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A STIN Model Adoption for Chatbot in Higher Education Online Learning

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Abstract: This study delves into the adoption of chatbot technology in higher education, with a focus on Indonesian online learning environments. Recognizing the potential of AI-driven tools to address academic support gaps, particularly in developing regions, the research explores how performance expectancy, effort expectancy, and facilitating conditions influence students' behavioral intentions and subsequent adoption of chatbots for academic use. The study employs Structural Equation Modeling (SEM) to analyze survey data from a diverse sample of university students, enabling a nuanced understanding of the complex relationships among these factors. The findings reveal that performance expectancy—the belief that chatbots will enhance academic performance and facilitating conditions, such as internet access and institutional support, play significant roles in motivating students to adopt chatbots. However, effort expectancy, or the perceived ease of use, does not directly drive adoption intentions. This suggests that students prioritize practical benefits over user-friendliness, an insight valuable for universities aiming to implement effective chatbot systems. Moreover, the results align with the Socio-Technical Interaction Network (STIN) model, which emphasizes the need for a cohesive social and technical framework to foster technological acceptance. The STIN model's perspective underscores that students' engagement with chatbots is not just a matter of usability but also of how well the technology is supported by the broader educational infrastructure. This study offers actionable insights for Indonesian universities and other institutions in similar contexts, proposing that enhancing campus resources, like reliable internet access and technical support, can drive chatbot adoption. By focusing on performance-based benefits and strengthening the socio-technical environment, universities can effectively integrate AI-based learning tools, addressing both technical and socio-cultural barriers. Such initiatives support students' learning experiences and foster an adaptive academic ecosystem where AI tools serve as essential assets in overcoming resource limitations. Thus, the study contributes a practical roadmap for advancing e-learning in resource-constrained settings through strategic support of AI technology adoption.

Keywords: Chatbot-Based online learning, e-Learning adoption, STIN model, Structural equation modeling

1. Introduction

AI-powered digital assistants may provide tailored assistance to students by addressing enquiries, streamlining administrative duties, and providing prompt feedback. Notwithstanding their increasing use across diverse industries, the integration of chatbots in educational settings remains comparatively insufficiently investigated, especially in underdeveloped nations such as Indonesia. The determinants affecting students' acceptance of chatbots in university environments need more research to enhance the integration of this technology in higher education. The integration of AI technology in education, such as chatbots, has shown favourable effects in enhancing learning outcomes. Multiple studies have emphasised the capacity of chatbots to provide tailored learning experiences and enhance administrative efficiency. (Kesarwani, Titiksha and Juneja, 2023). However, research on the specific variables influencing students' willingness to adopt chatbots remains limited, particularly in developing regions where factors such as inadequate infrastructure and lack of institutional support may pose significant challenges. While prior studies (Maulana and Arli, 2022; Muslem *et al.*, 2024) have

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explored aspects of online learning in Indonesia, there remains a gap in understanding the specific drivers behind chatbot adoption in this context. This study addresses this gap by focusing on three key factors: performance expectancy, effort expectancy, and facilitating conditions within Indonesian campuses.

The main objective of this study is to investigate how these elements—performance expectancy (the belief that chatbots will enhance academic performance), effort expectancy (the perceived ease of utilising chatbots), and facilitating conditions (the presence of institutional resources and support)—influence students' intention to engage with chatbot-based learning. This study will evaluate the direct and indirect impacts on students' actual adoption of chatbots by examining these variables using Structural Equation Modelling (SEM). This study presents a new theoretical framework, the Socio-Technical Interaction Networks (STIN) model, aimed at elucidating the relationship between social and technical elements in the adoption of AI-based technologies. This emphasis on the STIN model provides valuable perspectives on how educational institutions can enhance the alignment of their technical infrastructure with the needs of students.

This research presents a comprehensive analysis of the factors influencing chatbot adoption within the context of a developing country. Existing literature has examined various determinants of technology acceptance; however, limited research has addressed the specific socio-technical challenges encountered by students in Indonesia. This study examines the challenges associated with chatbot adoption in higher education, offering a detailed understanding of the barriers and facilitators involved. The integration of the STIN model enhances the originality by providing a distinct viewpoint on the relationship between technical systems, such as chatbots, and social contexts, including university support and resources.

This research provides significant contributions to the domain of educational technology. It offers practical insights for colleges aiming to integrate chatbot-based learning into their educational frameworks by emphasising the essential role of performance advantages and institutional backing. Secondly, the results provide pragmatic suggestions for surmounting adoption obstacles in poorer nations, where infrastructure and assistance may be inadequate. The study enhances the theoretical comprehension of technology adoption in educational contexts by including the STIN model, which may function as a foundational framework for further investigations into AI-driven learning technologies across various educational settings.

2. Literature Review

In recent years, Higher Education in Indonesia has faced multiple challenges that hinder the overall development of an effective learning environment. These issues, such as the scarcity of qualified teachers, limited resources, and infrastructural shortcomings, coupled with increasing academic demands and intense competition, have created a scenario where students struggle to access adequate academic support and guidance. As the academic pressures mount, Artificial Intelligence (AI)-driven tools, have emerged as potential solutions to these challenges. This literature review explores the critical issues in Indonesian higher education, the role of AI tools.

This chapter will provide an in-depth explanation of the Technology Acceptance Model (TAM) and Socio-Technical Interaction Network (STIN) Model, covering its fundamental components, theoretical extensions, and its application in various domains, particularly in higher education and AI-driven learning tools.

This approach can be analysed through the Technology Acceptance Model (TAM), which explains how users accept and use technology (Davis, 1989; Venkatesh *et al.*, 2003). In the context of higher education in Indonesia, students and lecturers need to feel that AI tools are truly beneficial in improving the learning experience and reducing academic workload. If AI-based tools, such as intelligent tutoring systems and academic chatbots, are perceived as easy to use as well as providing tangible benefits in improving material comprehension and study efficiency, then it is more likely that these technologies will be widely accepted and adopted in academic settings, this study proposes a Research Design model as shown in Figure 1.

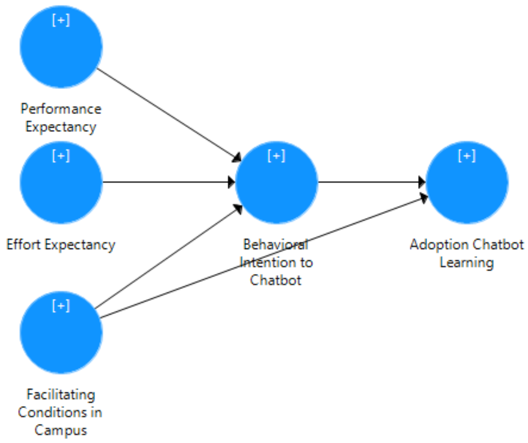

Figure 1: TAM for Research Design

2.1 Performance Expectancy in Higher Education

One of the most notable factors influencing technology adoption is performance expectancy, which refers to the belief that using a particular technology will enhance one's performance. In educational environments, especially those constrained by limited resources, tools that provide clear academic benefits are more likely to be embraced by students. For instance, (Chatterjee and Bhattacharjee, 2020) demonstrate that students are inclined to use technologies like chatbots when they perceive them as advantageous to their academic success. Similarly, (Chew and Cerbin, 2021; Pratita *et al.*, 2025) found that students who believed chatbots could simplify complex concepts and provide immediate academic assistance were more likely to express a strong intention to use the technology. Both studies underscore the importance of perceived academic benefits in driving adoption.

However, these studies also present some limitations. (Chatterjee and Bhattacharjee, 2020) focused on a generalized perception of chatbot utility without exploring variations across different subjects or disciplines, which could have revealed more nuanced insights into performance expectancy. Meanwhile, (Chew and Cerbin, 2021) primarily examined short-term engagement, leaving room to explore long-term impacts on academic performance and sustained adoption. The present study addresses these gaps by examining performance expectancy not only in terms of immediate academic success but also considering the long-term utility of chatbots across various educational domains.

In contrast, (José-María *et al.*, 2023) explored chatbot adoption specifically in the university setting, emphasizing its use for complex thinking. This approach is more aligned with subject-specific investigations, but it also lacks depth regarding how performance expectancy interacts with infrastructure and support systems in developing regions. (Artur, 2023, 2024) and (Sultan and M., 2024) further extend the UTAUT framework by examining how factors like social language and proactivity affect chatbot adoption, yet still within more developed contexts, leaving gaps in understanding how these factors operate in under-resourced environments.

The relationship between performance expectancy and behavioral intention is well-supported by the Technology Acceptance Model (TAM), which posits that perceived usefulness is a key predictor of technology adoption (Zaineldeen *et al.*, 2020; Suryanto *et al.*, 2022, 2023; Abuhassna *et al.*, 2023) . In academic settings, if students believe that chatbots will help them complete tasks more efficiently, they are more likely to integrate these technologies into their study routines. Previous empirical studies, such as those by (Liao *et al.*, 2018) and (Alassafi, 2022), consistently show a positive correlation between performance expectancy and behavioral intention these studies often focus on technical features rather than pedagogical effectiveness.

Considering the Performance Expectancy factor is crucial for ensuring the successful adoption of educational technologies, as it directly influences students' motivation to integrate these tools into their academic activities and achieve long-term learning benefits.

2.2 Effort Expectancy and Technological Adoption

Effort expectancy, defined as the perceived ease of use of technology, has been consistently recognized as a key factor influencing students' technology adoption. (Villanueva and Aguilar-Alonso, 2021) affirm that students are more inclined to adopt AI-driven tools when they find them easy to use, which aligns with the core premise of the Technology Acceptance Model (TAM), where ease of use is a significant predictor of user acceptance (Zaineldeen *et al.*, 2020; Fauzi *et al.*, 2021; Abuhassna *et al.*, 2023).

However, prior studies reveal certain limitations in understanding effort expectancy's impact. (Hair *et al.*, 2017; Hsiu-Ling, Gracia and H., 2020; Xinjie and Zhonggen, 2023) highlight that, while ease of use promotes behavioral intention, its influence is often overshadowed by performance expectancy, suggesting that users might value technology's functional benefits more than ease of use. This is particularly relevant in resource-constrained settings like Indonesian universities, where students prioritize practical outcomes over usability due to limited access to technology. On the other hand (Ondas, Pleva and Hladek, 2019) emphasize that in environments where students lack digital literacy, effort expectancy becomes a more critical factor. In such contexts, ease of use is paramount, as students with lower technical proficiency are more likely to embrace technology if it is intuitive and user-friendly.

The current study addresses these gaps by examining both the contextual significance of effort expectancy and its interaction with chatbot. Unlike previous research, this study considers the varying levels of students' technological exposure, providing a more nuanced understanding of how ease of use influences behavioral intention across different educational environments.

2.3 The Role of Facilitating Conditions in Campus Settings

(Meennapa, Napasorn and P., 2022) and (José, T. and J., 2020) argue that facilitating conditions, including infrastructure and institutional support, are critical for successful chatbot adoption. This is further validated by (Villanueva and Aguilar-Alonso, 2021), unfortunately, these studies only focus on technical support and ignore the impact of campus encouragement that contributes to students. Which include the availability of resources, infrastructure, and institutional support, are crucial in determining whether students will adopt technologies like chatbots. (Arun, Srinagesh and Ganga, 2019) argue that when students have access to stable internet connections, technical assistance, and encouragement from faculty, their likelihood of engaging with AI-driven tools increases significantly. Scott and Husain (2021) further validate this by emphasizing that institutional support plays a key role in fostering strong behavioural intentions to adopt new technologies among students.

However, previous studies have certain limitations in fully explaining how facilitating conditions affect both the intention to adopt and actual use of technology. For instance, while (Arun, Srinagesh and Ganga, 2019) highlights the importance of resources and support, they do not explore how these conditions interact with other factors, such as students' digital proficiency or motivation. (Ghorpade-Aher, 2019) adds that without adequate support structures, even the recognition of potential academic benefits may not translate into technology adoption. Yet, this study falls short in addressing the nuanced challenges faced in resource-limited environments, such as those in many Indonesian universities, where inadequate internet connectivity and a lack of faculty involvement may significantly hinder chatbot adoption.

Additionally, studies such as those by (Rumangkit, Surjandy and Billman, 2023) underscore that facilitating conditions do not only shape behavioral intention but also directly impact the actual adoption of chatbots. The absence of essential resources, such as reliable internet infrastructure, can obstruct students from fully integrating AI tools into their learning process, regardless of their intentions. These earlier studies primarily focus on the availability of infrastructure but often overlook the role of faculty training and preparedness, which are also critical in fostering the actual use of technology in academic settings.

The current study fills these gaps by not only investigating the availability of resources but also considering how institutional support, faculty involvement, and infrastructure interact to move students from behavioral intention to actual chatbot adoption. Unlike prior research, this study highlights the importance of a holistic approach to facilitating conditions, including continuous faculty development and adaptive technical support to accommodate varying levels among students.

2.4 Behavioral Intention to Chatbot Use in Indonesia

Behavioral intention is a critical predictor of whether students will adopt chatbots for learning, shaped by perceptions of usefulness, ease of use, and available support systems. (Rosmayanti, Noni and Patak, 2022; Artur, 2024; Weiqi *et al.*, 2024) emphasize that when students believe chatbots can improve task efficiency, their intention to use them strengthens. However, while effort expectancy contributes to this intention, its influence is often secondary to the perceived performance benefits. This is supported (Lutfi *et al.*, 2022) and (Candra *et al.*, 2024), who found that even if students believe chatbots will improve their academic performance, they may not adopt the technology without strong behavioral intention.

Despite its central role in adoption, behavioral intention's relationship with local contextual factors remains underexplored, particularly in developing countries like Indonesia. Previous studies, including those by (Marfuah *et al.*, 2022) and (Binowo *et al.*, 2024), have predominantly focused on developed regions, where high chatbot and widespread access to advanced technology are assumed. These studies often overlook the challenges faced by Indonesian universities, which may grapple with inadequate infrastructure, inconsistent internet access, and varying levels of digital proficiency. The adoption models, such as TAM and UTAUT , while effective in Western contexts, may not fully capture the complexities of behavioral intention in resource-constrained environments.

Additionally, while (Imdadullah and Yasser, 2023) and (Ayanwale and Ndlovu, 2024) explore educators' adoption of AI, providing insights into how behavioral intention is shaped by perceived ease of use and institutional support. However, like many studies, they do not account for variations in campus contributions, particularly in developing countries such as Indonesia, which provides an opportunity for deeper observation.

Therefore, the research suggests that factors like performance and effort expectancy interact dynamically with local conditions, they do not delve deeply into how these interactions are influenced by infrastructural and cultural differences, especially in non-Western settings. For example, students with limited exposure to advanced technologies in Indonesian universities might perceive chatbots as more complex or challenging to use, affecting their intention and overall adoption differently compared to their counterparts in more digitally advanced regions.

The current study addresses these shortcomings by focusing specifically on the Indonesian context, offering a more nuanced understanding of how behavioral intention is shaped by local factors such as chatbot, infrastructural constraints, and cultural attitudes toward AI technologies. Unlike previous studies, this research not only applies global models like TAM and UTAUT but also critically evaluates their relevance in a developing-country context, providing fresh insights into the unique factors driving chatbot adoption in Indonesian higher education.

2.5 STIN Model

However, AI technology adoption is not only influenced by individual factors as described in TAM, but also by social and technical interactions within an educational ecosystem. This is where the Socio-Technical Interaction Network (STIN) introduced (Walker and Creanor, 2009) becomes relevant . STIN emphasises that the success of technology implementation depends not only on the characteristics of the technology itself, but also on the social networks that use it, including institutional policies, infrastructure readiness, and the dynamics of relationships between students, lecturers, and administrators (Berleur, Nurminen and Impagliazzo, 2006; Meyer, 2006; Narayan and Macher, 2023). In higher education ecosystem, the implementation of AI should consider how this technology will interact with the existing education system, including how institutions manage policy changes, build supporting infrastructure, and ensure the active involvement of stakeholders.

