they meet real-world demands and standards.

One of the key advantages of the CDIO approach is its emphasis on hands-on learning and experiential education. As Suksong et al. (2023) have demonstrated, this model not only enhances technical skills but also promotes the development of critical soft skills such as teamwork, communication, and project management. The collaborative nature of CDIO encourages students to work in teams, mimicking the dynamic environments of professional engineering projects. This teamwork aspect is especially beneficial in preparing students for the industry, where interdisciplinary collaboration is often necessary to solve complex problems. Furthermore, by allowing students to engage in the full cycle of product development, CDIO instills a sense of ownership and responsibility for the outcome of their projects, which can significantly improve their confidence and readiness for the professional world.

Previous research has shown that the CDIO framework significantly improves students' technical abilities and understanding of the product creation process (Suksong, Chomsuwan and Suamuang, 2023). Additionally, studies have demonstrated that practical simulations and structured project phases enhance students' ability to conceive, plan, and execute complex engineering tasks (Yang and Zhou, 2023). However, these studies often emphasize expensive digital tools, leaving a gap in the literature for more accessible and economical approaches to replicating real-world engineering assignments (Song, 2022). This research addresses this gap by introducing a novel method integrating cardboard simulations within the CDIO framework to teach woodworking skills.

While the CDIO framework has been extensively applied in mechanical and electrical engineering fields, its application to more craft-oriented disciplines, like woodworking, is relatively underexplored. Woodworking, which requires a high degree of manual skill and material familiarity (Lee, 2023), can benefit from CDIO's structured approach but also faces unique challenges in integrating this methodology. Incorporating physical simulations, such as using cardboard models, provides an innovative adaptation of CDIO to woodworking education, offering students a hands-on experience that aligns with the framework's emphasis on real-world application. This study explores how this adaptation can enhance woodworking education by providing the conceptual and practical skills needed for the industry.

2.3 Cardboard Simulations in Woodworking Education

Physical simulations, such as cardboard models, have emerged as a promising solution to some of the challenges associated with digital simulations and traditional teaching methods in woodworking education. Unlike digital simulations, which may lack the tactile feedback crucial for mastering manual skills (Singhaphandu *et al.*, 2024), cardboard simulations allow students to engage with their designs physically, better understanding spatial relationships, material properties, and construction techniques (Seiringer *et al.*, 2022). By working with cardboard, students can experiment with scale models of their projects, cutting, folding, and assembling the material to mimic the processes they will use with wood. This hands-on approach provides a low-risk environment where mistakes can be made and corrected without the expense of wasted wood (Suckling *et al.*, 2024), enabling students to refine their designs and improve their craftsmanship.

One of the primary benefits of using cardboard for simulations is its accessibility. As Song (2022) points out, cardboard is a readily available, inexpensive material, making it a practical option for educational institutions with limited budgets. It offers a sustainable alternative to wood, which can be costly and environmentally taxing, particularly for large-scale projects. Furthermore, cardboard is easy to manipulate, allowing students to modify their designs quickly and iterate on their ideas. This flexibility is crucial in the learning process, as it encourages creativity and problem-solving while reinforcing the technical skills required for woodworking. By integrating cardboard simulations into the CDIO framework, educators can offer a comprehensive learning experience that includes conceptual and practical aspects of engineering design.

Despite its advantages, cardboard simulations also have certain limitations that must be addressed. While they offer an effective way to simulate design and construction processes, cardboard lacks wood's structural integrity and material properties, meaning that students may not fully grasp the challenges they will face when working with actual timber. The time and effort required to create accurate cardboard models can also be significant, particularly for complex designs. However, reduced material costs, enhanced student engagement, and improved learning outcomes make cardboard simulations valuable in woodworking education, particularly when used with other hands-on learning methods. This study aims to evaluate the effectiveness of cardboard simulations within the CDIO framework and assess their impact on students' technical skills, creativity, and readiness for professional woodworking tasks.

2.4 VR vs. Hands-On Simulations

VR and hands-on simulations represent two prominent yet fundamentally different approaches to experiential learning for engineering education (May *et al.*, 2023). Both systems seek to reconcile theoretical knowledge with practical abilities; nevertheless, they markedly differ in sensory engagement, accessibility, cost, and educational outcomes.

From a cognitive engagement standpoint, VR provides an immersive digital world where students can navigate three-dimensional locations, mimic intricate operations, and obtain real-time feedback (AlGerafi *et al.*, 2023; Song, Shin and Shin, 2023). This digital immersion improves conceptual comprehension, particularly in abstract subjects such as stress analysis or circuit logic. Nevertheless, it frequently lacks haptic input, essential for cultivating fine motor skills and tactile awareness required in woodworking or mechanical activities. In contrast, tactile simulations—like cardboard prototyping—enable learners to interact with materials directly, enhancing kinaesthetic learning and spatial reasoning (Nazlidou *et al.*, 2024). This approach improves skill and practical insight, which are challenging to reproduce in a digital setting.

Regarding cost and accessibility, hands-on simulations like cardboard modeling are considerably more economical. Institutions can implement these strategies without investing in advanced VR technology or complex infrastructure. Physical simulations are especially beneficial in resource-constrained environments where digital fairness is ongoing (Kamdjou *et al.*, 2024). Conversely, VR entails substantial initial headgear, software, and training expenditures. Maintenance and upgrades hinder widespread application (Iqbal *et al.*, 2024).

From an instructional design perspective, VR provides scenario-based learning and virtual experimentation. It enables students to participate in repeatable, secure simulations replicating hazardous or high-stakes engineering activities. Nonetheless, as indicated in previous research, the lack of actual engagement may lead to shallow learning when the objective is to create physical objects (Wong and Liem, 2022). Practical methods, however, constrained in scenario adaptability, offer concrete problem-solving experiences—allowing learners to handle actual materials, identify manual errors, and progressively enhance their techniques.

The transferability of skills is another significant factor to consider. VR assists students in acclimating to digital tools and workflows prevalent in contemporary business, including CAD integration and virtual prototyping, thus augmenting their digital literacy. Conversely, practical simulations enhance physical dexterity, precision, and meticulousness, essential in craft-oriented and material-centric fields.

Numerous academics have advocated for integrated methodologies that merge the advantages of VR and practical simulations (Solmaz *et al.*, 2021; Abbas Shah *et al.*, 2024). To improve realism and immersion, cardboard simulations can be enhanced with AR overlays or virtual validation processes. These hybrid approaches demonstrate the potential to deliver a well-rounded educational experience that is both digitally proficient and substantively anchored.

The theoretical comparison of VR with hands-on simulations indicates a complementing relationship rather than a competitive one. Although VR excels in replicating intricate systems and surroundings, practical simulations are crucial for developing physical skills and enhancing tactile cognition. Optimal engineering education may benefit from strategic integration, contingent upon learning objectives, institutional capacities, and discipline-specific prerequisites (Beldad and Miedema, 2025).

3. Method

This study employed a mixed-method approach, combining both qualitative and quantitative data (Matović and Ovesni, 2023) to thoroughly assess the effectiveness of cardboard simulation in developing woodworking skills using the CDIO framework. The research was conducted over two months at Nusa Cendana University, with participants drawn from the Wood Practice course. Two groups of students were involved: Group A, which followed traditional woodworking methods, and Group B, which utilized cardboard simulations before working with wood. Seventy-six students participated in the study, with 36 students in Group A and 40 in Group B. Both groups were tasked with designing and constructing a bookshelf, following the exact technical specifications.

Each group was evaluated based on their performance across four distinct phases: product design, product manufacture, work attitude, and product assessment. These phases were chosen to reflect key CDIO framework aspects, ensuring that conceptual and practical competencies were adequately assessed (Alarcon-Pereira *et al.*, 2023). A detailed evaluation rubric assessed student performance in each phase, covering technical accuracy, creativity, teamwork, and problem-solving abilities. This comprehensive evaluation allowed for a deeper understanding of how cardboard simulations impact different facets of the woodworking process.

3.1 Research Design

The research was structured around the CDIO methodology (Martseva *et al.*, 2021). In the Conceive phase, students from both groups were asked to generate design ideas for a bookshelf with a branching structure, which would be produced during the later stages. This phase focused on creativity and innovation, with each group tasked with developing technical blueprints and preparing for the manufacturing phase. Group A moved directly from the design to the manufacturing stage using wood. At the same time, Group B utilized cardboard to simulate the design before moving to actual wood. In the Design phase, Group A created traditional technical drawings. In contrast, Group B first designed a scaled-down prototype using cardboard. The prototype allowed them to test the construction process and make necessary adjustments before working with wood. This approach gave Group B a hands-on, experimental opportunity to address potential issues in design, such as structural integrity or alignment problems, which they could rectify in the cardboard simulation (Hariharasakthisudhan *et al.*, 2025). This additional step aimed to reduce material wastage and improve final product quality in the later stages. Table 1 provides an overview of the research stages and their descriptions, outlining the tasks assigned to each group during each phase of the study.