By combining TAM and STIN, a holistic approach can be used to evaluate the effectiveness of AI implementation in Indonesian higher education. TAM helps understand technology acceptance from an individual perspective, while STIN provides insights into how AI technologies can be effectively integrated within the broader social and technical environment. If AI can be implemented with these two models in mind, then AI-based solutions have the potential to significantly improve the accessibility and quality of higher education.

3. Materials and Methods

3.1 Sample and Data Collection

This research employs a quantitative approach to explore factors influencing chatbot adoption among university students in Indonesia. Probability sampling is used to obtain samples of 299 respondents will be selected from various study programs to ensure representation of the diverse student population. Data collection will occur from January to June 2024 using both online and offline questionnaires.

The research method begins with the development of a structured questionnaire aimed at capturing data on performance expectancy, effort expectancy, facilitating conditions, behavioral intention, and actual chatbot adoption. The questionnaire will consist of validated measurement scales to ensure reliability and validity. Following this, a pilot test will be conducted with a small group of students to refine any ambiguous questions based on their feedback.

Data collection will then be implemented through online platforms, such as Google Forms, and in-person distribution at selected universities across Indonesia. This dual approach accommodates different access levels, ensuring wider participation. Once data collection is complete, the data will be cleaned and prepared for analysis using Structural Equation Modeling (SEM). SEM is ideal for this research as it allows for the simultaneous assessment of complex relationships and testing of hypotheses, as highlighted in studies by (Hair *et al.*, 2017), (Chatterjee and Bhattacharjee, 2020), and (Villanueva and Aguilar-Alonso, 2021). This analysis will identify direct and indirect effects of performance expectancy, effort expectancy, and facilitating conditions on students' behavioral intention and chatbot adoption.

3.2 Structural Model

Provides a detailed explanation of key variables used in this study, ensuring clarity and consistency in measurement. Each variable is defined based on relevant literature and adapted to the research context to enhance validity and reliability, explained in more detail for definition operational in table 1 and questioner item's in table 2.

Table 1: Definition Operational

Variable	Operational Definition	Reason for Inclusion	References
Performance Expectancy (PE)	The degree to which students believe that using chatbots will enhance their academic performance and efficiency in learning tasks.	This variable is crucial as studies have shown that students who perceive a positive impact on their performance are more likely to adopt new technologies	(Chatterjee and Bhattacharjee, 2020; Chew and Cerbin, 2021; Rosmayanti, Noni and Patak, 2022; Rumangkit, Surjandy and Billman, 2023; Artur, 2024)
Effort Expectancy (EE)	The perceived ease of use associated with engaging with chatbots in learning environments.	Understanding this variable helps identify if the user-friendliness of chatbots influences students' willingness to use them	(Chatterjee and Bhattacharjee, 2020; Villanueva and Aguilar-Alonso, 2021; Alamsyah *et al.*, 2022; Mohd Rahim *et al.*, 2022; Rosmayanti, Noni and Patak, 2022; Artur, 2024)
Facilitating Conditions in Campus (FC)	The availability of resources, support, and infrastructure necessary for effective chatbot usage within the campus environment.	This variable highlight how external factors like institutional support and technology accessibility can facilitate or hinder chatbot adoption	(Yadav, Herzog and Bolchini, 2020; Scott and Husain, 2021; Sarfraz, Khawaja and Ivascu, 2022; Zhou *et al.*, 2022; Rumangkit, Surjandy and Billman, 2023; Strzelecki, 2023)
Behavioral Intention to Chatbot (BIC)	The inclination or readiness of students to use chatbots for learning purposes based on their perceptions and experiences.	Behavioral intention is a strong predictor of actual usage behavior, linking perceived benefits and usability to the likelihood of adopting chatbots	(Cheng-Min, 2019; Shingte *et al.*, 2021; Ayanwale and Ndlovu, 2024; Candra *et al.*, 2024; Abdi *et al.*, 2025)
Adoption Chatbot Learning (ACL)	The actual utilization of chatbots by students in their learning processes and academic tasks.	This variable is the ultimate outcome of interest in this research, as it measures the effectiveness of efforts to enhance chatbot adoption and integration into learning.	(Arista and Abbas, 2022), (Lutfi *et al.*, 2022), (Rosmayanti, Noni and Patak, 2022), (Alamsyah *et al.*, 2022).

Table 2: Quesioner Item's

No.	Var.	Question
1	ACL1	The implementation of Chatbot on campus is beneficial for the academic community.
2	ACL2	Integrating Chatbot into campus life will enhance the interactivity of the learning process.
3	ACL3	Utilizing Chatbot on campus will make learning more effective and efficient.
4	BIC1	I believe Chatbot is easy for beginners to learn.
5	BIC2	I am willing to use Chatbot to support my self-directed learning.
6	BIC3	I believe Chatbot can be used to assist with academic assignments.
7	BIC4	I would recommend exploring Chatbot as part of the independent learning initiative.
8	BIC5	I intend to use Chatbot as a new culture of independent learning.
9	EE1	I recognize that I need to put in significant effort to learn how to use Chatbot.
10	EE2	I can easily learn how to use Chatbot.
11	EE3	I can quickly find answers to my questions using Chatbot.

No.	Var.	Question
12	FC1	My campus has all the necessary resources to effectively utilize Chatbot.
13	FC2	I have access to all the necessary resources to use Chatbot.
14	PE1	Learning activities supported by Chatbot will enhance learning efficiency.
15	PE2	The responses generated by Chatbot are valuable for self-directed learning.
16	PE3	Intelligent educational content can be developed using Chatbot technology.

4. Results

This section presents empirical findings from the statistical analysis performed in the study, structured according to the measurement model, descriptive statistics, and the structural model evaluation. The results are systematically organized in a series of tables to enhance clarity and support interpretation.

4.1 Outer Model Analysis

To ensure the accuracy of the constructs used in this study, an outer model analysis was carried out. This analysis checks whether the indicators correctly measure the intended variables. First, convergent validity was tested using the Average Variance Extracted values shown in Table 3. Next, discriminant validity was assessed through cross-loading in table 4 and the Fornell-Larcker Criterion in table 5. Lastly, reliability was confirmed using Cronbach's Alpha and Composite Reliability, as presented in table 6.

Table 3: Convergent Validity Average Variance Extracted (AVE)

	Average Variance Extracted (AVE)
Adoption Chatbot Learning	0.832
Behavioral Intention to Chatbot	0.669
Effort Expectancy	0.696
Facilitating Conditions in Campus	0.750
Performance Expectancy	0.663

The analysis of convergent validity shows that the Average Variance Extracted (AVE) for all constructs is greater than 0.50, with the highest value being for Adoption Chatbot Learning (0.832). This indicates that the indicators of each construct explain more than 50% of the variance, meaning that each construct reliably measures the intended phenomenon. For instance, the adoption of chatbots for learning has a strong understanding among users, as evidenced by the high AVE value.

Table 4: Discriminant Validity Cross Loading

	Adoption Chatbot Learning	Behavioral Intention to Chatbot	Effort Expectancy	Facilitating Conditions in Campus	Performance Expectancy
ACL1	0.881				
ACL2	0.946				
ACL3	0.908				
BIC1		0.763			
BIC2		0.791			
BIC3		0.894			
BIC4		0.853			
BIC5		0.781			
EE1			0.766		
EE2			0.870		
EE3			0.862		

	Adoption Chatbot Learning	Behavioral Intention to Chatbot	Effort Expectancy	Facilitating Conditions in Campus	Performance Expectancy
FC1				0.870	
FC2				0.863	
PE1					0.813
PE2					0.831
PE3					0.798

The analysis of cross loadings provides strong evidence of discriminant validity. The high loadings of indicators on their respective constructs, compared to their loadings on other constructs, indicate that the measurement items are appropriately differentiated across constructs. This confirms that each latent variable in the model is distinct and well-represented by its indicators, thereby enhancing the reliability and interpretability of the structural equation model.

Table 5: Fornell-Larcker Criterion

	Adoption Chatbot Learning	Behavioral Intention to Chatbot	Effort Expectancy	Facilitating Conditions in Campus	Performance Expectancy
Adoption Chatbot Learning	0.912				
Behavioral Intention to Chatbot	0.795	0.818			
Effort Expectancy	0.523	0.571	0.834		
Facilitating Conditions in Campus	0.556	0.625	0.732	0.866	
Performance Expectancy	0.604	0.639	0.590	0.596	0.814

The Fornell-Larcker criterion reveals that the correlation between each construct and its indicators is higher than the correlation between the construct and other constructs. The highest correlation is for Adoption Chatbot Learning (0.912), followed by Behavioral Intention to Chatbot (0.818). This shows that students have a strong tendency to adopt chatbots if they have a strong behavioral intention to use them.

Table 6: Reliability

	Cronbach's Alpha	Composite Reliability
Adoption Chatbot Learning	0.899	0.937
Behavioral Intention to Chatbot	0.875	0.910
Effort Expectancy	0.781	0.872
Facilitating Conditions in Campus	0.667	0.857
Performance Expectancy	0.746	0.855

The Cronbach's Alpha and Composite Reliability values are all above 0.7 for all constructs, affirming the reliability of the instruments used in this study. Adoption Chatbot Learning has very high reliability (0.899 and 0.937), indicating that the questions measuring this variable consistently assess students' perceptions of using chatbots in learning.

4.2 Descriptive Analysis

Our study included a representative sample of 299 participants derived from data obtained via student surveys. The questions were administered both online and offline from January to June 2024. Shown in figure 2, the participants were actively involved in courses using AI technologies as course facilitators throughout the 2024-2025 academic year.

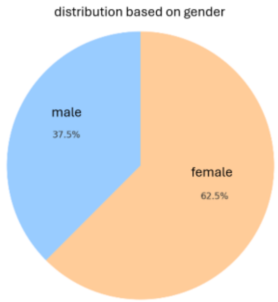

Figure 2: Distribution of Respondents by Gender

Here is the pie chart showing the assumed gender distribution based on names, with Male and Female the two categories. Show in figure 3, this is an estimate assuming the gender based on typical name patterns, where Female represents the larger proportion of the dataset.

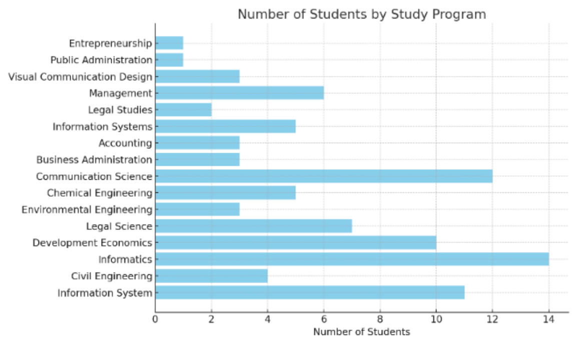

Figure 3: Distribution of Respondents by Study Program

The most represented programs are Information Systems, Informatics, and Communication Science, with other programs like Development Economics, Legal Science, and Management also having notable student counts.

Here is the pie chart showing how frequently students use Chatbot. It demonstrates the distribution among the categories very often, often, rarely, based on the data you provided. The largest proportion of respondents use Chatbot very often (59.9%), followed by those who use it often (37.5%), and a small number who rarely use it (3.0%).

Chatbot, an AI-based tool, has been widely used by students across various academic programs. Female students dominate the usage of Chatbot, accounting for around 62.5% of respondents. This suggests that female students, particularly in fields requiring substantial writing and research, are more likely to use it for tasks such as drafting, editing, and information retrieval. Male students, on the other hand, may still be a strong contingent, particularly in technical fields like Information Systems or Informatics.

The frequency of use for Chatbot is also high, with 61.1% of students using it very often, suggesting that the platform has become integral to their academic workflow. The remaining 38.5% use it for specific tasks, such as exam preparation or larger projects. As shown in figure 4, the small proportion of students who reported rarely using Chatbot might represent those who are unaware of its benefits, prefer traditional learning tools, or are in programs that do not demand frequent use of AI-driven applications.

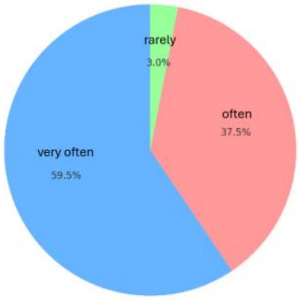

Figure 4: Distribution of Respondents by Intensity

Students from Information system, Informatics, and Communication Science show significant representation, where Chatbot is likely leveraged for its ability to assist with both technical and content-driven tasks. However, other fields like Civil Engineering and Entrepreneurship show lower adoption rates, suggesting that these students may find less utility in Chatbot for their specific academic needs or have alternative tools better suited for their disciplines. So, Chatbot's growing role as a vital academic tool is evident across various student demographics and academic programs. Future research could focus on understanding how different students use AI in their academic work and developing strategies to bridge the gap for less frequent users.

4.3 Inner Model Analysis

Inner model analysis is used to evaluate the relationships between the key variables in the study and test the research hypotheses. As shown in table 7, the path coefficients indicate the strength and direction of influence between constructs. To assess how much variation is explained by the model, the R-Square (R^2) values are presented in table 8. The effect size (f^2), shown in table 9, helps determine the contribution of each variable to the model. Lastly, table 10 presents the model fit indices, which show that the structural model fits the data adequately.

Table 7: Path Coefficient Significance

Variable Hypotesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Behavioral Intention to Chatbot → Adoption Chatbot Learning	0.734	0.739	0.041	17.934	**0.000**
Effort Expectancy → Behavioral Intention to Chatbot	0.115	0.120	0.083	1.386	0.166
Facilitating Conditions in Campus → Adoption Chatbot Learning	0.097	0.091	0.064	1.504	0.133
Facilitating Conditions in Campus → Behavioral Intention to Chatbot	0.312	0.311	0.078	3.994	**0.000**
Performance Expectancy → Behavioral Intention to Chatbot	0.385	0.386	0.061	6.276	**0.000**

Behavioral Intention to Chatbot → Adoption of Chatbot Learning: The strongest path, with a coefficient of 0.734, a T-value of 17.934, and a p-value of 0.000, indicates a highly significant positive effect. This suggests that individuals' behavioral intention to use the chatbot strongly predicts the adoption of chatbot learning.

Effort Expectancy → Behavioral Intention to Chatbot: The coefficient is 0.115 with a T-value of 1.386 and a p-value of 0.166. This path is not significant, implying that the ease of use (effort expectancy) does not significantly impact the behavioral intention to use the chatbot. Facilitating Conditions in Campus → Adoption of Chatbot Learning: With a coefficient of 0.097, a T-value of 1.504, and a p-value of 0.133, this path is also not significant. Thus, facilitating conditions (e.g., resources or support at campus) do not significantly affect chatbot adoption directly.

Facilitating Conditions in Campus → Behavioral Intention to Chatbot: The coefficient is 0.312 with a T-value of 3.994 and a p-value of 0.000, showing a significant positive effect. Facilitating conditions do influence users' intention to use the chatbot. Performance Expectancy → Behavioral Intention to Chatbot: The path is significant with a coefficient of 0.385, a T-value of 6.276, and a p-value of 0.000. This indicates that users' belief that the chatbot will improve their performance significantly impacts their intention to use it.

Table 8: R-Square (R^2)

	R Square	R Square Adjusted
Adoption Chatbot Learning	0.637	0.635
Behavioral Intention to Chatbot	0.507	0.502

R-Square values of more than 0.50 for both variables (Adoption Chatbot Learning and Behavioral Intention to Chatbot) indicate that the model has good predictive power. In a social context, R^2 values above 0.60 are often considered quite strong, as many external factors influence individual behaviour. Consequently, our findings demonstrate that the factors included in the model (including performance expectation, effort expectancy, and conducive campus settings) substantially affect students' decisions to adopt a chatbot and their intention to use it.