Table 1: Research Stages and Their Descriptions

Stage	Group A Task	Group B Task
1. Conceive	Brainstorm design ideas and create technical drawings for bookshelves.	Brainstorm design ideas and create technical drawings for bookshelves.
2. Design	Create technical drawings and detailed specifications for wood products.	Design and construct cardboard models before finalizing technical drawings.
3. Implement	Build bookshelves using wood based on technical drawings.	Use cardboard prototypes to build the final bookshelf with wood.
4. Operate	Evaluate final product quality, structural integrity, and aesthetics.	Evaluate final product quality, structural integrity, and aesthetics based on prototype.

3.2 Participants and Sampling

The participants in the study were undergraduate students enrolled in the Wood Practice course at Nusa Cendana University. A purposive sampling method was used to ensure a balanced and representative sample (Zhao, 2021). Both groups included students with varying levels of prior experience in woodworking. Before the experiment, a pre-test was administered to gauge students' baseline knowledge and technical skills, ensuring comparability between Group A and Group B. This pre-test covered basic woodworking concepts like material selection, tool usage, and safety procedures.

Group A consisted of 36 students who worked solely with wood throughout the project. Group B, with 40 students, used cardboard to simulate their designs before transitioning to wood. Demographic data such as age, gender, and previous woodworking experience were collected to control for variables affecting performance. These variables were analyzed to ensure that no significant differences between the groups could skew the results.

3.3 Materials and Tools

Group A utilized traditional woodworking materials and tools such as saws, chisels, drills, and sandpaper to craft their bookshelves. The wood used was pre-specified in the design brief, ensuring uniformity in material selection across the group. Students were expected to follow the technical drawings they created in the Design phase and construct the bookshelf without any prior physical simulation. This group focused on directly translating conceptual designs into wooden structures.

Group B, on the other hand, first constructed their bookshelves using cardboard sheets, glue, tape, scissors, and box cutters. The cardboard simulation allowed them to prototype their designs in a less costly and more forgiving medium before moving on to wood. This allowed Group B to experiment with different techniques for creating wood joints and connections and test the overall stability and appearance of their designs. Once satisfied with the cardboard prototype, students transitioned to wood for the final construction. This approach was expected to reduce material wastage and improve the precision of the final product (Clancy, O'Sullivan and Bruton, 2023). Table 2 shows a detailed breakdown of the materials and tools used by each group, along with the evaluation criteria for assessing tool use and material handling.

Table 2: Materials and Tools Used by Each Group and Evaluation Criteria

Group	Material/Tool	Evaluation Criteria
A	Wood	Quality of wood preparation
A	Saw	Precision in cutting
A	Chisel	Skill in using chisels for joints
A	Drill	Accuracy in drilling
B	Cardboard	Accuracy in simulating design
B	Glue	Effectiveness in assembling
B	Scissors	Precision in cutting cardboard
B	Box Cutter	Safety and precision in cutting

This study mostly centers on cardboard simulations. However, an AR support pilot was implemented using a mobile-based AR viewer created with Unity and the Vuforia SDK. This AR component enabled students in Group B to scan their cardboard models using smartphones or tablets, receiving digital overlays with construction instructions and dimensional accuracy (McCord *et al.*, 2022). The technology delivered instantaneous feedback on prevalent faults (misalignment and joint gaps) using object identification markers affixed to the prototype. This experimental feature facilitated improved spatial verification and directed learning. The AR implementation was restricted to visualization and instructional overlays rather than comprehensive digital prototyping. It was utilized to augment design understanding during the "Design" and "Operate" phases of the CDIO cycle.

3.4 Procedure

The study adhered strictly to the CDIO framework, ensuring students engaged in all four stages: Conceive, Design, Implement, and Operate. During the Conceive phase, students were introduced to the design brief. They were encouraged to brainstorm creative solutions for the bookshelf design. In the Design phase, Group A created detailed technical drawings of their bookshelf. At the same time, Group B followed a similar process but then proceeded to build a scaled cardboard prototype. This simulation phase allowed Group B to identify potential design flaws, such as weak joints or unbalanced structures, and rectify these issues before working with wood.

In the implementation phase, both groups built their bookshelves. Group A worked directly with wood, while Group B transitioned from cardboard models to wood. The operation phase involved evaluating the final product. The assessment focused on several factors: structural integrity, aesthetic quality, and project completion time. Both groups were also evaluated on their work attitude, including teamwork, adherence to safety protocols, and problem-solving abilities. Table 3 outlines the assessment components and indicators used in the evaluation process. These criteria were applied consistently to both groups to ensure an objective performance comparison.

Table 3: Assessment Components and Indicators

Stage	Assessment Components	Indicators
Design	Product drawing, working drawings, simulation accuracy (Group B)	Accuracy of design drawings, completeness of details, simulation correctness
Product Manufacturing	Tool preparation, material preparation, cutting, and assembly accuracy	Efficiency in preparation, precision in cutting, assembly neatness
Work Attitude	Collaboration, discipline, honesty, responsibility	Level of collaboration in groups, adherence to project deadlines, integrity
Product Assessment	Product presentation, final product quality, adherence to specifications	Overall product quality, structural integrity, time management

3.5 Data Collection

Data were collected through objective product assessments, observational data, and self-reported student experiences. The objective evaluations focused on the quality of the final bookshelf, with specific attention to technical accuracy, adherence to design specifications, and material wastage (Li, Xiong and Qu, 2023). Students' work attitude, including teamwork, discipline, and responsibility, was also evaluated through observational data recorded by the instructors during the manufacturing process. This data was complemented by post-test scores, which assessed students' technical knowledge at the end of the project.

In addition to quantitative data, qualitative data were gathered through semi-structured interviews and questionnaires. Students were asked to reflect on their learning experiences, challenges, and perceptions of the cardboard simulation. These qualitative responses were coded thematically to identify common themes related to the usefulness of the cardboard simulation, the ease of transitioning from cardboard to wood, and any perceived improvements in problem-solving and technical skills.

3.6 Assessment and Evaluation

The assessment rubric used in this study included several categories: design accuracy, material preparation, construction technique, finishing quality, and work attitude (Amarasinghe, Hong and Stewart, 2024). Each category was rated on a scale from 1 to 5, with specific benchmarks for each score. For instance, a 5 in design accuracy score was given if the final product closely matched the original technical drawing. In contrast, a lower score indicated significant deviations. In addition to assessing the final product, teamwork and time management were also evaluated as part of the rubric, recognizing the importance of these skills in engineering education.

For Group B, an additional evaluation was conducted on their cardboard prototypes. This evaluation focused on the accuracy of the prototype compared to the final product, the insights gained during the simulation phase, and how effectively these insights were applied in the wood construction phase. The results from both groups were compared to determine whether the cardboard simulation had a measurable impact on the quality of the final product and the student's learning experience.

3.7 Data Analysis

Quantitative data were analyzed using statistical methods, including t-tests and ANOVA (Liu and Wang, 2021), to determine if there were significant differences in the performance outcomes between Group A and Group B. These tests helped identify whether the use of cardboard simulation had a statistically significant effect on the quality and efficiency of the final products. In addition to product assessment, data from the post-tests were also analyzed to measure the improvement in technical knowledge among students in both groups.

Qualitative data from the interviews and questionnaires were analyzed using thematic coding (Anderson *et al.*, 2022). The responses were categorized based on recurring themes, such as the perceived usefulness of the cardboard simulation, the challenges faced in transitioning from cardboard to wood, and the overall learning experience. This qualitative analysis provided valuable insights into how students felt about using simulation in woodworking education and its impact on their confidence and technical abilities.

Group A and B's comparative analysis yields significant insights. However, scientists recognize that cardboard and wood possess inherently distinct physical features. The investigation concentrated on the final product performance and process-based variables, including planning quality, tool preparation, and error reduction during execution. The evaluation criteria were modified to prioritize design precision and problem-solving in the initial stages, where material differences were less significant. This method facilitated a more equitable evaluation of cognitive and procedural learning outcomes, as opposed to solely material-dependent craftsmanship.

4. Results and Discussion

The study's findings are categorized into three groups: the researchers' assessment of student practical competence and the students' appraisal of wood product competency. Students were instructed to explain their response choices. Table 4 compares grades and items generated by classes A and B.