Table 9: Effect Size (f^2)

	Adoption Chatbot Learning	Behavioral Intention to Chatbot
Adoption Chatbot Learning		
Behavioral Intention to Chatbot	0.905	
Effort Expectancy		0.011
Facilitating Conditions in Campus	0.016	0.083
Performance Expectancy		0.179

From the Effect Size (f^2) results, the influence of Behavioral Intention to Chatbot on Adoption Chatbot Learning is very large (0.905), indicating that students' behavioral intention to use chatbots is the primary determinant in their adoption. On the other hand, the influence of Effort Expectancy (0.0011) and Facilitating Conditions (0.0083) on behavioral intention is relatively small. This shows that while environmental support and ease of use expectations are important, they are not as significant as behavioral intention.

Table 10: Model Fit Indices

	Saturated Model	Estimated Model
SRMR	0.078	0.079
Chi-Square	755.221	763.151
NFI	0.763	0.761

The model fit indices show that the SRMR (Standardized Root Mean Square Residual) for the saturated model is 0.078, which is below the 0.08 threshold, indicating that the model fits well. This is further supported by the NFI (Normed Fit Index) value of 0.763, which, although slightly below 0.90, is still acceptable in the context of this study.

5. Discussion

The findings from the data analysis displayed in Table 7 indicate a significant correlation between Performance Expectancy, Facilitating Conditions on Campus, and the Behavioural Intention to Utilise Chatbots within the learning environment. The impact of these variables was substantial, suggesting that students' views on the effectiveness of a chatbot (Performance Expectancy) and the available supporting infrastructure on campus (Facilitating Conditions) are essential in determining their intentions to utilise AI-based tools in their educational pursuits. Refer to table 10.

5.1 Impact of AI-Driven on Online Learning

Performance Expectancy refers to students' perception of how well chatbots can enhance their academic performance. In environments where teaching staff may be limited or overwhelmed, particularly in developing countries, chatbots offer a timely solution by providing accurate academic support. For example, in Indonesian universities, where there is often a high student-to-teacher ratio, chatbots can fill gaps by answering common questions, clarifying concepts, and helping with assignments. Students who believe that chatbots will help them achieve better academic outcomes are more likely to adopt these technologies. In such scenarios, chatbots help alleviate the burden on faculty, enabling them to focus on more complex tasks while the chatbot handles routine inquiries. This aligns with prior studies (Chatterjee and Bhattacharjee, 2020; Chew and Cerbin, 2021) that underscore the significance of performance expectancy in adoption of driving technology, but adds that in resource-constrained environments, the utility of chatbots becomes even more pronounced. However, unlike these previous studies, this research highlights the contextual role of teaching staff limitations in enhancing the perceived value of chatbot systems. This unique finding suggests that chatbots serve as an essential supplement in educational settings with limited human resources.

The adoption of new technologies like chatbots also depends heavily on Facilitating Conditions, such as reliable internet access, sufficient IT infrastructure, and institutional support. Many universities in developing regions, including Indonesia, face challenges in delivering these conditions due to financial and logistical limitations. Without adequate infrastructure, the potential benefits of chatbots cannot be fully realized. This study found that when universities provide strong Wi-Fi coverage, well-maintained computer labs, and user-friendly learning management systems, students are more likely to adopt chatbot technologies. These findings are consistent with prior research (Scott and Husain, 2021; Villanueva and Aguilar-Alonso, 2021) which demonstrates that technical and infrastructural support significantly influences the adoption of e-learning tools. However, the current research diverges by showing that even when infrastructure is modest, institutional support—such as faculty encouragement and training programs—can mitigate some technological gaps, fostering a positive attitude toward chatbot usage. This underscores the idea that in developing contexts, institutional facilitation plays a more critical role than previously suggested in literature.

Behavioral Intention reflects a student's willingness to use chatbots in the future, influenced by both performance expectancy and facilitating conditions. In regions where teaching resources are limited, students may be more inclined to adopt chatbots as a means of overcoming these educational gaps. For instance, Indonesian students, who are generally adept at navigating digital tools, are likely to adopt chatbots when they perceive clear academic benefits, such as rapid responses to questions or personalized study assistance. If the necessary infrastructure supports easy access and use of these tools, students are more likely to integrate chatbots into their daily academic routines, leading to improved interaction within online learning environments. This corresponds with findings from (Chatterjee and Bhattacharjee, 2020) on the importance of behavioral intention in technology adoption yet differs in that it emphasizes the scarcity of human teaching resources as a critical factor driving behavioral intention in this context. The current research suggests that chatbots are perceived not just as supplementary tools, but as essential in filling educational gaps created by a lack of available teaching staff.

The Adoption of Chatbot Learning occurs when students fully incorporate chatbots into their academic processes. Even if the perceived ease of use (Effort Expectancy) is low, students are still likely to adopt chatbots if they see substantial academic benefits. For instance, even if students initially face challenges in navigating chatbot interfaces, they are more likely to continue using them if they believe the technology helps manage their workload more efficiently. This is particularly true in environments where direct access to teaching staff is limited. Like previous research (Rumangkit, Surjandy and Billman, 2023), this study highlights that ease of use is not the primary driver of chatbot adoption; rather, perceived performance benefits are. This study also reveals that in environments with inadequate teaching resources, the perceived necessity of chatbots increases adoption rates, even when the technology is not intuitive. This suggests that students in under-resourced environments are more adaptable and willing to overcome initial challenges when they perceive chatbots as essential academic tools.

In Higher Education institutions face limitations in teaching staff and struggle to provide students with adequate resources to explore their academic interests, the integration of AI tools such as chatbots becomes increasingly important. This research demonstrates that Performance Expectancy and Facilitating Conditions, combined with strong Behavioral Intentions, play crucial roles in the adoption of chatbot-based learning. By addressing the quality of teaching staff and enhancing institutional support through improved infrastructure and training, universities can better leverage chatbots to foster autonomous and engaged learners. While previous research has emphasized performance expectancy and technical infrastructure, this study adds that in contexts where teaching resources are scarce, chatbots take on a more critical role, not just as supplementary tools, but as essential components of educational experience.

5.2 A STIN Model Generation on Higher Education

In some ways, this study backs up what other research has found. However, it also shows some differences depending on certain environmental factors. In terms of what people expect from their success, the study agrees with (Pasmore *et al.*, 2019; Yao *et al.*, 2019), which underscore the importance of perceived performance benefits in technology adoption. The finding that performance expectancy significantly impacts students' intention to use chatbots demonstrates that students are more inclined to adopt technology when the academic benefits are clearly perceived. This support is also consistent with (Pirzadeh, Lingard and Blismas, 2021) who indicate that users are more likely to adopt technology that offers immediate performance advantages, which in this context translates to improved learning efficiency.

The study further supports the views of (Beamer, 2019; Yin *et al.*, 2022) regarding the significance of facilitating conditions, including sufficient infrastructure and institutional support, in the implementation of socio-technical systems. In the educational context of developing countries such as Indonesia, institutional support, including internet access and technical assistance, is essential for promoting chatbot adoption. The findings suggest that successful technology adoption depends on both the quality of the technology and the supportive socio-technical environment.

However, this study diverges from the findings of (Jarrahi and Sawyer, 2019) regarding the significance of ease of use as a primary factor in technology adoption. Current findings indicate that ease of use (effort expectancy) does not directly affect students' intentions to adopt chatbots. Indonesian students prioritize concrete academic benefits over usability, likely due to infrastructural limitations that require them to focus on immediate, performance-related outcomes. Here, the unique local context influences user priorities in technology adoption. This study substantiates (Suthers, 2011; Manny *et al.*, 2022), who emphasize the necessity of social support in the adoption of STIN-based technology. This underscores that effective technology adoption requires a synergy between technical and social support, with institutions providing a conducive environment for users.

Employing a generalised model such as the Socio-Technical Interaction Networks (STIN) model is essential for addressing future challenges in technology adoption within Higher Education, as it effectively encompasses both social and technological dimensions. A structured framework is essential for effective technology integration, especially in chatbot-based online learning. The STIN model, as proposed by (Walker and Creanor, 2009) serves as an effective framework that offers a comprehensive perspective on the interaction between technology and social elements within educational institutions. The STIN model analyses the interactions among institutions, technology, students, and support systems, providing essential insights into their collective role in facilitating the effective adoption of AI-driven learning tools such as chatbots which is suggestion implementation in table 11.

This approach guarantees that technology is implemented effectively, socially accepted, supported by necessary infrastructure, and aligned with institutional objectives, the correlation of which is illustrated in Figure 5. This facilitates the establishment of a novel culture of online learning in universities, wherein both social and technical elements work together to foster a seamless and efficient learning environment.

Table 11: Adoption Online Learning with STIN Model

Aspect	Chatbot Implementation Planning Suggestions
Analytical focus	A university might implement a chatbot to assist students in navigating course content, answering administrative questions, and participating in discussion forums. Students can interact with the chatbot to get instant feedback on quizzes, while instructors monitor participation in forums, tracking the impact of the technology on learning outcomes and student engagement within the institution's digital learning network.
Actors	In implementing chatbot-based learning, the university involves various actors such as IT support teams to maintain the system, faculty to integrate the chatbot into the curriculum, students as end-users, and external providers to supply the chatbot software. Administrative staff might also use the chatbot to answer queries regarding registration or deadlines.
Conceptions of actors	Students not only use the chatbot for educational purposes but also interact with it in extracurricular activities (e.g., club management). Staff might utilize the chatbot in their daily workflows for scheduling or troubleshooting, while technical support ensures the system is fully operational across multiple departments and functions.
Treatment of IT	The university's chatbot integrates with the institution's existing Learning Management System (LMS) and is customized based on faculty input to offer tailored academic responses. For example, the chatbot might be configured to automatically suggest additional reading materials based on student queries or behavior, enhancing personalized learning.
IT infrastructure	The chatbot's effectiveness could depend on the robustness of the university's IT infrastructure. A well-maintained, high-speed internet network is essential to ensure real-time interaction with the chatbot, while server capacity must be sufficient to handle peak usage during exams or assignment deadlines. Technical assistance is readily available to troubleshoot any issues students or faculty might encounter.

Aspect	Chatbot Implementation Planning Suggestions
Social behavior	Peer influence can be seen when students recommend using the chatbot for quick answers during study groups or when faculty encourage its use during class sessions. Outside the university, students might use other educational platforms or social media that link back to university chatbots, blending external and internal learning resources.
Resource flows and business models	Universities might allocate part of their budget to acquire and maintain the chatbot system, including purchasing licenses and investing in cloud infrastructure. Additionally, the institution ensures compliance with privacy regulations (such as GDPR) when handling student data, which the chatbot interacts with to provide personalized learning experiences.
E-forum legitimacies	The university secures funding and institutional support for chatbot implementation, with senior administrators promoting its use across departments. Faculty endorsements also lend credibility to the system, making students more likely to engage with technology as a legitimate and helpful academic tool.

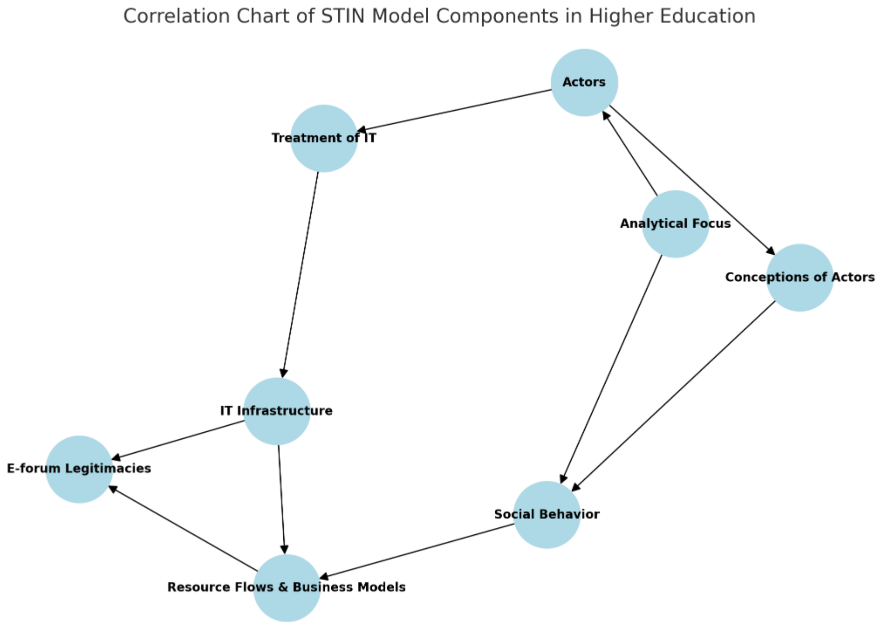

Figure 5: STIN Model of Purpose Online Education

The analytical focus of chatbot-based online learning in higher education emphasises the roles of key actors, including students, faculty, and IT staff. The success of technology adoption is influenced by these actors, highlighting the significance of understanding how stakeholders interact with chatbots through their impact on social behaviour. The relationship between the Analytical Focus and Actors highlights the need for institutional policies that encourage active engagement from both students and faculty in the utilisation of AI-based tools.

For instance, teachers utilise chatbots to help students learn, and students may use them to help them with their academic work. Regarding actors, their various roles influence actors' conceptions, or how staff, instructors, and students see and use chatbot technology in the classroom. These ideas influence how IT is treated, particularly how chatbots are included into curricula. Faculty and students are more willing to interact with chatbots if they are seen as useful tools, which will increase the effort to tailor the technology to the demands of the user. Actors therefore have an impact on the technical and social elements of IT systems, such as system design and user expectations.

The evolution of actor conceptions greatly impacts social behaviour inside educational institutions. The perceptions and interactions of stakeholders using chatbot systems influence the overall learning network. Students who see chatbots as integral to their educational experience may enhance their involvement in online forums, resulting in elevated overall engagement within the university. The management of IT and its correlation with IT Infrastructure dictates the calibre of the infrastructure behind these technologies.

Elements like as internet connectivity, server capacity, and technical assistance are crucial in guaranteeing the efficient functioning of chatbot systems. A more integrated infrastructure enhances the efficiency and fluidity of the chatbot experience for both students and professors. The IT infrastructure also influences resource flows, business models, and the legitimacy of e-forums. Investments in information technology, such server enhancements and software licensing, demonstrate a university's commitment to advancing chatbot systems. Robust infrastructure bolsters E-Forum Legitimacies, augmenting the credibility and broader acceptance of chatbots via sufficient technical assistance, academic endorsements, and regulatory compliance.

Lastly, as greater institutional investment in AI tools may result from higher chatbot interaction, social behaviour feeds back into resource flows and business models. A more technology-driven learning culture may be reinforced by universities allocating additional funds to improve chatbot functionality in response to favourable feedback. Universities should concentrate on how social and technological elements that influence chatbot adoption align to further the practical implications of these results.

Even though the study highlights the significance of user interaction and infrastructure, further research is necessary to determine how organisations may successfully expand chatbot-based learning across various educational environments. Universities should also look for ways to improve training programs for staff and students, encourage ongoing technology advancements, and include chatbots into more general academic regulations. Additionally, by comprehending input on chatbot performance and student happiness, colleges will be able to modify their systems to accommodate changing demands. For chatbot-based learning aids in higher education to be as successful and sustainable as possible over the long run, certain actions are essential.

6. Conclusions

In summary, this study illustrates that the effective implementation of chatbot-based learning in Indonesian higher education is significantly influenced by students perceived academic advantages (performance expectancy) and the availability of supportive institutional resources (facilitating conditions). The identified factors play a crucial role in influencing students' behavioural intentions regarding the utilisation of chatbots, whereas the ease of use (effort expectancy) does not have a direct impact on adoption intentions. This indicates that learners are mainly driven to incorporate chatbots into their educational experiences when they perceive that the technology will improve their academic outcomes and when the campus infrastructure sufficiently facilitates its implementation.

In accordance with the Socio-Technical Interaction Network (STIN) model, these findings highlight that successful technology adoption necessitates a strong social and technical ecosystem. A university setting that offers robust digital infrastructure and comprehensive institutional support is crucial for promoting the integration of AI-driven tools. In Indonesian universities, addressing resource limitations that may affect technology utilisation is crucial. By focussing on performance-driven advantages and strengthening support systems, the adoption of chatbot-based learning can be significantly improved.

Future research should priorities the development of context-aware, AI-driven chatbots that enhance academic support while preserving and promoting written cultural and historical heritage. Integrating AI with humanistic disciplines presents complexities that necessitate the development of chatbot frameworks capable of accurately processing and interpreting historical texts and culturally significant narratives. It is essential for researchers to investigate advanced Natural Language Processing (NLP) models that are trained on region-specific datasets to ensure that chatbots accurately represent local dialects, Indigenous knowledge, and historical manuscripts.

Furthermore, the advancement of chatbot models must include the concepts of becoming process learning, consisting of two aspects. The first aspect, flexibility in learning process and responds generating process, one of potential technology for this aspect semi-supervised learning AI. Second aspect concern to the reflective question and answering generation using combination of open and closed domains, this new domain can be considering a semi-open domain.

This study provides insights into advancements in e-learning, emphasizing the significance of strategic resource allocation and student-centered support for AI technologies. By addressing these socio-technical factors, educational institutions in comparable developing contexts can establish adaptive learning environments that utilize AI technologies to enhance student engagement and learning outcomes.

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Practical Implications of Generative AI on Assessment: Snapshot of Early Reactions to Assessment Redesign in an HRM and a Psychology Course

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Abstract: The advent of Generative AI (GAI) tools such as ChatGPT, Google Gemini, and Microsoft Copilot has significantly impacted higher education. This exploratory study investigates the current perspectives of lecturers in Human Resource Management (HRM) and Psychology on adapting assessment strategies in response to GAI developments. Through an online survey, qualitative data was collected from 12 academics, revealing a shift towards more authentic and process-oriented assessments. The findings highlight the dual role of GAI: while it poses risks to academic integrity, contrary to the common perception, it also offers opportunities to enhance assessment authenticity and student engagement. Participating educators reported various adaptations, including the integration of GAI into assessment tasks, increased use of group-based projects, and the implementation of time-limited and context-specific assignments. The study emphasises the need for continuous evolution in assessment practices to maintain academic integrity and effectively measure student learning outcomes in the GAI era. Further research should focus on longitudinal studies to track the impact of these changes over time, to identify the merits and any shortcomings of these new assessment approaches.

Keywords: Generative AI, Assessment design

1. Introduction

The proliferation of Generative AI (GAI) tools such as ChatGPT, Google Gemini and Microsoft Bing chat (Copilot), have presented many opportunities and challenges for Learning, Teaching and Assessment in HE (Russell group principles on use of AI in HE, 2023). A lot has been written on the need for assessment strategies to become more 'authentic' i.e., equipping students with the necessary real-world skills to succeed in the job market upon graduation (Advance HE Authentic Assessment in the era of AI, 2023; McArthur, 2022). GAI tools can become the catalyst and speed up the adoption of authentic assessment tasks in two ways: a) if universities aim to produce employment-ready graduates, then GAI literacies and skills should be embedded in the curriculum and b) assessment tasks need to be reconsidered so that they embed the critical adoption of GAI tools and minimise the possibilities for academic misconduct. The underlying motivation of the paper is to explore how the advent of GAI is influencing assessment strategies in Higher Education. This research aims to uncover the current thinking of lecturers in Human Resource Management (HRM) and Psychology around the ways they have adapted or intend to adapt their assessment strategies in response to the recent GAI developments. While there is a growing body of literature sources regarding the impact of GAI on assessment, there is a gap in the literature about actual changes made in assessment practices as a result of GAI advancements in specific subject areas such as HRM and Psychology. This study addresses this gap.

The paper is structured in the following order: the background literature section reviews existing research on GAI's implications on assessment, emphasising the challenges to academic integrity and identifying ways these can be addressed. The current study section outlines the research purpose, and methodology followed, detailing how lecturers in HRM and Psychology have adapted, or planning to adapt, their assessment strategies in response to GAI developments. The results section is divided in two analyses: the first examines educator approaches to assessment pre and post GAI, while the second explores future-focused textual data, highlighting educators' hopes and doubts about GAI's impact. The discussion emphasises the need for balanced and thoughtful integration of GAI tools and the adoption of innovative assessment strategies taking into account equitable access to the tools used and the digital literacy skills required to use these ethically and productively.

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The study strengths and limitations are then discussed alongside future research directions and the paper is concluded emphasising the importance of re-evaluating traditional assessment approaches for the new GAI-infused era.

2. Background Literature on the Implications of GAI on Assessment

Researchers and professional organizations have been concentrating on the potential impact of GAI tools on assessment, exploring how assessment practices need to evolve due to the widespread use of these tools (AdvanceHE, 2023; Bower *et al*., 2024; QAA, 2023). A scoping review on how GAI transforms assessment in HE (Xia *et al.*, 2024) found that over half of the 32 reviewed articles in this area highlighted that the emergence of GAI presented a significant challenge to academic integrity as GAI tools can potentially encourage cheating and academic dishonesty. A systematic literature review on AI and academic integrity that included 25 studies, also highlighted the new challenges posed by GAI tools and emphasised the need for a balanced approach to using the benefits of AI in education while upholding ethical standards (Ballale & Pannilage, 2025). Weng *et al*., (2024) in their scoping review of assessment and learning outcomes for GAI in higher education have emphasised the need for traditional assessments to be reviewed and call for the design of innovative assessments and career-driven competencies and lifelong learning skills as new focused learning outcomes. Humble *et al*., (2024) suggests that GAI tools will bring new teaching and learning practices and that lecturers need to adapt to this technology to successfully assess students' knowledge and skills. The need for assessment redesign has been highlighted by other authors too. Firat (2024) argues that some of the traditional assessment methods may soon become obsolete and emphasises the importance of critical thinking skills, digital and AI literacies to be integrated in the curricula.

As GAI tools continue to advance and become more widespread, the UK Quality Assurance Agency (QAA, 2023), a quality assurance service for higher education providers in the UK offering advice, guidance and support to help UK universities and colleges to provide the best possible student experience, warns that certain types of assessments may no longer effectively demonstrate that students have achieved the necessary learning outcomes. This concern arises because students might utilize GAI tools unethically to produce and submit essay-type assignments, which could easily go undetected. Research on detection tools for AI-generated text shows that these tools are inaccurate and unreliable (Elkhatat, Elsaid & Almeer, 2023; Weber-Wolff *et al*., 2023). Consequently, generic essay-type questions are particularly susceptible to misuse, as they provide an opportunity for students to use these tools inappropriately. This highlights the need for educators and educational institutions to rethink and adapt their assessment strategies to ensure academic integrity and accurately measure student learning (Klyshbekova & Abbott, 2024). To this end, the QAA (2023) recommends three key outcomes when reviewing assessment strategies in light of the recent GAI developments: reducing the summative assessment volume and adding more formative checkpoints, shifting towards synoptic assessments, and developing authentic assessments.

Authentic assessment focuses on learners using and applying knowledge and skills in real-life situations and can assist towards the development of work-ready graduates. The call for authentic assessments is not new, however it has been amplified by the recent GAI developments and there is extensive literature on the necessity for assessment strategies to become more 'authentic,' equipping students with essential real-world skills for success in the job market upon graduation (Advance HE, 2023; AdvanceHE, 2024; Brownlie, Burke and van der Laan, 2024; McArthur, 2023). The need for a shift to more authentic assessment tasks and to focus more on the process of assessment providing increased supervision were among the findings of a large-scale international survey with teachers and academics aiming to identify their perceptions regarding the changes needed in teaching and assessment in response to the proliferation of GAI tools (Bower *et al.,* 2024).

3. The Current Study

Generative AI is leading to a re-evaluation of the purpose of higher education and learning as it has significant implications directly impacting existing teaching methods and assessment practices (Malik *et al*., 2023). As discussed in the previous section, the use of GAI tools can potentially pose risks to assessment, such as false evidence of learning and amplify academic integrity issues. Despite these challenges, the use of GAI can open avenues for assessing a wider spectrum of professional and subject-specific competencies, offering students more choices in showcasing their learning. This research aims to investigate the impact of GAI on assessment in HE and in particular on HRM and Psychology courses by asking lecturers in these subjects to explain any modifications they have implemented, or are planning to implement, on their assessment approaches to either counter the risks posed by inappropriate student use of GAI, or to integrate GAI aiming to build their students

GAI literacies and critical thinking. Additionally, we asked participants to speculate on how assessments will look in five years' time.

3.1 Researchers' Professional Background and Research Participants

One of the authors' expertise lies on educational development and digital education, while the other two authors of this study are engaged in teaching Human Resource Management (HRM) and Psychology. Collectively, they hold over 30 years of experience in designing, delivering, and assessing modules at undergraduate and postgraduate levels. Their professional expertise includes curriculum development, assessment design, and digital pedagogies, with a shared research interest in the educational implications of emerging technologies such as GAI. The study was conducted within the context of two post-1992 UK institutions, one in England and one in Northern Ireland, with a strong focus on teaching and learning enhancement. The participants included academic staff involved in assessment design, quality assurance, and pedagogical innovation in HRM and Psychology courses.

3.2 Method

We used an online survey to gather qualitative data. Participants were asked to describe their current assessment approaches. They were then invited to consider how recent developments in GAI might challenge these approaches. Next, they explained how they had redesigned—or were planning to redesign—assessments in a module they teach. Finally, participants reflected on the perceived strengths and weaknesses of these new approaches and shared their thoughts on what assessment in their subject area might look like in five years.

3.3 Research Procedure

Following ethical approval by both participating universities, the survey took place in the summer of 2024. We collected data through a bespoke questionnaire tool, specifically designed for the purposes of this exploratory study. The questions were formulated based on a focused review of the emerging literature on GAI in higher education, particularly in relation to assessment practices. To enhance clarity and relevance, we peer-reviewed the questionnaire internally among the author team, drawing on our combined disciplinary expertise. Following that, the questionnaire was piloted with two colleagues, one from HRM and one from Psychology, before it was finalised. The online questionnaire that was sent to academics can be found below:

- What course(s)/modules do you teach?
- Please describe an example of an assessment method or task you used in a module you taught last year (in the pre-ChatGPT era). Include specific details such as the type of assessment, its objectives, the exact wordings of the tasks, and how it was conducted.
- Reflecting on the assessment method you described, and in light of the recent advancements in Generative AI tools (ChatGPT, Google Gemini, Microsoft Bing Chat etc.), what do you consider to be the significant weaknesses or limitations of this approach, if any, in effectively evaluating student learning?
- Considering the advent of advanced AI tools like ChatGPT (post-November 2022), how have you changed, or how do you intend to change, your assessment methods? Please provide an example of a new form of assessment you have adopted, or plan to adopt.
- What is one key strength or advantage of the new assessment method you have implemented or are planning to implement in the era of advanced AI tools like ChatGPT?
- What is one key limitation or difficulty of the new assessment method?
- In your opinion and based on what you know about Generative AI, what will assessments look like in your subject/discipline in 5 years' time?

The questionnaire was distributed to the entire HRM course team at one university—eight academics in total—of whom six responded. It was also sent to ten lectures of psychology at the other participating university, with six responses received. This resulted in an equal split of participants across the two disciplines.

3.4 Analytic Approach

As a result of our pre-planned questionnaire design, we were able to identify two distinct sets of textual data in the first round of reading the text responses. The first category—derived from responses to questions 1 to 6—comprised a clearly sequenced set of accounts reflecting educators' experiences and viewpoints on responding to GAI through reactive assessment changes, within specific modules. The second category—which includes responses to question 7—was broader and more speculative in nature, capturing general reflections and concerns about the longer-term impact and implications of GAI on assessment in higher education. Given the differing focus and character of these two data sets, we analysed them separately, each using methods appropriate to their structure and content.

The first set of data, i.e., the viewpoints of how lecturers responded to GAI, contained a coherent sequential narrative of pre-existing assessment, educator assessment-related actions (where apparent) in response to the post-GAI era, and educator evaluations concerning the efficacy of action taken. The focus of our analysis was identifying the details of each educator account. Hence, we used a summative content analysis process (Hsieh and Shannon, 2005) which involves counting and comparisons, usually of keywords or content, followed by the interpretation of the underlying context. We began our analysis by identifying frequently occurring terms (e.g. essays, research report) across responses, manually. We calculated word frequencies and noted the source of each instance to better understand how particular terms were used to describe the assessment types. This allowed us to explore the context in which specific words or phrases appeared. Through this process, we were able to interpret the range of assessments participants applied, and relate these practices to broader themes in the data. This process provided basic insights into how assessment forms were used within the subject areas (See Table 1).

The second set of data, i.e., concerning speculative general viewpoints about GAI-related assessment, was subjected to a reflective thematic analysis (Braun and Clarke, 2019). Using the steps prescribed in Braun & Clarke (2019), initially, two of the authors read the text responses independently and generated preliminary codes. They followed an inductive approach to coding, grouping similar codes into broader categories through iterative discussions. To enhance the reliability of our analysis, the third author reviewed our coded data and provided critical feedback on the refinement of themes. Any disagreements were resolved through collaborative discussion until we reached a consensus. We derived the themes presented in this paper, through repeated comparison across responses, paying close attention to recurring patterns in experiences, concerns, and pedagogical responses to the use of GAI in assessment contexts.

4. Results

We present two distinctive analyses in this section. We first present educator survey responses to assessment pre/post GAI emergence. We then consider a discrete corpus of textual data concerning speculations about future assessment approaches, in light of the GAI developments.

4.1 Analysis 1: Educator Approaches to Assessment Pre/Post GAI Emergence

Given the narrative form of this data we present these findings, educator by educator, as Table 1. Table 1 includes educator extracts in summarised form to permit a standard, clear account of textual data. Assessment types at the pre-GAI timepoint were somewhat heterogenous, reflecting the range of assessment approaches undertaken within that disciplinary area. Pre-GAI, participating educators mostly used traditional essay-type submissions (e.g., 3000-word essays, 2500-word research proposals). Most modules had one clearly identified assessment component (9 of 12) while three modules included two components (3 of 12).

Table 1: Pre and post GAI assessments

	Assessment pre-GAI		**Assessment post-GAI**		
ID	**Assessment description (pre-GAI)**	**Evidence of how GAI impacted on the assessment**	**Was assessment changed, post-GAI?**	**Details of changed assessment post-GAI (where applicable).**	**Evaluation of new assessment post GAI.**
P1 PSY	Research report	GAI eases research methods assessment anxiety but is difficult to detect.	No.	n/a	Students may cheat and it is hard to detect.
P2 PSY	Assessment 001: 15-minute motivational interviewing session with a client. Assessment 002: critical reflection.	Students mentioned the use of ChatGPT as an Academic tool. It led to many well written reflections which did not actually relate to what was covered on the module.	No.	n/a	It is very easy for ChatGPT to be utilised, resulting in well written but often inaccurate reflections.