Table 4: Assessment results of making wood products

Stages	Assessment Components	Indicator	Group A	Group B
1	2	3	4	5
Stage 1 Product Feasibility Study - R&D **II**	Planning the task (Score 10%)	Drawing Product design Making working drawings (appearance - detail) Making pictures projection	76,60 78,50 74,50	76,50 78,50 76,80
	Mean value I		76,53	77,27
	Make a wood product task simulation (Score 20%)	2.1 Prepare cardboard boxes, glue, insulation, scissors, cutters, etc. 2.2. Construction drawing in cardboard 2.3. Cut the cardboard accordingly Image 2.4 Assemble simulation products 2.5. Correctness of measure 2.6. Correctness of construction 2.7. Simulation time and results	0,00 0,00 0,00 0,00 0,00 0,00	80.60 78,20 74,60 78,80 80.40 78,80
Average value II			0,00	77,60
Stage 2 Product Manufacturing	Preparation of tools and materials (Score 10%)	3.1. Preparing the workplace 3.2. Prepare tools and machine 3.3. Preparing materials 3.4. Preparing tools work safety	75,00 72,00 78,00 72,00	75,00 78,00 78,00 82,00

Stages	Assessment Components	Indicator	Group A	Group B
1	2	3	4	5
Average value III			74,25	78,25
IV	Process (Systematics and Way of Working) (Score 20%)	4.1. Measuring materials	72,00	78,00
		4.2. Construction drawing in wood	72,60	78,60
		4.3. Correctness of construction	73,00	84,00
		4.4. Cutting, sawing, smoothing wood	76,00	84,00
		4.5. Assembling the product	74,80	86,40
		4.6. Tidying up the product	65,00	84,80
		4.7. Initial finishing of the product (smoothing, smoothing, caulking, polishing)	74,00	84.00
Average score IV			72,49	82,63
V	Wood product results and presentation (30% score)	5.1. Conformity of drawings to wood products	74,00	84,00
		5.2. Correctness of size and construction	72,00	88,00
		5.3. Product robustness	70,70	86,80
		5.4. Final finishing	74,40	88.80
		5.5. Time to complete the task	74,80	86,40
			72,00	85.00
Mean value V			72,98	87,07
	Product presentation (10% score)	6.1. Make a product report	78,00	86.00
		6.2. PPT making	82,00	85,00
		6.3. Task Presentation	76,00	86,00
		6.4. Answering questions from lecturers and students	76,00	84,00
			78,00	85,00
VI	Work Attitude (Maximum score 10)	6.1. Cooperation	72,00	84,60
		6.2. Discipline	72,00	86.80
		6.3. Hard work	74,00	88,60
		6.4. Honest	75,00	80.20
		6.5. Responsibilities	80,00	85,00
VI average value			74,60	86,07

Table 4 demonstrates Group B's superiority over Group A due to using cardboard simulations. During the product design stage, group B exhibited higher average scores in task planning and modeling the wood product work. This demonstrates that the cardboard simulation enhanced students' ability to visualize and engage in more intricate and meticulous planning (Chisunum and Nwadiokwu, 2024). Group B demonstrated exceptional performance in preparing tools and materials and the working process, achieving average scores of 7825 and 8263, respectively. This indicates that the cardboard simulation offers a superior comprehension of the necessary equipment and supplies and more organized and effective work procedures (Špirková, Straka and Saniuk, 2024). This demonstrates that using simulation can minimize inaccuracies and enhance work efficiency.

Furthermore, regarding the product results, group B exhibited superior scores in fit, sturdiness, and finishing, averaging 8707, as opposed to group A's average of 7298. This implies that using simulated cardboard contributed to creating a superior end product in terms of quality and aesthetics. The work attitude of Group B was exceptional, as evidenced by their average score of 8607. This indicates a higher level of discipline, collaboration, and responsibility. These results demonstrate that the cardboard simulation serves as both a visual assistance and a successful tool for enhancing students' technical skills, work processes, and professional attitudes in wood practice (Ortega-Gras *et al.*, 2023).

This study primarily concentrated on low-cost physical simulations utilizing cardboard while investigating an initial incorporation of AR support. A mobile AR viewer was utilized in a pilot study to enable students to superimpose digital guidelines over their cardboard prototypes. This technology, developed using Unity and Vuforia, allowed students to visualize assembly instructions and verify their designs in real-time (Kumar, Mantri and Dutta, 2021). While not a fundamental element of the primary intervention, the AR-assisted simulation effectively enhanced spatial comprehension and increased assembly accuracy. Future implementations may evolve this component into a comprehensive educational module, facilitating enhanced interaction between physical models and digital overlays.

Nevertheless, caution is warranted when assessing direct performance comparisons due to the intrinsic disparities in material properties between cardboard and wood. The results are more accurately interpreted as enhancing planning, visualization, and process precision rather than directly assessing physical production quality. Figure 1 displays both the simulation product and the final wood practice piece.

Figure 1: Simulation Results of the Cardboard

Figure 1 displays the outcomes of a simulation, including using cardboard to imitate a wooden product. Within the CDIO framework, this pertains to the "Conceive" and "Design" stages. During the "Conceive" phase, students engage in the process of conceptualizing and creating concepts for wood goods. They engage in sketching product designs and producing detailed technical drawings. During the "Design" step, the idea is transformed into an early physical representation using cardboard. This simulation enables them to assess the concept and design before moving forward with the physical wood substance. This minimizes the likelihood of design mistakes and guarantees the accuracy of all building components before subsequent execution. Moreover, employing cardboard for simulation is a cost-efficient and highly adaptable method, facilitating rapid and successful design iterations, , as demonstrated in the final product shown in Figure 2.

Figure 2 depicts the ultimate wooden product resulting from the implementation and operating process. This refers to the "Implement" and "Operate" stages of CDIO. During the "Implement" phase, students gather and organize the necessary equipment and materials and adhere to structured and methodical working methods. The cardboard prototype seen in Figure 1 provides a step-by-step demonstration of the precise actions involved in cutting, assembling, and refining the wooden product. This phase encompasses all the operations involved in the process, starting from cutting the wood, making the pieces, and concluding with the last finishing touches, such as polishing the surfaces and applying a protective coating. During the "Operate" phase, the completed wood items are assessed based on their functionality and appearance. Students showcase their final deliverables, demonstrating their ability to fulfill customer requirements and adhere to high-quality benchmarks. The superiority of group B, as shown by the cardboard simulation, was visible in the high quality and efficiency of their process and the superior end product they produced. The strengths and weaknesses of each CDIO phase, as observed in this study, are summarized in Table 5.

Figure 2: Bookshelf product

Table 5: Strengths and weaknesses of the study

Aspects	Pros	Disadvantages
Conceive	• Make it easier to visualize design ideas and concepts. • Reduce the risk of errors in the early stages of planning.	• Requires additional time to make simulations before making the actual product.
Design	• It provides an opportunity to refine and perfect the design before implementation. • Cardboard is cheaper and easier to modify than wood.	• It does not entirely reflect the actual strength and material characteristics of wood.
Implement	• Provides clear guidance for the cutting and assembly process. • Reduce technical errors in product manufacturing and improve artistry efficiency.	• Additional skills are required to create accurate and detailed simulations.
Operate	• The final product results are better in terms of quality and aesthetics. • Promote a more disciplined and collaborative work attitude.	• Simulations cannot thoroughly test the durability and performance of the product under actual use conditions.

Table 5 demonstrates that although cardboard simulation entails certain disadvantages, such as the requirement for extra time and specialized expertise, its benefits in streamlining visualization, enhancing efficiency, and generating superior quality goods are substantial. The limitations can be solved via training and knowledge, rendering cardboard simulation an invaluable tool in engineering education and product creation.

Student feedback on implementing the CDIO approach in the practical application of bookcase production using cardboard simulations. The favorable feedback from students emphasized the notable advantages of utilizing this simulation, such as the capacity to more effectively strategize and evaluate the product before commencing actual production. Additionally, they highlighted that using cardboard decreased manufacturing errors, enhanced the preparation of all materials, and accelerated production time and product completion. Furthermore, the end outcome of the bookshelf product created utilizing simulated cardboard is asserted to be superior, and the time needed is more optimized. The responses to the pupils' inquiries are seen in Table 6.