	Assessment pre-GAI		**Assessment post-GAI**		
ID	**Assessment description (pre-GAI)**	**Evidence of how GAI impacted on the assessment**	**Was assessment changed, post-GAI?**	**Details of changed assessment post-GAI (where applicable).**	**Evaluation of new assessment post GAI.**
P3 **PSY**	A 1,500-word essay submitted on Turnitin	Turnitin can identify GAI use as text appears different to surrounding text e.g. it is boxed or grey. We have ensured that all exams are on campus with several invigilators and are developing other approaches to written work.	No.	n/a	All exams are on campus with several invigilators, and we are developing other approaches to written work.
R4 **PSY**	Research Report Writing.	The reflective statement part was identified as the one element more prone to AI misuse.	Yes.	Students were asked to gather and analyse their own data. They also had the opportunity to create their own research question.	Engaging students further and adding specificity in the reflective statement might also make the assessment less prone to the use of AI.
P5 **PSY**	10 min Screencast Presentation.	Assessment submissions all now have to be checked to ensure that the content is not entirely drawn from GAI tools.	No.	n/a	Checking the authenticity of the content. Checking that the student has embedded their learning points.
R6 **HRM**	3000-word essay	Students tend to write AI-tool-generated ideas on talent attraction and retention, as if those ideas have been used in their local organisations. What the students actually learned in the class were not identified in this assessment.	Yes.	The essay task was changed to students writing six, short, online journal postings (200 words each) every week, and a shorter critical response essay (1400 words) that evaluates a post published by their peers.	Writing blog posts on a topic discussed in the class, and the posts are published for other peers to view. In the second task, students write a critical essay based on one of their peers' posts. The arguments are generated based on what is taught in the class.
R7 **HRM**	A 2500-word research proposal.	The literature review section is poorly written. It lacked cohesion, criticality and comprehension. Students tend to use AI tools to generate proposals that are too descriptive.	Yes.	The task was changed to two tasks of writing a Literature Review-based Academic Essay (1250 words - 30%) and producing a research Proposal (2000 words - 70%) that uses the output of the first task as a component in the proposal.	The literature-review based essay prepares the students on writing literature review sections and helps them get feedback. Students then use the feedback to develop the literature review section as part of their proposal. By dividing the assessment into two pieces of coursework, lecturers are able to see students' work in Stage 1. If any unusual patterns are found in Stage 2, then this gives a chance for lecturers to identify if the submitted work is the students' or not.

	Assessment pre-GAI		Assessment post-GAI		
ID	**Assessment description (pre-GAI)**	**Evidence of how GAI impacted on the assessment**	**Was assessment changed, post-GAI?**	**Details of changed assessment post-GAI (where applicable).**	**Evaluation of new assessment post GAI.**
R8 PSY	Short answer essay; answer 2 questions (out of 4) with a 500-word essay for each question.	Potential AI misuse as students can use AI to answer the essay and ultimately adapt or polish their answers into better-finished work.	Yes.	Change made for this year - gave students the ChatGPT answers to all the short questions, so that they could not just use the basic answer that ChatGPT would produce.	Incorporating ChatGPT responses as learning materials can improve the learning experience and might act as a deterrent. Inherent limitation of the essay as an assessment method as essays can always be polished or adapted by AI tools.
R9 HRM	1500-word Essay. 3000-word Research Proposal	The biggest weakness of these assessment types is that students can use GenAI tools to generate answers. Students' original ideas are not that visible in their works.	Yes.	Introduced two time-limited tasks, releasing both tasks only 24 hours before the deadline and specified that local context must be used as reference in their answers.	The emphasis on the local Northern Irish context restricts students to focus more on their own thinking and contextual reflections. The limited time allowed for them further restricts their ability to use AI-generated contents extensively.
R10 HRM	1500-word Essay. 3000-word Case Study.	Students began to use AI tools to brainstorm ideas and presented them as their own. Although it was obvious that they are not their own ideas, I was not able to prove this.	Yes.	The traditional essay assessments were changed to a Lab-based task of HR analytics Simulation and a group presentation of their Analytics Dashboards.	The key strength now is the whole class is in the lab. Everyone is sitting in front of computers. They use the data and the software which I supplied. It is a monitored exercise. The group presentation and the Q&A session that follows gives ample opportunities to test learning gains.
R11 HRM	Analysis of their own company organisational structure using the company's annual report and suggest improvements.	No limitations identified, although students could use AI tools to analyse the company's documents.	Yes.	Change from individual to group project (In groups of 5 create an organisational structure for a specific company).	Authentic task researching a local company, proposing a structure and get it evaluated by a member of that company. No perceived limitations.
R12 PSY	To write a STEEPLE analysis report. Second task to write an essay.	AI tools give STEEPLE analysis of several companies. Students' answers resemble ChatGPT generated scripts.	Yes.	Changed the submission format types to include two modes of submissions: Live, in-class presentation or video recorded, narrated presentation.	Demonstrating the understanding of the content. AI use still possible, but the risk of copying directly is minimised.

Educators identified a range of evidence relating to the impact of GAI on assessment. An educator thought that GAI could be misused to develop a higher standard assessment response than would otherwise have been possible (R8). However, other educators mentioned that GAI tools tended to reduce the overall assessment quality by producing overly descriptive and relatively less coherent work (R7, R2). Other educators emphasised that a main challenge was the impossibility of demonstrating that GAI had been used to generate content (R1, R9, R10). In some responses it was apparent that educators did not identify a major impact of GAI on assessment (R11, R4) and an educator claimed that current processes and resources in place successfully identified inappropriate GAI use linked to assessment (P3). Notably, two thirds of participating educators (n=8) formally changed their assessment approach in some way following the widespread availability of GAI tools and the associated awareness of how these might be used in educational environments among educators and learners, while the remaining educators either made no change or made changes to the process surrounding submissions rather than the assessment specification itself (n=4).

Responses indicated varied methods for changing the assessment approach post-GAI, where change had occurred. Some changes were very minor including retaining the same overall assessment approach but shifting one element (R4), students required to generate their own datasets or, more substantially, retaining the approach but creating a choice of different submission formats that mitigated inappropriate use of GAI (evident in R12's live or video-recorded submission formats). Other changes involved amendments which foregrounded GAI in some way by introducing it into the assessment approach (R7, R8). For example, R7 reported changes that involved using GAI to create a literature review which learners then needed to provide a critical response to. Some educator responses indicated change involving movement toward group-based assessments (R10, R11). Group-based assessments had the benefit of being able to see learners engaging in their assessment in real time, with peers, on campus (R10), while other responses showed inventive ways of involving online peer engagement in an assessment change requiring learners to produce a critique of assessment-mandated peer produced journal posts concerning module topics (R6). Another example of inventive responses included localising the assessment focus (R4, R9) so that learners needed to focus on (e.g.) their own business/local context, and learners being granted limited time (e.g., 24 hours) to produce their response (R9).

Several responses suggested that there had already been evidence of improvements to submitted work, in terms of reduced AI-generated work, following GAI-related assessment changes. For example, time-limited approaches to deadlines seemed to reduce inappropriate GAI usage (R9), and incorporating GAI transparently into assessment appeared to serve as a deterrent to inappropriate adoption of GAI tools among learners in the experience of some educators (R7, R8). Other data indicated how students' work became more familiar to educators following changes whether by having more oral/presentation type assessments (R10) or by providing an opportunity for a formative/ early warning mechanism for identifying inappropriate GAI use at an early stage and subsequently addressing this via feedback to relevant learners.

4.2 Analysis 2: Future-Focused Textual Data

Material in this section concerns a thematic study of textual responses generated in response to the speculative question: "what will assessment look like in your discipline in 5 years' time?". As reported below, we identified two simple themes – 'Hopes' and 'Doubts' – from this analysis.

4.2.1 Educators' hopes: priority emphasis on process, groupwork and authentic assessment

Notably, most responses were optimistic about GAI's anticipated impact on assessment and learning experiences and approaches within HE more widely. Optimism was grounded in how "*GAI technologies will be incorporated as learning tools in teaching*" (R8); and in a movement towards "*students being able to demonstrate their learning in various ways, including in-class, routine, bite-size tasks*" (R11). Grounds for optimism were particularly strongly expressed in terms of more emphasis placed on process and groupwork and away from product in learning experiences: "*shifted focus from product to process and relationships, co-created assessments, peer marking, self-assessment and emphasis on developmental feedback... but these changes may take more than 5 years*" (R12); "*we will focus more on 'HOW' students learn A, B and C and APPLY them in real world, than on 'WHAT' they learn in formal settings*" (R7). One educator went further still, suggesting that the growth of GAI in the context of HE assessment might have positive implications for learner mental health, "*future assessment be more enjoyable, personalised and engaging because of the possibilities of gamification... if teachers are creative and skilful, it is possible to help students enjoy the assessments and thus reducing their anxiety and promote wellbeing in universities... assessments times may be less stressful in the future*" (R10).

One final reason for optimism concerned the possibility for more transparent and relationally sophisticated relationship between educators and learners because of the emergence and growth of GAI in the context of assessment. This was apparent in an extended and eloquent response from one educator, "*I directly acknowledge GAI's appeal when speaking to learners and talk about how I would have used it myself had it been available as an undergraduate... I explain why using it would have been massively inhibitive to my personal and academic growth, and why I am so glad that I was forced to write my own assessments... this leads to talking* *about foundational reasons for attending university (personal growth, confidence, career progression), and how using ChatGPT could undermine these things... students may still go on to use ChatGPT, but having this helpful discussion always strikes a chord with students*" (R1).

4.2.2 Educators' doubts: unassured quality and expanded inequity.

Despite a mainly optimistic forecast, there were clear issues of concern voiced by some educators. Clear risks were identified including the risk to the reputation and quality assurance of higher education as an institution for providing a skilled workforce and delivering on raising individual aspiration: "*there are costs of GAI in the learning experience: the more automated tech is relied on, the less learners get to exercise social communication skills... GAI assessment methods cut out essential interpersonal, relational and experiential components of learning*" (P5). Another clear area of risk concerning the growth in GAI technology was how it may contribute to unfairness. This might involve inequity in access to, or familiarity with, GAI technology among learners and educators alike, "*the (inevitable) use of AI by some students should not mean other students should have their academic growth stunted*" (R1). Similarly, another educator suggested that GAI might serve to exacerbate the divide between access to higher quality, more technologically sophisticated higher education experiences between relatively more and less wealthy countries, "*in advanced countries, and particularly in postgraduate and professional courses, more immersive, dialogue-based and interactive experiences may be used in assessments, possibly by using AI-enabled, wearable tools. In developing countries, however, more emphasis might be given to the traditional pen and paper, closely proctored, campus-based assessments to combat students' use of AI-generated answers*" (R9).

5. Discussion

Generative AI (GAI) tools such as ChatGPT have presented considerable challenges and possibilities for how educators approach assessment design within higher education delivery. This research aimed to uncover the current thinking of lecturers in Psychology and HRM on the ways they have adapted or plan to adapt their assessments in light of the recent GAI developments. Based on the views of 12 UK-based academics, we show four significant threads in their responses to GAI integration and their vision for future assessment practices.

First, our findings reveal that two-thirds of participating educators have made meaningful changes to their assessment practices, highlighting the substantial impact of GAI. Notably, some of these changes were not just minor adjustments; academics actively developed innovative approaches to enhance learning. For example, some academics are integrating GAI directly into the learning process, alongside a shift toward group-based and time-limited assessments that reflect a broader movement in higher education; additionally, there is a notable trend toward using localised, context-specific tasks that require students to connect theoretical knowledge with real-life or professional contexts, in line with authentic assessment principles. This shift shows that educators are rethinking assessment—moving beyond traditional integrity concerns to what we might call 'post-GAI assessment trend.' These new assessment trends do not challenge GAI usage simply by making the questions more complex; they demand authentic human engagement and contextual insight. Such a shift signals a promising move in how we evaluate student learning, from simply recalling information to truly applying knowledge in real-world contexts. Our findings confirm and extend the recent shifts in assessment approaches highlighted by Weng *et al*. (2024) and Lang (2024) and align with various sources that highlight the need for assessment redesign in light of the recent GAI developments (Firat, 2023; Naidu & Sevnarayan, 2023; QAA, 2023; Yeadon *et al*., 2023). As Humble *et al.* (2024) have highlighted, the assessment of basic skills and knowledge will need to be reconsidered. The trend toward authentic assessments that emphasise context-based skills and lifelong learning outcomes represents a promising shift toward innovative approaches, that support more holistic student development. We see that this trend will benefit students by equipping them with transferable skills that align more closely with industry demands, allowing them to build capabilities essential for lifelong learning in professional environments.

Second, the study also revealed academics' evaluation of GAI's impact on students' submissions. While some educators expressed concerns that GAI allows for enhanced performance, others noted a different trend. Often, AI-generated content resulted in work that was less rigorous, relying heavily on descriptive elements while lacking depth, coherence, or critical analysis. This variation in educators' experiences underscores the complex nature of GAI's influence on learning. On one hand, GAI can help students organise and articulate ideas more fluently; this support may be particularly beneficial for international students, who often face additional language and structural challenges. On the other, it may inadvertently encourage an overreliance on AI-generated content over synthesis and insight. These mixed results underscore the need for continued exploration into how GAI impacts both the form and substance of student submissions, raising important questions about how we construct learning outcomes, design assessment criteria, and evaluate student performance. This complexity calls into question current grading practices and the basis on which judgments about learning gains are made, suggesting a need to rethink traditional approaches to assessing student understanding and skill development in a GAI-influenced environment. Contributions such as the AI Assessment Scale by Perkins *et al.,* (2024) hold promise for the ethical integration of GAI in educational assessment.

Third, our study brings forward several concerns and challenges surrounding the integration of GAI in assessment, calling for a broader perspective that considers the varied global uptake of GAI tools. Our findings highlight that unequal access to GAI could lead to inconsistent learning outcomes and variable academic support across student groups, thereby increasing educational inequities. The absence of access to GAI tools may not only widen achievement gaps but also limit opportunities for students to practice and refine their interpersonal and communication skills through authentic, real-world tasks. Additionally, this lack of access highlights a risk of growing disparities in assessment approaches, particularly between developed and developing countries, where access to GAI technology may vary significantly. Such disparities call for a critical examination of how GAI is integrated into education, emphasising the importance of equitable access and a careful consideration of its broader effects on skills development and international assessment standards. We also observe that none of the participants referenced scenarios in which GAI could be utilised in assessment contexts as a co-intelligence model, as suggested by Mollick & Mollick (2024), where GAI works collaboratively with students to enhance learning quality. This reveals an underexplored potential of GAI as a transformative educational tool. By fostering an interactive, co-intelligence-based approach, GAI could support a more dynamic learning process, augmenting students' creative and analytical abilities. Such a model could enable students to produce richer, more comprehensive outputs, highlighting the value of harnessing GAI not merely as a functional tool but as an integrated partner in diverse learning contexts.

Fourth, differences in disciplinary priorities appear to shape how GAI is being interpreted and addressed in assessment practices. HRM academics often referenced the importance of preparing students for the world of work and focused on adapting assessment tasks to reflect practical, applied, and authentic formats that GAI cannot easily replicate. In contrast, psychology academics were more likely to raise questions about students' cognitive development, critical reflection, and conceptual understanding. These distinctions suggest that subject-specific traditions—such as HRM's emphasis on employability and applied skills, and psychology's attention to cognitive and developmental learning—may influence how academic staff perceive the risks and opportunities of GAI in higher education assessment. This highlights the need for institutions to consider the disciplinary context when supporting staff to respond to GAI in teaching and assessment.