Table 6: Question Answers to Students

No.	Aspect Answer	Classification
1.	Make it easier for students to apply drawing plans to simulated cardboard products.	Positive
2.	Students better understand the final product that needs to be done.	Positive
3.	Students can better analyze the steps that must be done first, thus reducing errors.	Positive
4.	It is easier for students to replace the cardboard if they make size, cutting, or assembly mistakes.	Positive
5.	Reduce errors in work because you have prepared all the materials and work steps.	Positive
6.	Save time by doing the initial finishing before the wood is assembled.	Positive
7.	Assembling wood is faster because all parts are already prepared with the right size and construction.	Positive
8.	Removing and gluing wooden joints is faster because the construction is done correctly.	Positive
9.	The final finishing is done faster because of the pre-finishing before the wood assembly.	Positive
10.	The results of the bookshelf product are better, and the time required is faster.	Positive
11.	Students completed making a branching bookshelf faster and with better results.	Positive
12.	It takes 1 - 2 weeks to make a simulation by disassembling the parts of the bookshelf.	Negative
13.	Thin cardboard is not good because it is not as rigid as wood.	Negative
14.	It costs more to use cardboard, paper glue, and cutters.	Negative
15.	The simulation must be made correctly, as it will be the same as the resulting wood product.	Negative

Conversely, pupils who responded negatively emphasized the difficulties and disadvantages they encountered when using the cardboard simulation. It was observed that constructing the simulation involved more significant effort (Seiringer *et al.*, 2022) and intricacy in dismantling the cardboard bookshelf components. Furthermore, thin cardboard was deemed inadequate due to its lack of rigidity compared to wood and the added expenses associated with acquiring old cardboard, paper glue, and other necessary equipment. However, the data presented in this table indicates that despite a few challenges, the utilization of cardboard simulation offers numerous substantial advantages in both the educational experience and the enhancement of students' hands-on abilities in woodworking.

The CDIO idea is methodically employed in industry to create new goods that effectively fulfill market demands with superior quality and maximum production efficiency. The Conceive stage encompasses identifying the target market and conducting thorough trend research (Zabalawi, Kordahji and Mourdaa, 2022). This is followed by the Design stage, where Computer-Aided Design (CAD) software is utilized to create the product design. Additionally, digital simulations are performed to provide initial validation of the design (Wagg *et al.*, 2020). Implementation encompasses the process of manufacturing according to design specifications with rigorous quality control measures. On the other hand, the operation stage concentrates on conducting final testing, facilitating distribution, and providing customer support to guarantee optimal product performance and responsiveness to market feedback. This stage supports ongoing innovation and enables a quick time-to-market.

4.1 Enhancing Simulation-Based E-Learning with Augmented Reality (AR) and Interactive Digital Guides

Incorporating AR and interactive digital aids into simulation-based e-learning offers a revolutionary prospect for engineering and vocational education. Although physical simulations like cardboard modeling give beneficial practical experience, their efficacy can be improved by integrating AR technologies that deliver interactive overlays, instantaneous feedback, and customizable learning trajectories. By integrating these methodologies, students can cultivate technical competencies and digital literacy, equipping them for the industry's increasing requirements.

AR improves visualization by enabling students to superimpose 3D models over their physical simulations. Students can scan their cardboard prototypes using AR-enabled programs and obtain immediate advice on assembly methods, structural integrity, and design precision. This function mitigates prevalent errors during the first learning phase, lowering material loss and enhancing the quality of the final output (Joseph Nnaemeka Chukwunweike *et al.*, 2024). Furthermore, AR allows students to investigate alternate designs, examine cross-sectional details, and engage with virtual components before utilizing actual materials. This digital support layer facilitates a comprehensive comprehension of woodworking principles while preserving the advantages of practical experience.

Integrating interactive digital aids enhances the learning experience by offering organized, self-directed training. These guides may encompass video demonstrations, sequential lectures, and AI-powered assessment tools that monitor student progress and offer tailored recommendations. By including these components, students can obtain immediate feedback on their assignments, enhancing their capacity to recognize and rectify errors autonomously. Moreover, digital guides facilitate flexible learning, enabling students to interact with course materials remotely and enhancing e-learning accessibility.

Integrating AR with physical simulators fosters a more immersive and practical educational experience. Conventional cardboard models provide an economical method for design and assembly practice; however, when enhanced with AR overlays, they transform into potent instruments for interactive education. This method enables students to acquire immediate insights into their work while preserving the advantages of hands-on interaction. It also equips them for professional settings where digital technologies are progressively incorporated into engineering and manufacturing processes.

Notwithstanding its benefits, the execution of AR-assisted learning presents obstacles. Creating AR material necessitates technology infrastructure, software enhancements, and training for students and educators. Certain institutions may have financial limitations in implementing these technologies, requiring scalable and economical solutions like mobile-based AR apps. Moreover, it is essential to meticulously address the cognitive burden of transitioning between physical and digital worlds to guarantee a seamless and successful learning experience.

Integrating AR and interactive digital guides into simulation-based e-learning enables educational institutions to establish a more immersive and flexible learning environment. This integrated method increases student involvement, boosts error identification, and facilitates autonomous learning, ultimately elevating skill mastery. Future studies should examine the enduring effects of AR-assisted physical simulations on student performance and industry preparedness and assess the scalability of these technologies across various educational environments.

4.2 Comparison of Cardboard Simulations, Augmented Reality (AR), and Hybrid AR-Cardboard Approaches

The swift advancement of technology in education has resulted in several simulation-based learning methodologies designed to augment student engagement and enhance skill acquisition. In engineering and vocational education, conventional hands-on training techniques are progressively enhanced by digital tools, such as AR, to foster more engaging and immersive learning experiences. Although physical simulators, such as cardboard models, offer economical and hands-on educational experiences, they may be deficient in the technical advancements required for precise learning and immediate feedback. In contrast, AR-based simulations provide highly dynamic environments but frequently fail to accurately replicate the physical limitations and human dexterity necessary for real-world applications.

A hybrid strategy that combines cardboard simulations with AR technology has emerged as a possible way to address these gaps (Iqbal, Mangina and Campbell, 2022). This combination utilizes the advantages of tactile material interaction alongside digital overlays for improved visualization, evaluation, and direction. This review examines the advantages and limitations of three techniques in engineering education: cardboard-only simulations, AR-based learning, and hybrid AR-cardboard integration. The analysis evaluates factors such as cost, engagement, error detection, scalability, and industry preparedness to ascertain which method provides the most efficient and accessible learning experience. Table 7 presents a comprehensive comparison analysis of these three learning methodologies, emphasizing their advantages and disadvantages across diverse educational and technical criteria.

Table 7: Comparative Analysis of Cardboard, AR, and Hybrid AR-Cardboard Approaches in Engineering Education

Aspect	Cardboard Simulation	(AR)	Hybrid AR-Cardboard Simulation
Cost	Low-cost, accessible to all institutions	The high initial cost of software, hardware, and development	Moderate cost (uses AR with low-cost cardboard materials)
Material Representation	It simulates physical handling but lacks actual wood properties	Virtual visualization lacks honest tactile feedback	Balances digital visualization with hands-on material interaction
Learning Experience	Hands-on, encourages spatial awareness and craftsmanship	Interactive and dynamic, but lacks physical engagement	Best of both worlds: real-world interaction with digital enhancements
Error Identification	Manual error detection, trial-and-error process	Instant AI-based feedback, but may not detect hands-on mistakes	AR-assisted error detection with real material handling
Flexibility & Scalability	Easy to implement in any institution	Requires technological infrastructure, software updates	Scalable with mobile AR apps and physical materials
Engagement & Motivation	Engaging but may feel repetitive for tech-savvy students	High engagement due to interactive digital elements	It is most engaging as it blends tactile learning with digital interactivity
Collaboration & Remote Learning	Requires in-person interaction	Enables remote learning and collaboration	Supports both in-person and remote learning scenarios
Implementation Time	Requires time to create and test models	Quick access to simulations but with a learning curve for AR	It may take time to integrate both tools, but it offers long-term benefits
Industry Readiness	Improves manual skills but lacks real-world automation experience	Familiarizes students with digital tools used in industries	Develops both manual craftsmanship and digital competency
Cognitive Load	Medium – students focus on physical execution	High – requires cognitive adaptation to virtual spaces	Balanced – students experience both physical and digital learning modalities
Sustainability & Resource Use	It is environmentally friendly if recycled materials are used	Energy-intensive, dependent on electronic devices	Sustainable if combined with low-energy AR applications

From Table 7, each method—cardboard simulations, AR, and the hybrid AR-cardboard model—presents unique benefits and drawbacks in engineering education. Cardboard simulations offer students a practical, economical method to enhance spatial awareness, problem-solving abilities, and craftsmanship before engaging with actual materials. This approach is especially advantageous for resource-constrained institutions, as it obviates the necessity for costly software and hardware. Moreover, cardboard allows students to engage in hands-on design alterations, promoting creativity and iterative learning. A significant drawback is that cardboard does not entirely emulate the material characteristics of wood, including texture, weight, and durability. This may create a disparity between virtual practice and real-world application, necessitating further training to move effectively to practical woodworking. Moreover, error detection in cardboard simulations is contingent upon manual assessment, so relying on instructor oversight heightens the possibility of subjective evaluation.

Conversely, AR-based learning provides an interactive and visually rich method that improves conceptual comprehension and accuracy. AR enables students to superimpose 3D models onto practical environments, facilitating the exploration of design complexities, experimentation with various configurations, and acquisition of immediate feedback on inaccuracies. This minimizes trial-and-error methods and assists students in enhancing their designs prior to undertaking practical prototypes. Furthermore, AR-based simulations facilitate remote learning, rendering them accessible to students without access to conventional workshops. Despite these benefits, AR lacks the physical interaction essential for cultivating practical skills. Students utilizing AR simulations may encounter difficulties in material handling when applying concepts in real-world scenarios, as they lack exposure to the physical restrictions of weight, resistance, or texture. Moreover, the application of AR necessitates substantial technological investment, including appropriate gear, software development, and instructor training, rendering it less viable for institutions with financial limitations.

The hybrid AR-cardboard model aims to amalgamate the advantages of both methodologies, merging the cost-effectiveness and tactile involvement of cardboard simulations with the interactivity and accuracy of AR. This approach enables students to construct prototypes while employing AR overlays for immediate advice, error identification, and instructional assistance. Students may enhance accuracy and minimize design errors by scanning their cardboard models using an AR-enabled device to check their work against digital benchmarks. The hybrid method enhances industry preparedness by cultivating manual dexterity and digital literacy, which are vital in contemporary engineering and manufacturing contexts (Nithyanandam, Munguia and Marimuthu, 2022). This method necessitates extra preparation time and coordination since students must switch between physical and digital instruments. Moreover, although hybrid models diminish expenses relative to complete AR simulations, they still necessitate investment in AR apps and digital learning resources, which may present difficulties for specific institutions.

The selection between these methodologies is contingent upon educational objectives, resource availability, and student learning inclinations. Cardboard simulators are the most accessible and economical choice for practical training, yet they may lack accuracy and digital integration. AR-based learning shines in visualization and remote accessibility. However, it does not adequately facilitate the development of physical skills. The hybrid paradigm provides a balanced approach, augmenting physical education with digital accuracy, albeit necessitating a moderate technical investment. Future studies should investigate the effects of these methodologies on long-term skill retention and industry readiness, ensuring that engineering education adapts to the requirements of a technology-driven labor market.

4.3 Cardboard Models vs. Virtual Reality (VR) Models

In contemporary engineering education, simulation-based learning methodologies are essential for connecting theory with practice. Two increasingly popular methodologies are physical simulations employing cardboard models and digital simulations utilizing VR. Although both seek to improve conceptual comprehension and skill development, they vary in sensory engagement, learning outcomes, cost, and accessibility.

As mentioned in this study, cardboard models offer students tactile, three-dimensional representations of their creations. They are exceptionally proficient in woodworking and other material-centric fields where tactile manipulation and spatial precision are crucial. The tactile aspect of cardboard simulations enables students to acquire proficiency in cutting, assembling, and manipulating actual components—skills essential in technical disciplines that depend on manual craftsmanship.

Conversely, VR-based digital models provide comprehensive, immersive visualisations that enable students to engage with intricate ideas in a safe, simulated setting. VR facilitates real-time feedback, walkthroughs, and interaction with digital prototypes that would be challenging or costly to reproduce physically. This renders it exceptionally appropriate for tasks requiring high abstraction, perilous environments, or iterative design evaluation. Nonetheless, VR lacks material realism and tactile input, crucial for cultivating motor skills and comprehending physical limitations.

From an educational standpoint, cardboard simulations highlight iterative problem-solving and promote students' profound engagement with the creative process. They endorse experiential learning that aligns with the CDIO paradigm, facilitating seamless transitions from design to implementation. Conversely, VR simulations correspond more closely with cognitive load theory by minimising superfluous burdens, enabling students to visualise systems comprehensively and explore various perspectives dynamically. The selection between the two is contingent upon educational objectives, resource accessibility, and discipline emphasis. Table 8 provides a comprehensive comparison of these two methodologies.

Table 8: Comparison of Cardboard Simulations and VR Models in Engineering Education

Aspect	Cardboard Models	VR-Based Digital Models
Learning Style	Kinesthetic, tactile, hands-on	Visual, immersive, exploratory
Feedback Type	Manual, instructor-guided, peer-reviewed	Real-time system feedback, guided pathways
Skill Development	Manual dexterity, craftsmanship, tool handling	Spatial reasoning, digital fluency, systems thinking
Cost & Accessibility	Very low cost; accessible to all institutions	High initial cost; requires headsets, software, and infrastructure
Material Representation	Simulates real assembly, limited in material authenticity	Highly flexible, lacks physical feedback

 ISSN 1479-4403

Aspect	Cardboard Models	VR-Based Digital Models
Setup & Implementation	Easy setup, but time-consuming to build manually	Fast simulation deployment requires technical support
Error Detection	Human assessment and revision	AI-guided error identification, visual cues
Suitability by Discipline	Woodworking, product design, fabrication	Architecture, mechanical systems, high-risk simulations
Scalability	Scalable with recycled materials	Scalable with cloud-based access but limited by hardware needs
Student Engagement	Encourages hands-on creativity and teamwork	Enhances motivation through gamified learning
Cognitive Load	Moderate, distributed over manual and visual tasks	Potentially high, requires adaptation to virtual navigation
Industry Readiness	Strengthens material understanding and practical assembly skills	Builds familiarity with industry-standard design software

From Table 8, cardboard and VR-based simulations significantly enhance engineering education through different methods. Cardboard models are exceptional for imparting practical skills and spatial precision, rendering them suitable for fabrication-focused fields. VR models offer immersive visualisation and cognitive support, especially beneficial in intricate systems or conceptually dense subjects. Educational programs that optimise learning results should adopt blended methodologies, integrating physical simulations with digital visualisation tools to ensure student proficiency in handcraft and digital skills.

Cardboard models exemplify an economical, tactile methodology rooted in experiential learning. These simulations are fundamentally kinaesthetic, enabling students to handle materials, utilize hand tools, and perceive the spatial aspects of a design at an actual scale. This tactile interaction is particularly advantageous for fields such as carpentry or product design, where comprehending the physical properties of components, such as weight distribution, joint integrity, or manual alignment, is crucial. Cardboard models inherently promote patience, the development of fine motor skills, and an appreciation for craftsmanship—skills frequently overlooked in entirely digital environments.

Conversely, VR-based digital models primarily serve visual and spatial learners, providing an immersive experience that can replicate intricate systems and settings with negligible material risk. VR demonstrates exceptional conceptual clarity, enabling learners to manipulate, analyse, and engage with three-dimensional creations in ways unattainable in the physical world. This capacity renders VR exceptionally effective for comprehending abstract technical systems, such as fluid dynamics or circuit logic. Nevertheless, VR may prioritize visual learning to the detriment of tactile engagement, rendering it less successful for fields where sensory-motor connection is essential.

A frequently overlooked distinction pertains to the nature of feedback and reflection promoted by each strategy. Error detection with cardboard models predominantly depends on peer discourse, instructor oversight, and reflective practice, fostering collaborative learning and communication (Ataş and Yıldırım, 2025). Conversely, VR provides system-based feedback, frequently automated or AI-enhanced, which may expedite error correction but diminish opportunities for dialogic learning and peer evaluation (Rana and Chicone, 2025).

A further concealed layer pertains to learner autonomy and cognitive strain. Cardboard simulations enable learners to progress at their speed, physically arranging their concepts and modifying plans through iterative adjustments. This facilitates contemplative cognition and profound comprehension. Conversely, although VR can provide structured simulations for learners, it may also present a more challenging learning curve, necessitating users to acclimate to navigation controls and interface norms before engaging in substantive learning—thereby increasing cognitive demands, particularly for beginners.

From a sustainability standpoint, cardboard models constructed from recycled materials effectively correspond with environmentally responsible educational objectives (Ikemiyashiro Higa and Taki, 2024). Despite being paperless, VR systems depend on high-energy gadgets and regular updates, which raises worries regarding their long-term environmental impact and electronic waste. Institutions pursuing green education may favor physical models for economic considerations and their reduced ecological impact.

Regarding scalability and equity, cardboard models significantly outperform those used by under-resourced organizations. They necessitate no technical assistance and can be executed in virtually any classroom. VR, however, creates an accessibility gap—students lacking access to high-performance computers or VR equipment may face exclusion or disadvantage (Acevedo *et al.*, 2024). This component pertains to educational equity, an issue of growing significance in global dialogues around digital change.