Taken together, these findings contribute to our understanding of how GAI is reshaping assessment in higher education, suggesting that successful adaptation requires three key approaches to assessment design and implementation: balanced integration of GAI tools while preserving core educational values, designing assessment strategies that leverage GAI's potential while mitigating its risks, and ensuring equitable access to prevent disparities in learning achievement. We suggest that there is an urgent need for discipline-specific educator development programmes in universities that empower them to stay ahead of both GAI advancements and student adaptations, equipping educators to anticipate changes, refine assessment strategies, and continue to genuinely care about their students of all abilities. To this end, our findings serve to provide a source of qualitative evidence to guide understanding by highlighting educators' experiences and guiding future efforts in adapting assessments.

6. Study Strengths, Limitations and Future Research Priorities

Strengths and limitations of our study are considered alongside implied areas for future research in this area. First, we acknowledge that the small sample size (n=12), selected from two UK universities, with a focus on HRM and Psychology departments limit the generalisability of these findings. While the sample size is small, it enabled a more in-depth, qualitative exploration of educators' views and decision-making activities, generating richer insights into how GAI is shaping assessment design. Although the data were drawn from only two disciplines, this narrower focus allowed us to examine specific practices more closely and to capture discipline-informed responses. We believe the experiences and concerns raised by our participants may resonate with educators in other subject areas, offering relevance beyond the immediate sample.

Second, we also acknowledge that using a free-text survey tool to capture educator responses worked well as a convenient way of generating a substantial but manageable volume of textual data to address our research aims. However, we point out that educator narratives around previous module assessment, design responses post GAI and general apprehensions about the impact of GAI on higher education assessment were mixed in terms of detail and focus, partly as a function of the survey tool approach. Future research can now address this by interviewing a subset of educator survey respondents to generate fuller, spontaneous insights into individuals' views, experiences and feelings.

Third, while our decision to approach educator viewpoints at a module specific level meant we could rapidly survey colleagues simply and efficiently, we acknowledge that this meant we were unable to consider prior and reactive educator responses at the level of an entire curriculum for particular courses or disciplines. Taking this broader approach was beyond the scope of our study. We recommend that future research builds on the scope and scale of our study by a more comprehensive mapping exercise - e.g. of GAI-related assessment changes for a whole course or a set of courses in an entire disciplinary area. In addition, exploring assessment approaches in response to GAI developments across a wider range of disciplines is now required.

Fourth, our research study design was appropriate given the novelty of the phenomenon under exploration. Our data has provided a snapshot insight into how educators have responded to a pressing demand on the integrity of their assessment approaches in the context of an unprecedented technological upheaval. However, we were unable to explore a wider range of questions concerning change over time and viewpoints/ experiences among different stakeholders recorded in time series. We suggest that a longitudinal expansion of the current study could follow the 'journey' of a new, GAI-informed, set of course assessment across multiple modules, drawing on the perspectives of both educator and learner stakeholders, to identify the relative merits and shortcomings of approaches taken.

Future research could address these limitations in several ways. Investigating student perspectives on these modified assessments would add valuable depth, helping educators understand how GAI integration impacts students’ learning and engagement. Research across varied disciplines could also uncover discipline-specific effects, clarifying whether certain fields benefit more from GAI-based approaches. Finally, exploring methods to maintain assessment integrity in a GAI-enabled environment remains essential, especially as technology continues to advance. Additionally, the rapidly evolving nature of GAI technology means that the findings may require regular updating. These efforts would collectively enhance our understanding of GAI’s impact and guide best practices in assessment.

7. Conclusion

The integration of Generative AI (GAI) tools in higher education is prompting a re-evaluation of traditional assessment methods. There has been sector speculation that future assessments in HE will emphasize process over product, with less summative and more continuous, formative assessments providing ongoing feedback and support. GAI has the potential to enhance personalized learning experiences, provided educators and students have the necessary skills and resources. We sought to understand experiences and viewpoints of using GAI for assessment purposes among lecturers in HRM and Psychology. Our findings highlight the need for educational institutions to adapt their strategies to maintain academic integrity while leveraging GAI benefits. While GAI presents significant challenges to traditional assessment methods, it also offers opportunities for more authentic, engaging, and effective assessment practices. By addressing the associated risks, higher education institutions can better prepare students for the modern workforce and promote ethical GAI use.

AI statement: AI tools have not been used in any phase of this research including the writing of the paper.

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Thematic Synthesis and Future Outlook in Digital Entrepreneurial Education

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Abstract: The rapidly evolving field of digital entrepreneurial education has been significantly shaped by advancements in technologies such as augmented reality (AR), virtual reality (VR), and artificial intelligence (AI). While these technologies have opened new possibilities for entrepreneurial learning, much of the existing research is fragmented, focusing on isolated tools or specific interventions. This piecemeal approach complicates efforts to identify overarching trends, theoretical frameworks, and practical applications relevant to educators, policymakers, and researchers. To address these challenges, this study employs a Bibliometric-Systematic Literature Review (B-SLR) methodology, combining quantitative bibliometric analysis with qualitative synthesis to offer a comprehensive and balanced perspective on the field. We reviewed 261 articles published between 2005 and 2024, capturing diverse geographical regions, subject areas, and publication outlets. This approach enabled us to identify prevalent research themes, uncover emerging methodologies, and highlight areas that warrant deeper investigation. Our analysis revealed four main clusters: (1) Technology-Enhanced Entrepreneurship Education, examining how AR, VR, AI, and digital platforms foster engagement and skill-building; (2) Experiential and Project-Based Learning Approaches, highlighting gamification, simulations, and collaborative projects that stimulate practical competencies and adaptability; (3) Entrepreneurial Competencies, Mindset, and Social Dimensions, exploring cultural, generational, and gender-related factors that shape learner readiness and intentions; and (4) Future-Oriented and Transformative Approaches, emphasizing sustainability, global collaborations, and ethical considerations that guide the long-term evolution of entrepreneurial learning. The findings indicate that technological tools alone do not guarantee enhanced entrepreneurial outcomes. Instead, successful digital entrepreneurial education relies on cultural relevance, supportive policies, comprehensive educator training, and inclusive pedagogical designs. The study proposes an integrative framework that synthesizes technological, experiential, socio-cultural, and forward-looking strategies, offering actionable insights for improving educational practices and advancing theoretical understanding in the field. This research highlights critical areas for future exploration, including the development of learner-centred curricula, investments in digital infrastructure, and the promotion of international collaborations. By addressing these gaps, stakeholders can establish adaptable, inclusive, and ethically grounded ecosystems that equip learners with the skills and mindset needed to navigate the complexities of entrepreneurship in an increasingly dynamic global environment.

Keywords: Digital entrepreneurial education, Bibliometric-systematic review, AR/VR learning, AI tools, Entrepreneurial mindset, Experiential learning

1. Introduction

The digital era has revolutionised education, reshaping the delivery and acquisition of knowledge across disciplines, including entrepreneurship. Traditional entrepreneurship training, which relied heavily on lectures and case studies, has evolved into digital, online, and blended modalities that leverage digital platforms, immersive technologies like augmented reality (AR) and virtual reality (VR), and artificial intelligence (AI)-driven tools. These advancements enhance accessibility, engagement, and interactivity in entrepreneurial learning (Sulistianingsih, 2023; Rosli, 2023). Such innovations create flexible, interactive environments that allow students to engage with dive resources and collaborate globally (Liguori & Winkler, 2020; Secundo et al., 2021; Manurung, Purwadi, and Sugiharto 2022).

Digital platforms play a pivotal role in modern entrepreneurial education by providing extensive resources and fostering collaboration. For example, platforms like Launchpad Albania enable university students to develop business ideas, connect with peers and mentors, and evaluate their concepts' viability (Begum, 2023; Pano & Gjika, 2020). Immersive technologies, including AR and VR, further enrich learning by simulating real-world entrepreneurial challenges, which enhance practical skills and foster essential entrepreneurial mindsets (Khan & Sethi, 2022; Vaičiukynaitė et al., 2022). AI-driven tools add another dimension by personalising learning experiences and providing real-time feedback. They analyse student performance to tailor content to individual

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needs, improving engagement and learning outcomes (Williamson, 2020; Vargo et al., 2020). These tools also simulate market conditions and consumer behaviours, allowing students to experiment with business strategies in controlled environments (Chen & Yau, 2021; Cao, 2023).

Despite these advancements, the literature on digital entrepreneurial education remains fragmented. Studies often focus on specific technologies or interventions without offering a comprehensive overview of digital-focused themes (Neck & Greene, 2010; Rosli, 2023). Furthermore, while research frequently evaluates program outcomes, there is a lack of systematic and bibliometric analyses to identify dominant themes, methodologies, and trends (Satalkina & Steiner, 2020; Kraus et al., 2018). This fragmentation limits educators, policymakers, and researchers in understanding the field comprehensively or guiding future innovations effectively (Li, 2023; Liguori et al., 2021).

A methodological approach capable of synthesising extensive research, uncovering patterns, and highlighting emerging areas is essential to address this gap. The Bibliometric-Systematic Literature Review (B-SLR) combines the quantitative precision of bibliometric analysis with the qualitative depth of systematic reviews, offering a comprehensive understanding of the research landscape (Alegre, Callahan, & Iszatt-White, 2023). This study applies the B-SLR approach to map existing literature on digital entrepreneurial education, identify key themes and trends, and highlight critical gaps for further exploration.

This study addresses three key research questions: What are the prevalent research themes in digital entrepreneurial education? What novel topics and methodologies are emerging, particularly concerning technological advancements? What critical gaps exist, and how can future studies advance the understanding and practice of digital entrepreneurial education? By answering these questions, this research provides an overview of key clusters, identifies cutting-edge developments, and proposes a conceptual framework to guide future research.

The anticipated contributions of this B-SLR are multifaceted. Educators can refine curricula and select effective digital tools to enhance entrepreneurial competencies. Policymakers can allocate resources and devise strategies that support the integration of digital technologies into entrepreneurial education. Researchers can identify under-explored areas and adopt innovative methodologies to enrich the scholarly discourse and drive innovation. Ultimately, this study bridges the gap between fragmented research and a cohesive understanding of how digital technologies reshape entrepreneurial education, fostering a responsive entrepreneurial mindset for the digital economy (Yu et al., 2022; Kolarov, 2023).

In responding to the need for entrepreneurial education to remain relevant amid uncertainty, global competition, and technological disruption, this research underscores that digital skills and entrepreneurial mindsets are essential. Educational institutions must rely on informed, evidence-based strategies to cultivate entrepreneurs capable of navigating complex, digitally driven markets (Neck & Greene, 2010; Chen & Yau, 2021). This synthesis clarifies existing knowledge while proposing innovative directions for research and practice, ensuring entrepreneurial education prepares students for modern business challenges (Satalkina & Steiner, 2020; Kraus et al., 2018).

2. Methodology

This study applies the Bibliometric-Systematic Literature Review (B-SLR) methodology to explore the integration of digital technologies in entrepreneurial education. The B-SLR combines bibliometric analysis with systematic literature reviews, offering a structured approach to identify key themes and trends while addressing gaps in existing research (Marzi, Balzano, Caputo, & Pellegrini, 2024). This approach is particularly suited for interdisciplinary fields such as digital entrepreneurship education, which spans business, social sciences, and technology (Zupic & Čater, 2015).

The rationale for employing the B-SLR lies in its transparent procedures and reproducible protocols, which help reduce bias and ensure consistency compared to traditional narrative reviews (Donthu et al., 2021; Tranfield, Denyer, & Smart, 2023). Bibliometric techniques enable the visual mapping of intellectual structures and collaboration networks, offering insight into influential contributions and emerging trends (Wijaya, Setiawan, and Shapiai, 2023).

Scopus was selected as the primary database, with Web of Science (WoS) used for supplementary validation, ensuring robust indexing standards and comprehensive coverage (Mongeon & Paul-Hus, 2016; Bascur et al., 2023). The search string *(TITLE-ABS-KEY(digital OR online OR virtual OR "E-learning") AND TITLE-ABS-KEY("entrepreneurial education" OR "entrepreneurship education" OR "entrepreneurship training" OR* *"entrepreneurial learning"))* was used. Filters were applied for language, document type, year, and subject area, resulting in a refined dataset of 261 articles (Table 1).

Table 1: PRISMA Flow Diagram for Study Selection

Stage	Number of Records	Notes
Identification	849	Initial search in Scopus
Records after duplicates	849	No duplicates in initial search
Screening	420	Applied language, document type, publication years, and subject areas filters
Eligibility	420	Reviewed for relevance based on inclusion criteria
Articles excluded	159	Focused solely on general entrepreneurship education, lacked methodological rigor, or provided only descriptive analyses
Included	261	Final dataset for analysis

Bibliometric analysis was conducted using VOSviewer, incorporating co-word analysis, bibliographic coupling, and overlay visualisation techniques (van Eck & Waltman, 2010). Co-word analysis identified clusters of frequently co-occurring keywords that represent conceptual linkages across studies. In parallel, overlay visualisation was employed to map the temporal evolution of key research topics, thereby providing insight into the development of the field over time.

To address the methodological limitation of relying solely on keyword clustering, an additional layer of validation was incorporated. Each thematic cluster generated through co-word analysis was independently reviewed by two researchers. These reviewers examined the content of the source articles associated with each cluster to verify alignment between the keyword groupings and the actual thematic content. Any discrepancies in interpretation were resolved through structured discussion and consensus-building, thereby strengthening the reliability and conceptual validity of the thematic labelling.

In addition to the bibliometric procedures, a qualitative synthesis of the selected articles was undertaken to extract deeper thematic insights. This synthesis focused on identifying theoretical frameworks, dominant methodologies, and recurring conceptual patterns across the corpus (Breslin & Gatrell, 2023; Marzi et al., 2024). The integration of bibliometric and qualitative approaches enabled a richer interpretation of how digital technologies influence entrepreneurial learning, offering both breadth and depth in the analysis.

The review adhered to the PRISMA guidelines to ensure methodological rigour and transparency (Page et al., 2021). Inclusion and exclusion criteria were consistently applied throughout the review process. To ensure objectivity, inter-coder reliability was assessed using Krippendorff's Alpha (Krippendorff, 2019). While the study includes a broad and diverse selection of sources, the exclusion of non-English articles is acknowledged as a limitation. The integrated findings led to the development of four thematic clusters and an overarching conceptual framework, offering practical and theoretical contributions for educators, policymakers, and researchers (Schmiedel, Muller, & vom Brocke, 2018; Thomas & Tee, 2022).

3. Results

3.1 Descriptive Analysis

This section provides a detailed overview of the research corpus on digital entrepreneurial education, offering insights into its key characteristics. The final selection process resulted in a dataset comprising 261 articles published between 2005 and 2024 (Figure 1). This analysis highlights the temporal distribution of publications, authorship patterns, citation metrics, leading publication sources, and geographic spread.

The dataset consists of 261 academic articles authored by 725 contributors from diverse institutions and countries. On average, each article has 3.04 authors, reflecting a collaborative research culture. The average citation count per article is 11.95, with a total of 13,426 references cited. Such metrics underscore the growing scholarly engagement and the knowledge base supporting digital entrepreneurial education.

The corpus is internationally diverse, with 15.33% of publications involving cross-country collaboration, and an average article age of 2.79 years, indicating that research in this field remains current and rapidly evolving. An annual growth rate of 25.06% further underscores the increasing academic interest and relevance of digital entrepreneurial education in a technology-driven era. Focusing on key temporal patterns, the number of publications surged notably from 2018 onwards, peaking at 70 articles in 2024. This upward trend aligns with the proliferation of online platforms, immersive learning tools, and the demand for digitally savvy entrepreneurs.