Ultimately, both approaches have synergistic advantages when evaluating long-term alignment with industry standards. Cardboard simulations establish robust foundations in manual assembly, error resolution, and production planning—competencies pertinent to manufacturing, construction, or industrial design sectors. Simultaneously, VR provides students with proficiency in digital modeling, corresponding with modern architecture, systems engineering, and virtual prototyping practices. A hybrid methodology—initiating with cardboard for fundamental craftsmanship and augmenting with VR for systemic understanding—may offer the most thorough route to producing future-ready graduates.

4.4 Research Limitations and Future Research Directions

This study illustrates the efficacy of cardboard simulations in improving experiential learning in woodworking education; however, certain limitations must be recognized. A fundamental limitation resides in the portrayal of materials. Although cardboard offers a convenient and economical substitute for genuine wood, it fails to completely emulate the structural characteristics, including texture, weight, and durability. Consequently, pupils may not encounter the same degree of resistance and accuracy when engaging with authentic woodworking materials. This constraint may hinder the shift from simulation to practical applications, necessitating further practice with genuine materials to enhance students' skills.

A further constraint is the supplementary time and effort necessary for simulation preparation. Although cardboard simulations mitigate errors and enhance planning, they add a phase to the learning process, potentially prolonging the entire project duration. This may provide difficulties in educational environments with restricted class durations or stringent curriculum timelines. Moreover, fault detection in physical simulations predominantly relies on manual observation, necessitating vigilant oversight from instructors. In contrast to digital instruments that provide immediate feedback, students must depend on their judgment or peer evaluations, perhaps resulting in variations in assessment accuracy.

The research was performed at a single institution, rendering its findings context-dependent and possibly restricting generalizability. Differences in curriculum design, resource availability, and student demographics may affect the efficacy of cardboard simulations in various educational settings. Future research should investigate the efficacy of this strategy across diverse educational environments, including institutions with differing degrees of technological integration (Isaeva *et al.*, 2025). The study concentrated on short-term learning outcomes, evaluating immediate enhancements in skill acquisition. An extensive examination of the long-term effects of simulation-based learning, especially within industrial contexts, would yield a greater understanding of its efficacy in equipping students for professional careers.

Future studies should investigate the amalgamation of AR with physical simulations to mitigate these limitations (Crogman *et al.*, 2025). AR overlays enable students to obtain real-time feedback and interactive coaching, diminishing dependence on instructor oversight while promoting self-directed learning. The advancement of AI-driven assessment technologies may enhance the evaluation process by delivering automated input on design precision, construction methodologies, and project fulfillment. This hybrid methodology may address conventional physical simulations' limitations while preserving tactile involvement's advantages.

An interesting direction for future research is the scalability of simulation-based e-learning in distance education. The growing dependence on digital learning platforms necessitates the integration of affordable physical simulations with mobile AR applications to offer accessible training solutions for students in remote locations or institutions with constrained workshop facilities. Examining the efficacy of these models in hybrid and entirely online learning contexts would facilitate the broader implementation of blended learning methodologies in engineering and technical education.

Ultimately, longitudinal studies must be undertaken to assess the enduring advantages of simulation-based learning on students' preparedness for the business. Researchers can evaluate the effects of physical and AR-enhanced simulations on professional competencies, workplace flexibility, and technical proficiency over time by monitoring graduates who have participated in various training techniques. This research may provide significant insights for curriculum makers and educators aiming to enhance practical training methodologies in engineering education.

5. Conclusion

This study has shown that combining cardboard simulation and AR can improve engineering education quality, especially in vocational woodworking design. Utilizing the CDIO framework and segregating students into two learning cohorts revealed that the simulation-based methodology yielded significant technical correctness, planning precision, and student collaboration advantages. Students in Group B (simulation-based learning) quantitatively surpassed those in Group A (conventional learning) with an average score of 8607 compared to 7350.

Using cardboard as an economical, secure, and adaptable simulation medium allowed students to concentrate on design and problem-solving before interacting with actual materials. Despite the intrinsic distinctions between cardboard and wood, the simulation improved planning and visualization, resulting in superior real-world implementation. The preliminary application of AR technology, however, restricted in extent, enhanced value by delivering visual overlays for instructional assistance, thereby strengthening spatial comprehension throughout the prototype phase.

This research introduces a hybrid paradigm that integrates entirely digital and traditional learning methodologies from an e-learning perspective. It provides a pragmatic alternative for universities with restricted access to digital infrastructure or expensive materials, enabling them to adopt blended learning more inclusively and engagingly. The findings indicate that combining basic physical simulations with limited AR augmentation can enhance cognitive and technical results. Subsequent research may investigate the more profound integration of AR modules and extend the paradigm to more domains within engineering education.

AI Statement: The authors state that Artificial Intelligence tool was not used in thisstudy.

Ethics Statement: Ethics approval is not required

References

Abbas Shah, S. F., Mazhar, T., Shahzad, T., Khan, M. A., Ghadi, Y. Y., & Hamam, H. (2024) 'Integrating educational theories with virtual reality: Enhancing engineering education and VR laboratories', *Social Sciences & Humanities Open*, 10, p. 101207. doi: 10.1016/j.ssaho.2024.101207.

Acevedo, P., Magana, A. J., Benes, B., & Mousas, C. (2024) 'A Systematic Review of Immersive Virtual Reality in STEM Education: Advantages and Disadvantages on Learning and User Experience', *IEEE Access*, 12, pp. 189359–189386. doi: 10.1109/ACCESS.2024.3489233.

Al-khresheh, M. H. (2024) 'Bridging technology and pedagogy from a global lens: Teachers' perspectives on integrating ChatGPT in English language teaching', *Computers and Education: Artificial Intelligence*, 6, p. 100218. doi: 10.1016/j.caeai.2024.100218.

Al-Zoubi, A., San Cristobal, E., Shahroury, F. R., & Castro, M. (2024) 'The Middle East Higher Education Experience: Implementing Remote Labs to Improve the Acquisition of Skills in Industry 4.0', *IEEE Transactions on Learning Technologies*, 17, pp. 982–991. doi: 10.1109/TLT.2023.3341490.

Alarcon-Pereira, G., Rampasso, I. S., Tapia-Ubeda, F. J., Rojas-Aguilar, K., & Rojas-Córdova, C. (2023) 'The evolution of sustainability in engineering education research: a longitudinal analysis through bibliometrics and the CDIO initiative', *International Journal of Sustainability in Higher Education*, 24(6), pp. 1266–1289. doi: 10.1108/IJSHE-03-2022-0073.

AlGerafi, M. A. M., Zhou, Y., Oubibi, M., & Wijaya, T. T. (2023) 'Unlocking the Potential: A Comprehensive Evaluation of Augmented Reality and Virtual Reality in Education', *Electronics*, 12(18), p. 3953. doi: 10.3390/electronics12183953.

Amarasinghe, I., Hong, Y. and Stewart, R. A. (2024) 'Development of a material circularity evaluation framework for building construction projects', *Journal of Cleaner Production*, 436, p. 140562. doi: 10.1016/j.jclepro.2024.140562.

Anderson, R., Taylor, S., Taylor, T., & Virues-Ortega, J. (2022) 'Thematic and textual analysis methods for developing social validity questionnaires in applied behavior analysis', *Behavioral Interventions*, 37(3), pp. 732–753. doi: 10.1002/bin.1832.

Ataş, A. H. and Yıldırım, Z. (2025) 'A shared metacognition-focused instructional design model for online collaborative learning environments', *Educational technology research and development*, 73(1), pp. 567–613. doi: 10.1007/s11423-024-10423-4.

Beldad, A. D. and Miedema, H. A. T. (2025) 'Introducing a framework for designing an interdisciplinary engineering curriculum: educating new engineers for complex sociotechnical challenges', *European Journal of Engineering Education*, pp. 1–18. doi: 10.1080/03043797.2025.2507243.

Brunzini, A., Papetti, A., Messi, D., & Germani, M. (2022) 'A comprehensive method to design and assess mixed reality simulations', *Virtual Reality*, 26(4), pp. 1257–1275. doi: 10.1007/s10055-022-00632-8.

Bühler, M. M., Jelinek, T. and Nübel, K. (2022) 'Training and Preparing Tomorrow's Workforce for the Fourth Industrial Revolution', *Education Sciences*, 12(11), p. 782. doi: 10.3390/educsci12110782.

Cascella, M., Cascella, A., Monaco, F., & Shariff, M. N. (2023) 'Envisioning gamification in anesthesia, pain management, and critical care: basic principles, integration of artificial intelligence, and simulation strategies', *Journal of Anesthesia, Analgesia and Critical Care*, 3(1), p. 33. doi: 10.1186/s44158-023-00118-2.

Chisunum, J. I. and Nwadiokwu, C. (2024) 'Enhancing Student Engagement through Practical Production and Utilization of Instructional Materials in an Educational Technology Class: A Multifaceted Approach', *NIU Journal of Educational Research*, 10(2). doi: 10.58709/niujed.v10i2.2002.

Clancy, R., O'Sullivan, D. and Bruton, K. (2023) 'Data-driven quality improvement approach to reducing waste in manufacturing', *The TQM Journal*, 35(1), pp. 51–72. doi: 10.1108/TQM-02-2021-0061.

Crogman, H. T., Cano, V. D., Pacheco, E., Sonawane, R. B., & Boroon, R. (2025) 'Virtual Reality, Augmented Reality, and Mixed Reality in Experiential Learning: Transforming Educational Paradigms', *Education Sciences*, 15(3), p. 303. doi: 10.3390/educsci15030303.

Demirel, H. O., Ahmed, S. and Duffy, V. G. (2022) 'Digital Human Modeling: A Review and Reappraisal of Origins, Present, and Expected Future Methods for Representing Humans Computationally', *International Journal of Human–Computer Interaction*, 38(10), pp. 897–937. doi: 10.1080/10447318.2021.1976507.

ElSayary, A. (2025) 'Enhancing teachers' design thinking mindsets through reflective practice: Cultivating innovation in an upskilling STEAM training program', *Eurasia Journal of Mathematics, Science and Technology Education*, 21(3), p. em2600. doi: 10.29333/ejmste/16048.

Ferguson, S., Lai, K., Chen, J., Faidi, S., Leonardo, K., & Olechowski, A. (2022) '"Why couldn't we do this more often?": exploring the feasibility of virtual and distributed work in product design engineering', *Research in Engineering Design*, 33(4), pp. 413–436. doi: 10.1007/s00163-022-00391-2.

Forcael, E., Garcés, G. and Lantada, A. D. (2023) 'Convergence of Educational Paradigms into Engineering Education 5.0', in *2023 World Engineering Education Forum - Global Engineering Deans Council (WEEF-GEDC)*. IEEE, pp. 1–8. doi: 10.1109/WEEF-GEDC59520.2023.10344026.

Hariharasakthisudhan, P., Logesh, K., Sathickbasha, K., & Kannan, S. (2025) 'Enhancing project-based learning in engineering education: a hybrid DT-CDIO-RA framework for sustainable product design', *Discover Education*, 4(1), p. 138. doi: 10.1007/s44217-025-00579-3.

Hippe, D. S., Umoren, R. A., McGee, A., Bucher, S. L., & Bresnahan, B. W. (2020) 'A targeted systematic review of cost analyses for implementation of simulation-based education in healthcare', *SAGE Open Medicine*, 8, p. 205031212091345. doi: 10.1177/2050312120913451.

Ikemiyashiro Higa, D. and Taki, A. (2024) 'Examining Cardboard as a Construction Material for Sustainable Building Practices in Lima, Peru', *Sustainability*, 17(1), p. 10. doi: 10.3390/su17010010.

Iqbal, A. I., Aamir, A., Hammad, A., Hafsa, H., Basit, A., Oduoye, M. O., Anis, M. W., Ahmed, S., Younus, M. I., & Jabeen, S. (2024) 'Immersive Technologies in Healthcare: An In-Depth Exploration of Virtual Reality and Augmented Reality in Enhancing Patient Care, Medical Education, and Training Paradigms', *Journal of Primary Care & Community Health*, 15. doi: 10.1177/21501319241293311.

Iqbal, M. Z., Mangina, E. and Campbell, A. G. (2022) 'Current Challenges and Future Research Directions in Augmented Reality for Education', *Multimodal Technologies and Interaction*, 6(9), p. 75. doi: 10.3390/mti6090075.

Isaeva, R., Karasartova, N., Dznunusnalieva, K., Mirzoeva, K., & Mokliuk, M. (2025) 'Enhancing Learning Effectiveness Through Adaptive Learning Platforms and Emerging Computer Technologies in Education', *Jurnal Ilmiah Ilmu Terapan Universitas Jambi*, 9(1), pp. 144–160. doi: 10.22437/jiituj.v9i1.37967.

Joseph Nnaemeka Chukwunweike, Andrew Nii Anang, Adewale Abayomi Adeniran, & Jude Dike. (2024) 'Enhancing manufacturing efficiency and quality through automation and deep learning: addressing redundancy, defects, vibration analysis, and material strength optimization', *World Journal of Advanced Research and Reviews*, 23(3), pp. 1272–1295. doi: 10.30574/wjarr.2024.23.3.2800.

Kamdjou, H. M., Baudry, D., Havard, V., & Ouchani, S. (2024) 'Resource-Constrained EXtended Reality Operated With Digital Twin in Industrial Internet of Things', *IEEE Open Journal of the Communications Society*, 5, pp. 928–950. doi: 10.1109/OJCOMS.2024.3356508.

Kang, L. (2024) 'Revolutionizing Vocational Education: Information-Based Instruction and the Knowledge Economy', *Journal of the Knowledge Economy*. doi: 10.1007/s13132-024-01797-0.

Kumar, A., Mantri, A. and Dutta, R. (2021) 'Development of an augmented reality-based scaffold to improve the learning experience of engineering students in embedded system course', *Computer Applications in Engineering Education*, 29(1), pp. 244–257. doi: 10.1002/cae.22245.

Lee, I.-J. (2023) 'Applying virtual reality for learning woodworking in the vocational training of batch wood furniture production', *Interactive Learning Environments*, 31(3), pp. 1448–1466. doi: 10.1080/10494820.2020.1841799.

Lenin, N., Siva Kumar, M. and Selvakumar, G. (2023) 'Application of Conceive, Design, Implement and Operate (CDIO) Strategy for the Development of Engineering Education in Indian Perspective', *Journal of Education*, 203(1), pp. 41–48. doi: 10.1177/00220574211016446.

Li, Y., Xiong, X. and Qu, M. (2023) 'Research on the Whole Life Cycle of a Furniture Design and Development System Based on Sustainable Design Theory', *Sustainability*, 15(18), p. 13928. doi: 10.3390/su151813928.

Liu, Q. and Wang, L. (2021) 't-Test and ANOVA for data with ceiling and/or floor effects', *Behavior Research Methods*, 53(1), pp. 264–277. doi: 10.3758/s13428-020-01407-2.

Malhotra, R., Massoudi, M. and Jindal, R. (2023) 'Shifting from traditional engineering education towards competency-based approach: The most recommended approach-review', *Education and Information Technologies*, 28(7), pp. 9081–9111. doi: 10.1007/s10639-022-11568-6.

Martseva, L. A., Movchan, L. H., Vakaliuk, T. A., & Antoniuk, D. S. (2021) 'Applying CDIO-approach at technical universities', *Journal of Physics: Conference Series*, 1946(1), p. 012013. doi: 10.1088/1742-6596/1946/1/012013.

Matović, N. and Ovesni, K. (2023) 'Interaction of quantitative and qualitative methodology in mixed methods research: integration and/or combination', *International Journal of Social Research Methodology*, 26(1), pp. 51–65. doi: 10.1080/13645579.2021.1964857.

May, D., Terkowsky, C., Varney, V., & Boehringer, D. (2023) 'Between hands-on experiments and Cross Reality learning environments – contemporary educational approaches in instructional laboratories', *European Journal of Engineering Education*, 48(5), pp. 783–801. doi: 10.1080/03043797.2023.2248819.

McCord, K. H., Ayer, S. K., Perry, L. A., Patil, K. R., London, J. S., Khoury, V., & Wu, W. (2022) 'Student Approaches and Performance in Element Sequencing Tasks Using 2D and Augmented Reality Formats', *Education Sciences*, 12(4), p. 247. doi: 10.3390/educsci12040247.

Nazlidou, I., Efkolidis, N., Kakoulis, K., & Kyratsis, P. (2024) 'Innovative and Interactive Technologies in Creative Product Design Education: A Review', *Multimodal Technologies and Interaction*, 8(12), p. 107. doi: 10.3390/mti8120107.

Nithyanandam, G., Munguia, J. and Marimuthu, M. (2022) '"Digital literacy": Shaping industry 4.0 engineering curriculums via factory pilot-demonstrators', *Advances in Industrial and Manufacturing Engineering*, 5, p. 100092. doi: 10.1016/j.aime.2022.100092.