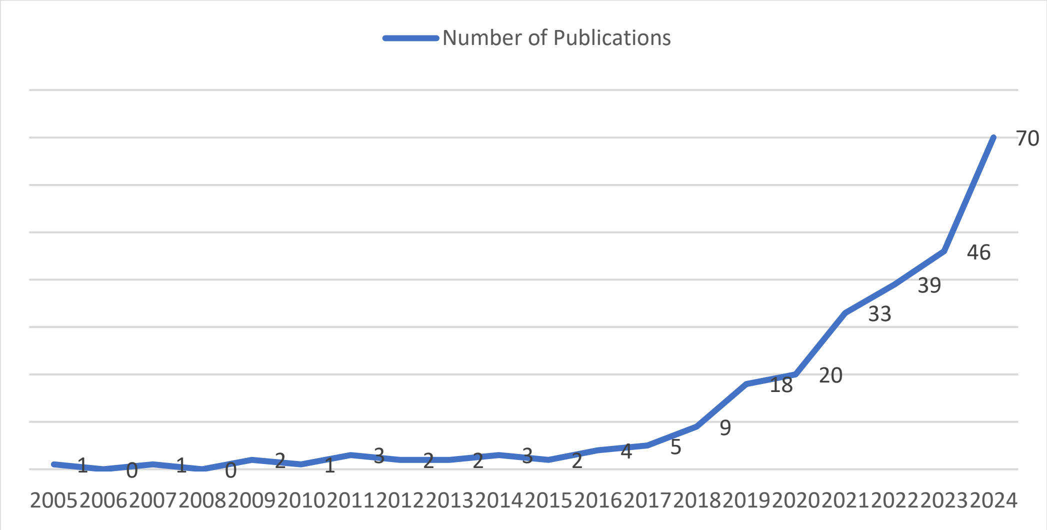

Figure 1: Temporal distribution of publications

Geographically, China and Indonesia dominate the landscape, possibly due to robust policy support and infrastructure development. In contrast, the United States, Italy, and the United Kingdom, with strong research ecosystems, bring diverse theoretical and methodological perspectives (Table 2).

Table 2: Geographic spread

Country	Number of Articles
China	120
Indonesia	77
United States	68
Italy	51
United Kingdom	41

Major publication outlets range from specialized journals focusing on entrepreneurship and education (e.g., International Journal of Management Education, Journal of Entrepreneurship Education) to more interdisciplinary sources (e.g., Sustainability, Technological Forecasting and Social Change). This mix suggests that the field's intellectual roots extend into sustainability, technological innovation, and global educational reforms (Table 3).

Table 3: Leading Journals Publishing in the Domain

Journal/Publication Scope	Number of Articles
International Journal of Management Education	14
Journal of Entrepreneurship Education	13
Applied Mathematics and Nonlinear Sciences	12
Entrepreneurship Education and Pedagogy	8
Industry and Higher Education	7
Sustainability (Switzerland)	7
Education Sciences	6
Technological Forecasting and Social Change	6
Education and Training	5
International Journal of Emerging Technologies in Learning	5

The field of digital entrepreneurial education demonstrates a highly collaborative and international nature, with an average of 3.04 authors per article and 15.33% involving cross-country collaborations. Research trends reveal a significant surge in publications since 2018, reflecting the increasing relevance of this field in the context of technological advancements. Geographically, major contributions from China, Indonesia, and the United States highlight the global importance of fostering digital skills through entrepreneurial education. Additionally, the field's interdisciplinary scope is evident in its diverse publication outlets, ranging from specialised entrepreneurship journals to broader interdisciplinary platforms, showcasing its wide-ranging impact across multiple domains.

3.2 Bibliometric Clustering

3.2.1 Co-Word analysis

In the following sections, we map co-word occurrences and bibliographic couplings. Beyond identifying keywords, we also note the theoretical orientations and methodologies characterizing each cluster to provide deeper insights into their intellectual structures. The co-word network offers a thematic map of digital entrepreneurial education, with "entrepreneurship education" at the centre, connected to key terms like "entrepreneurial learning," "digital entrepreneurship," "e-learning," and "student." Figure 2 illustrates the emphasis on integrating entrepreneurial skills with digital tools. Below are the key clusters:

- Core Entrepreneurial Pedagogy Cluster (Red/Blue Nodes): This cluster, anchored by "entrepreneurship education," focuses on integrating digital competencies, critical thinking, and technological fluency. Research here often employs experiential learning models and mixed-method case studies to evaluate digital curriculum innovations.
- Technological and Pedagogical Integration Cluster (Green Nodes): Highlighting terms like "education computing," "curricula," and "universities," this cluster explores the integration of digital tools in education. Studies blend quantitative assessments of digital platform effectiveness with qualitative evaluations of institutional readiness, reflecting the intersection of pedagogical theory and technology adoption.
- Experiential and Behavioral Dimensions Cluster (Purple Nodes): Keywords such as "experiential learning" and "entrepreneurial self-efficacy" focus on immersive environments and learner psychology. Research here often leverages behavioral theories and experimental designs to examine how digital simulations and gamified experiences influence entrepreneurial intentions.

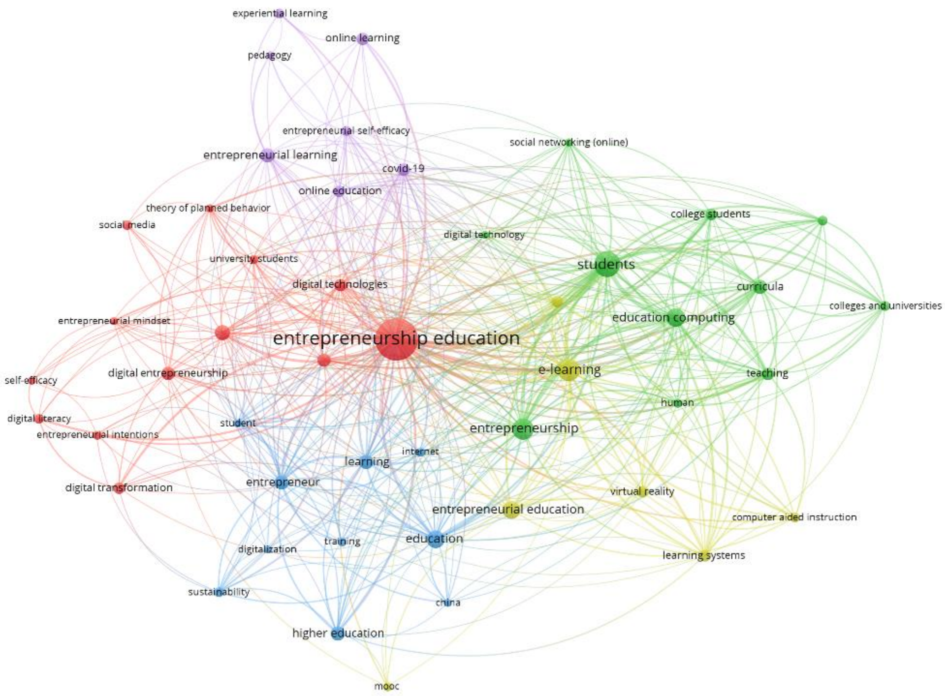

Figure 2: Co-Word Analysis

3.2.2 Bibliographic coupling by country

The visualisation in Figure 3 highlights how nations cluster based on shared references. Countries like China, Indonesia, India, and Australia (Asia-Pacific cluster) focus on digital entrepreneurship education in rapidly developing markets, often emphasising capacity-building and economic development. In contrast, European nations form a distinct cluster characterised by strong collaborative research traditions, prioritising policy frameworks, comparative analyses, and international partnerships. These clusters reflect regional priorities shaped by unique socio-economic and institutional contexts.

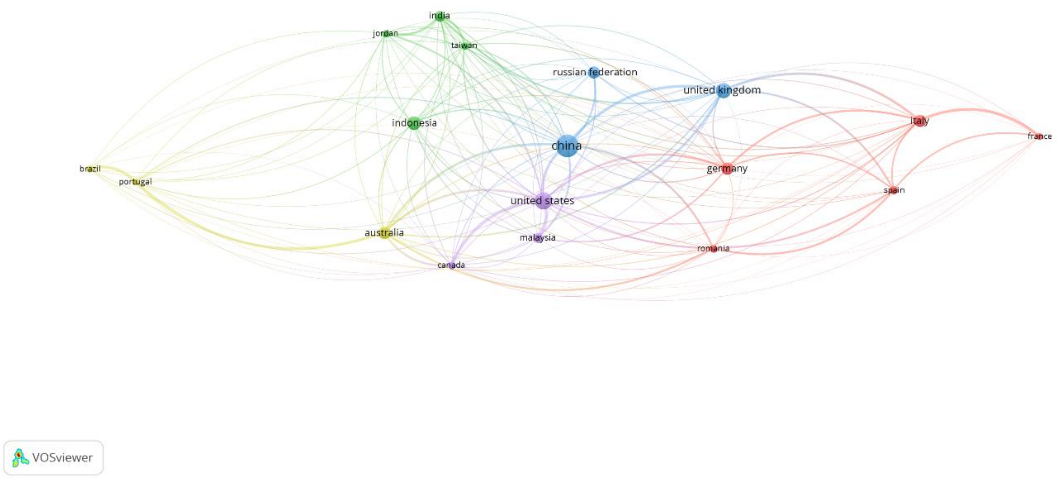

Figure 3: Bibliographic Coupling by Country

3.2.3 Bibliographic coupling by sources (journals)

Figure 4 illustrates how journals cluster into communities based on their disciplinary focus. Some clusters emphasise educational theory and entrepreneurial pedagogy, consistently publishing theory-driven research, while others concentrate on interdisciplinary or quantitative methods, prioritising data-driven studies on the technical aspects of digital tools. This pattern reflects a diverse methodological landscape, enabling a holistic understanding of digital entrepreneurial education's evolution.

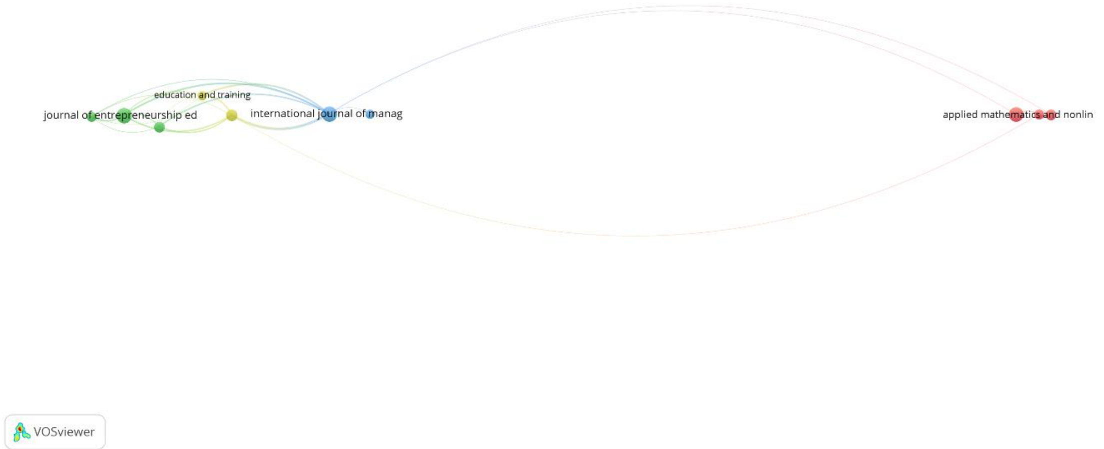

Figure 4: Bibliographic Coupling by Sources (Journals)

3.3 Overlay Visualization and Trend Analysis

3.3.1 Historical perspective on topic evolution

Overlay visualization (Figure 5) shows changes in keyword prominence over time. Foundational themes like "entrepreneurship education" and "digital entrepreneurship" were prominent early on (2018–2020), focusing on basic online methods and conceptual frameworks. By 2021–2023, "entrepreneurial mindset," "e-learning," and "digital literacy" gained traction, reflecting a move toward learner-centric and skill-oriented paradigms.

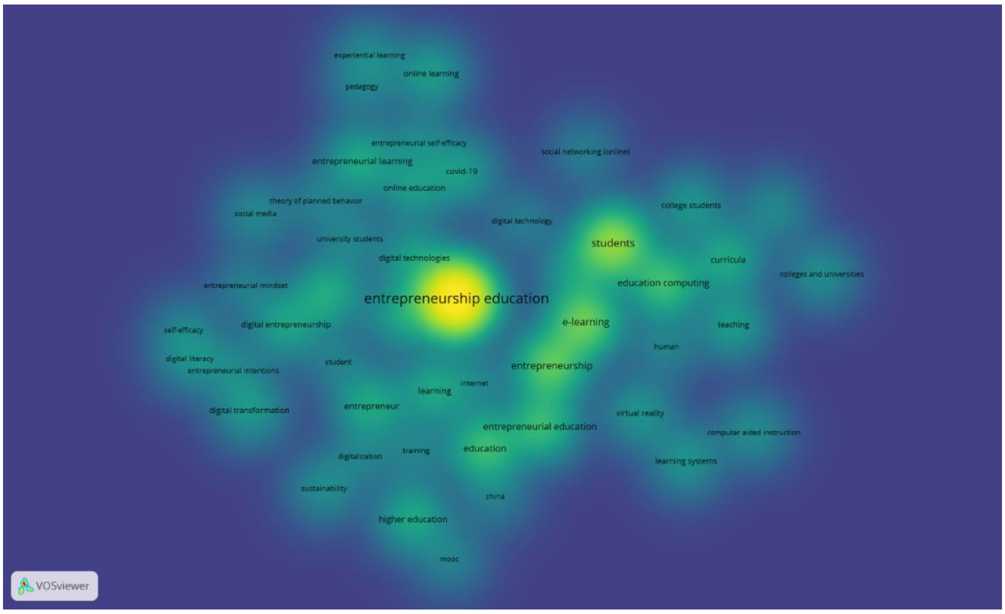

Figure 5: Density Visualization of Co-Word Analysis

Over time, as research matured and diversified (2021–2023), the nodes associated with more nuanced concepts started to gain prominence. Terms like *"entrepreneurial mindset"*, *"e-learning"*, and *"university students"* shifted towards the center of the thematic network, suggesting a growing emphasis on learner-centered approaches and the psychological and behavioral dimensions of digital entrepreneurship training. In parallel, keywords such as *"digital literacy"* and *"entrepreneurial intentions"* highlight an increasing interest in the skill sets and motivational factors that learners require to thrive in a technology-driven entrepreneurial ecosystem.

3.3.2 Identification of emerging areas

As highlighted in Figure 6 (Overlay Visualization of Co-Occurrence of Keywords), recent trends toward immersive technologies (e.g., VR), learner engagement strategies, and context-specific research emerge as digital infrastructure and AI-based tools advance. These shifts may be driven by educational policy reforms promoting digital inclusion, global entrepreneurship trends demanding adaptable skill sets, and rapid technological progress in AI-driven personalization. Such insights are valuable for practitioners. For example, knowing that immersive learning environments and culturally contextualized approaches are on the rise can guide educators and policymakers to invest in VR equipment, develop localized entrepreneurship modules, or tailor curricula to learners' backgrounds.