Ortega-Gras, J.-J., Gómez-Gómez, M.-V., Bueno-Delgado, M.-V., Garrido-Lova, J., & Cañavate-Cruzado, G. (2023) 'Designing a Technological Pathway to Empower Vocational Education and Training in the Circular Wood and Furniture Sector through Extended Reality', *Electronics*, 12(10), p. 2328. doi: 10.3390/electronics12102328.

Portillo, F., Soler-Ortiz, M., Sanchez-Cruzado, C., Garcia, R. M., & Novas, N. (2025) 'The Impact of Flipped Learning and Digital Laboratory in Basic Electronics Coursework', *Computer Applications in Engineering Education*, 33(1). doi: 10.1002/cae.22810.

Rana, S. and Chicone, R. (2025) 'AI-Enhanced Virtual and Augmented Reality for Cybersecurity Training', in *Fortifying the Future*. Cham: Springer Nature Switzerland, pp. 101–131. doi: 10.1007/978-3-031-81780-9_5.

Resch, K. and Schrittesser, I. (2023) 'Using the Service-Learning approach to bridge the gap between theory and practice in teacher education', *International Journal of Inclusive Education*, 27(10), pp. 1118–1132. doi: 10.1080/13603116.2021.1882053.

Rodríguez-Abitia, G., Martínez-Pérez, S., Ramirez-Montoya, M. S., & Lopez-Caudana, E. (2020) 'Digital Gap in Universities and Challenges for Quality Education: A Diagnostic Study in Mexico and Spain', *Sustainability*, 12(21), p. 9069. doi: 10.3390/su12219069.

Sahoo, P., Saraf, P. K. and Uchil, R. (2025) 'Identification of challenges to Industry 5.0 adoption in Indian manufacturing firms: an emerging economy perspective', *International Journal of Computer Integrated Manufacturing*, 38(5), pp. 649–674. doi: 10.1080/0951192X.2024.2382186.

Salinas-Navarro, D. E., Vilalta-Perdomo, E., Michel-Villarreal, R., & Montesinos, L. (2024) 'Using Generative Artificial Intelligence Tools to Explain and Enhance Experiential Learning for Authentic Assessment', *Education Sciences*, 14(1), p. 83. doi: 10.3390/educsci14010083.

Sapienza, V., Rodonò, G., Monteleone, A., & Calvagna, S. (2022) 'ICARO—Innovative Cardboard ARchitecture Object: Sustainable Building Technology for Multipurpose Micro-Architecture', *Sustainability*, 14(23), p. 16099. doi: 10.3390/su142316099.

Seiringer, W., Altendorfer, K., Castaneda, J., Gayan, L., & Juan, A. A. (2022) 'Potential of Simulation Effort Reduction by Intelligent Simulation Budget Management for Multi-Item and Multi-Stage Production Systems', in *2022 Winter Simulation Conference (WSC)*. IEEE, pp. 1864–1875. doi: 10.1109/WSC57314.2022.10015506.

Shahrezaei, A., Sohani, M., Taherkhani, S., & Zarghami, S. Y. (2024) 'The impact of surgical simulation and training technologies on general surgery education', *BMC Medical Education*, 24(1The impact of surgical simulation and training technologies on general surgery education), p. 1297. doi: 10.1186/s12909-024-06299-w.

Shuhaiber, A. and Aldwairi, M. (2023) 'A Best Practice Model of CDIO Implementation in IT Classrooms: Gamification Crowdsourcing Approach', in *2023 27th International Computer Science and Engineering Conference (ICSEC)*. IEEE, pp. 304–309. doi: 10.1109/ICSEC59635.2023.10329646.

Singhaphandu, R., Pannakkong, W., Huynh, V.-N., & Boonkwan, P. (2024) 'A Manual Assembly Virtual Training System With Automatically Generated Augmented Feedback: Using the Comparison of Digitized Operator's Skill', *IEEE Access*, 12, pp. 133356–133391. doi: 10.1109/ACCESS.2024.3436910.

Solmaz, S., Dominguez Alfaro, J. L., Santos, P., Van Puyvelde, P., & Van Gerven, T. (2021) 'A practical development of engineering simulation-assisted educational AR environments', *Education for Chemical Engineers*, 35, pp. 81–93. doi: 10.1016/j.ece.2021.01.007.

Song, C., Shin, S.-Y. and Shin, K.-S. (2023) 'Optimizing Foreign Language Learning in Virtual Reality: A Comprehensive Theoretical Framework Based on Constructivism and Cognitive Load Theory (VR-CCL)', *Applied Sciences*, 13(23), p. 12557. doi: 10.3390/app132312557.

Song, X. (2022) 'Application Research of CDIO Education Initiative in Reforming Online-Offline Hybrid Teaching of "Software Testing" Course', in *2022 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*. IEEE, pp. 270–275. doi: 10.1109/TALE54877.2022.00052.

Sounthornwiboon, P., Sriprasertpap, K. and Nilsook, P. (2025) ‘Simulation game-based learning for cognitive apprenticeship development: a focus on processing speed’, *Cogent Education*, 12(1). doi: 10.1080/2331186X.2024.2449280.

Špirková, S., Straka, M. and Saniuk, A. (2024) ‘VR Simulation and Implementation of Robotics: A Tool for Streamlining and Optimization’, *Applied Sciences*, 14(11), p. 4434. doi: 10.3390/app14114434.

Suckling, K., Patel, Y., Mann, K., & Collett, A. (2024) ‘Resilient Design with Upcycled Timber Within Architectural Design-Build Studio’, in *Integrating Resiliency into Future Sustainable Cities*, pp. 45–65. doi: 10.1007/978-3-031-63203-7_4.

Suksong, S., Chomsuwan, K. and Suamuang, W. (2023) ‘Work in Progress: Application of CDIO and Experiential Learning Theory for Developing the Problem Solving Ability of Technicians in Manufacturing’, in *2023 IEEE Global Engineering Education Conference (EDUCON)*. IEEE, pp. 1–3. doi: 10.1109/EDUCON54358.2023.10125201.

Tanveer, B. and Usman, M. (2022) ‘An Empirical Study on the Use of CDIO in Software Engineering Education’, *IEEE Transactions on Education*, 65(4), pp. 684–694. doi: 10.1109/TE.2022.3163911.

Venkatesan, S., Afroz, M., Navaratnam, S., & Gravina, R.(2023) ‘Circular-Economy-Based Approach to Utilizing Cardboard in Sustainable Building Construction’, *Buildings*, 13(1), p. 181. doi: 10.3390/buildings13010181.

Wagg, D. J., Worden, K., Barthorpe, R. J., & Gardner, P. (2020) ‘Digital Twins: State-of-the-Art and Future Directions for Modeling and Simulation in Engineering Dynamics Applications’, *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, 6(3). doi: 10.1115/1.4046739.

Weis, P., Smetanka, L., Hrček, S., & Vereš, M. (2024) ‘Interactive Application as a Teaching Aid in Mechanical Engineering’, *Computers*, 13(7), p. 170. doi: 10.3390/computers13070170.

Wong, Z. Y. and Liem, G. A. D. (2022) ‘Student Engagement: Current State of the Construct, Conceptual Refinement, and Future Research Directions’, *Educational Psychology Review*, 34(1), pp. 107–138. doi: 10.1007/s10648-021-09628-3.

Yang, Z. and Zhou, H. (2023) ‘Exploring and Construction On Practicality Instruction System in Engineering Education Based On CDIO Concept’, *World Journal of Educational Research*, 10(5), p. p269. doi: 10.22158/wjer.v10n5p269.

Younis, B. (2025) ‘Developing and Validating the Contextual Technology Andragogy/Pedagogy Entrepreneurship Work Content Knowledge Model: A Framework for Vocational Education’, *IEEE Transactions on Education*, 68(1), pp. 57–66. doi: 10.1109/TE.2024.3449636.

Zabalawi, I., Kordahji, H. and Mourdaa, R. (2022) ‘The “New” Normal of Business Education in a Post COVID Era: The CDIO Approach’, in *Higher Education in the Arab World*. Cham: Springer International Publishing, pp. 115–150. doi: 10.1007/978-3-031-07539-1_7.

Zhang, Z., Guo, B. H. W., Chang-Richards, A., Feng, Z., Jin, R., Zou, Y., & Miang Goh, Y. (2023) ‘Digital technology enhanced situation awareness for construction safety: Systematic review and future research directions’, *Safety Science*, 167, p. 106280. doi: 10.1016/j.ssci.2023.106280.

Zhao, K. (2021) ‘Sample representation in the social sciences’, *Synthese*, 198(10), pp. 9097–9115. doi: 10.1007/s11229-020-02621-3.