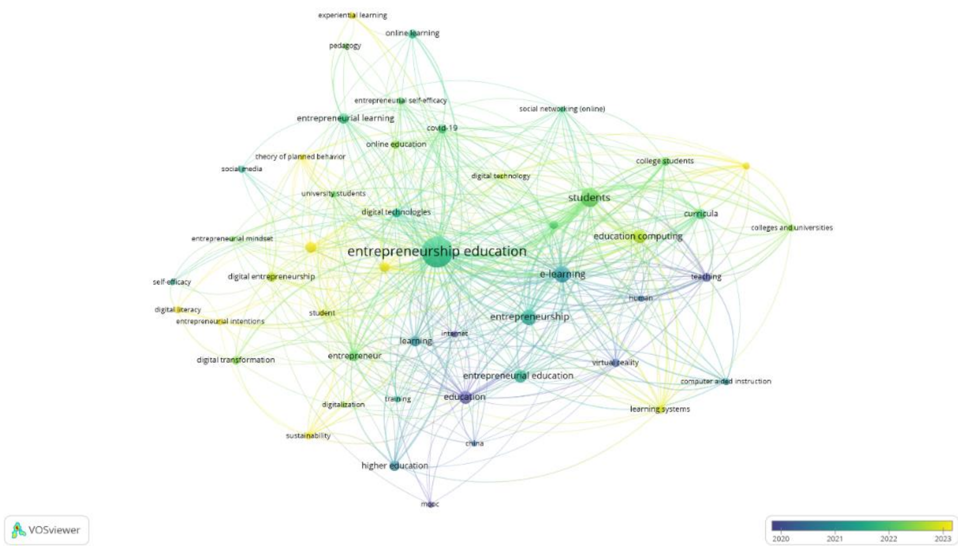

Figure 6: Overlay Visualization of Co-Occurrence of Keywords

While foundational literature established the potential of digital entrepreneurial education, the current emphasis is on immersive, adaptive, and learner-focused methods. Trends highlight the relevance of context-specific strategies, advanced technologies, and evaluation metrics that capture learner engagement and entrepreneurial outcomes. By considering these emerging themes, scholars can deepen theoretical models, and practitioners can leverage these insights to develop programs that resonate with diverse learner populations and technological ecosystems.

3.4 Systematic Literature Review and Thematic Synthesis

3.4.1 Holistic thematic analysis

This review of 261 articles on digital entrepreneurial education identified four main clusters of research themes and findings (Table 4).

Table 4: Key Clusters and Insights in Digital Entrepreneurial Education Research

Cluster	Key Insights	References
Technology-Enhanced Entrepreneurship Education	Explores diverse technologies such as metaverse platforms, VR-based training, AI-driven ideation tools, and semantic knowledge graphs, enhancing learning personalization and engagement. However, effective implementation requires well-trained educators, ethical guidelines, cultural relevance, supportive policies, and stable infrastructures.	Qiu, Isusi-Fagoaga, and García-Aracil, 2023; Ronaghi and Forouharfar, 2024; Schlimbach et al., 2024; Yu et al., 2024; Chen & He, 2023; Dai, 2024; Chen et al., 2024; Núñez-Canal, de Obesso, and Pérez-Rivero, 2022; Pritchard, Williams, and Miller, 2024; Zhou & Cen, 2024
Experiential and Project-Based Learning Approaches	Utilizes methods like co-design projects, hackathons, peer coaching, simulations, and industry collaborations to foster entrepreneurial skills, creativity, and adaptability. These methods enhance skills, attitudes, and self-efficacy but may not always increase entrepreneurial intentions, highlighting the need for digital tools, mentoring, and supportive policies.	Laptev & Shaytan, 2022; Pradana & Susanti, 2024; Chen et al., 2023; Patrício, Figueiredo, and Ferreira, 2024; Wu & Wang, 2024; Lafortune et al., 2024; Vecchiarini et al., 2024; Martini, 2024; Oliver & Oliver, 2022; Liu & Ni, 2024
Entrepreneurial Competencies, Mindset, and Social Dimensions	Psychological and social factors like cultural, religious, and sustainability values, gendered learning dynamics, generational traits, and socio-economic contexts shape entrepreneurial learning. Emotional factors such as fear and satisfaction influence intentions. Tailored approaches are needed for specific learner groups like women, Generation Z, seniors, and housewives, considering digital literacy and social support.	Robles, 2022; Pritchard, Williams, and Miller, 2024; Hasan M. et al., 2024; Nano et al., 2024; Al-Housani, Al-Sada, and Koç, 2024; Alzyoud, Harb, and Alakaleek, 2024; Lourenço et al., 2024; Khan et al., 2022; Srebro et al., 2023; Wardana et al., 2024; Atarodi, Ottmann, and Mbaye, 2024
Future-Oriented and Transformative Approaches	Highlights sustainability, humane entrepreneurship, and circular economy models. Preparing learners for uncertain environments (VUCA conditions) requires foresight tools, policy alignment, and agile curricula. Global collaborations, stable infrastructures, and ethical considerations are critical for adapting entrepreneurship education to market and technological changes.	Fülöp and Cifuentes-Faura, 2024; Rosienkiewicz et al., 2024; Li et al., 2023; Abaddi, 2024; Zhang and Rathakrishnan, 2024; Li et al., 2024; Ghannad & Sörensson, 2024; Knaut et al., 2024; Huang R. et al., 2024

The analysis shows that platform-based learning and blended pedagogies are foundational. Digital tools support flexible, interactive, and learner-centered environments. Educators combine traditional methods with online simulations, virtual labs, and AI-driven feedback loops (Wahidmurni et al., 2022; Sofiullah, Gomes Vale, and Darr, 2023). These blended approaches create a strong base for innovation, skill development, and personalized learning experiences.

Cutting-edge research focuses on immersive and AI-driven methods. VR simulations, metaverse platforms, semantic knowledge graphs, and advanced recommendation systems illustrate a move toward more personalized, experiential, and hands-on learning environments (Ronaghi and Forouharfar, 2024; Yu H. et al., 2024). This shift aims to enhance engagement, creativity, adaptability, and problem-solving skills. It also emphasizes cultural alignment, ethical considerations, and responsiveness to diverse learner groups and socio-economic contexts.

3.4.2 *Integrative framework development*

The findings suggest a holistic conceptual framework that connects advanced technologies, experiential methods, socio-cultural factors, and future-oriented strategies. At the centre of this framework is digital entrepreneurial education as a dynamic and adaptive ecosystem (Figure 7). This ecosystem is shaped by four interrelated elements: technology integration, experiential learning, socio-cultural and psychological dynamics, and future-oriented perspectives.

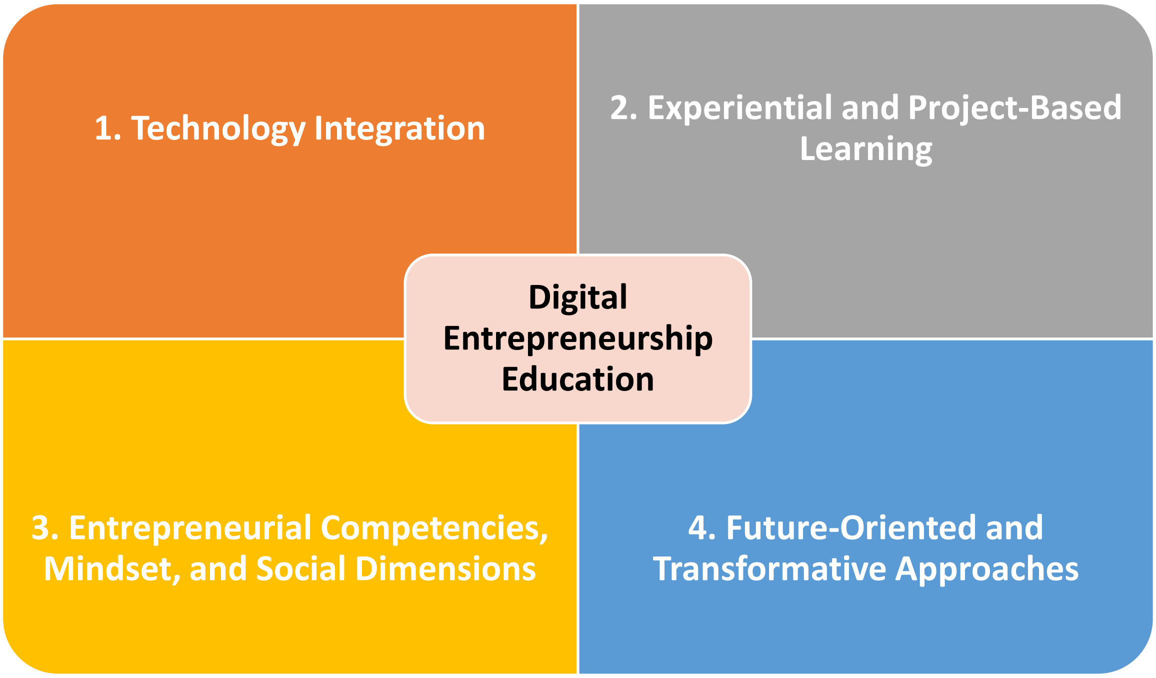

Figure 7: Digital Entrepreneurship Education as a Dynamic Ecosystem

1. **Technology Integration:** Tools such as virtual reality (VR), artificial intelligence (AI)-driven recommendations, semantic knowledge graphs, and metaverse platforms are transforming the delivery of entrepreneurship education. These tools enable personalised content delivery, creative exploration, and real-time feedback (Qiu, Isusi-Fagoaga, and García-Aracil, 2023; Yu H. et al., 2024; Schlimbach et al., 2024). However, as noted by Núñez-Canal, de Obesso, and Pérez-Rivero (2022) and Pritchard, Williams, and Miller (2024), effective deployment requires cultural sensitivity, ethical considerations, and educator competence in digital facilitation. In this light, technology must serve as an enabler, not a determinant, of meaningful entrepreneurial learning.
2. **Experiential and Project-Based Learning:** Learning methods such as gamification, co-design workshops, simulations, and industry collaborations facilitate the development of entrepreneurial skills, resilience, and problem-solving abilities (Wu S. & Wang, 2024; Martini, 2024). These approaches are most effective when embedded in authentic, learner-relevant contexts and supported by social mentoring and inclusive policy frameworks (Laptev & Shaytan, 2022; Patrício, Figueiredo, and Ferreira, 2024). Such methods support deeper engagement and allow learners to construct knowledge through iterative experimentation and reflection.
3. **Entrepreneurial Competencies, Mindset, and Social Dimensions:** Drawing on socio-constructivist and behavioural theories, this element addresses how learner identity, generational characteristics, and emotional factors shape engagement. Self-efficacy, satisfaction, and socio-cultural values critically influence how learners adopt digital tools and embrace entrepreneurial mindsets (Alzyoud, Harb, and Alakaleek, 2024; Lourenço et al., 2024). Building on the insights of Manurung, Purwadi, and Sugiharto (2022), this framework emphasises that creativity in entrepreneurship is not merely a technical skill, but a reflection of critical insight, prudence, and an integrated worldview. This philosophical dimension encourages a form of creativity that transcends digital tool proficiency and is rooted in life understanding, ethical awareness, and social sensitivity.
4. **Future-Oriented and Transformative Approaches:** Preparing learners for uncertain, volatile, and technology-driven futures requires aligning curricula with sustainability, circular economy principles, and global policy shifts (Fülöp and Cifuentes-Faura, 2024; Inada, 2024). This entails foresight-oriented

pedagogies, agile curriculum design, and international collaborations that cultivate adaptability and long-term thinking. Manurung, Purwadi, and Sugiharto (2022) highlight the need for digital learning processes that foster holistic creativity in response to cultural disorientation and algorithmic standardisation. As such, entrepreneurship education must also address learners' existential and ethical positioning, equipping them to navigate not only economic but also societal complexities.

The integrative framework underscores the importance of aligning educational practices with both technological advancements and deeper human values. It calls for a pedagogy that is responsive to generational preferences, reflective in its philosophical orientation, and inclusive in its structure.

Several gaps persist (Table 5). We need more empirical work in emerging economies to understand how digital entrepreneurship education evolves in different cultural and infrastructural settings. Cross-cultural comparative studies can reveal how regional values and social norms influence entrepreneurial intentions and outcomes. Longitudinal analyses of long-term learning results will help assess the lasting impact of digital tools, experiential methods, and policy changes. Addressing these gaps will inform more targeted strategies for policymakers, educators, and technology developers.

Table 5: Research Methods Used per Theme

Theme	Research Methods	Example Articles
Technology-Enhanced Entrepreneurship Education	Machine learning, VR simulations, big data analytics	Chen & He (2023), Qiu, Isusi-Fagoaga, and García-Aracil (2023)
Experiential & Project-Based Learning	Action research, co-design workshops, industry engagements	Laptev & Shaytan (2022), Oliver & Oliver. (2022)
Competencies, Mindset & Social Dimensions	Qualitative interviews, surveys, cultural comparisons	Pritchard, Williams, and Miller (2024), Hasan M. et al. (2024)
Future-Oriented & Transformative Approaches	Policy analysis, foresight, global collaboration frameworks	Inada (2024), Fülöp and Cifuentes-Faura (2024)

4. Discussion

The findings presented in the previous sections reveal a complex and evolving landscape of digital entrepreneurial education. Building on these results, this section interprets their implications through pedagogical, technological, and socio-cultural lenses. Tools like VR-based simulations (Ronaghi and Forouharfar, 2024), AI-driven ideation platforms (Schlimbach et al., 2024), and semantic knowledge graphs (Yu H. et al., 2024) enhance personalization and engagement in entrepreneurial learning (Qiu, Isusi-Fagoaga, and García-Aracil, 2023; Yu H. et al., 2024). However, technology alone is insufficient without educator digital competence and ethically guided frameworks (Núñez-Canal, de Obesso, and Pérez-Rivero, 2022; Pritchard, Williams, and Miller, 2024). Digitalization democratizes entrepreneurial education, providing access to underserved communities and supporting learners from diverse cultural and socio-economic backgrounds (Sofiullah, Gomes Vale, and Darr, 2023; Wahidmurni et al., 2022; Khan et al., 2022). Policies, cultural adaptation, and inclusive practices are essential to ensure opportunities for women, Generation Z, seniors, and housewives (Hasan M. et al., 2024; Wardana et al., 2024; Atarodi, Ottmann, and Mbaye, 2024).

Global reach expands through MOOCs, virtual labs, and platforms integrating nutritional education, e-commerce, and biotech, necessitating culturally sensitive content and strategies aligned with local needs (Wu & Tien, 2024; Luo X., 2024). This approach creates learner-centered environments fostering creativity, adaptability, and skill development (Oliver & Oliver., 2022; Chen J. et al., 2023). These insights pave the way for new theoretical frameworks that link entrepreneurship, educational technology, and innovation management. Traditional theories may fall short in explaining how digital tools shape entrepreneurial mindsets, but concepts like self-directed learning and autonomy can be expanded through AI-driven recommendations and metaverse platforms (Schlimbach et al., 2024; Qiu, Isusi-Fagoaga, and García-Aracil, 2023). Immersive tools like VR simulations and gamification enhance experiential learning, influencing resilience, risk tolerance, and problem-solving abilities (Wu & Wang, 2024; Lafortune et al., 2024).

Educators can leverage these findings to create engaging and culturally sensitive curricula, integrating strategies such as co-design projects (Laptev & Shaytan, 2022), industry collaborations (Patrício, Figueiredo, and Ferreira, 2024), and hybrid learning models (Ghannad & Sörensson, 2024). Mentorship, narrative creativity, and social support systems enhance confidence and self-efficacy (Zamkova et al., 2021; Alzyoud, Harb, and Alakaleek, 2024). Policymakers should invest in digital infrastructure, stable internet access, and affordable devices, while encouraging innovative teaching methods and locally adapted content for broader impact (Nano X. et al., 2024; Al-Housani, Al-Sada, and Koç., 2024). International collaborations, using COIL (Collaborative Online International Learning) approaches and triple/quadruple helix models, further facilitate cross-border knowledge exchange and innovation (Inada, 2024; Rosienkiewicz et al., 2024).

5. Future Research Agenda

Future studies should investigate the potential of emerging digital tools, such as blockchain-based training platforms and AI-driven mentoring systems, to assess their effectiveness in enhancing entrepreneurial learning outcomes (Schlimbach et al., 2024). Research could also delve into the use of data analytics and learning analytics for personalising education, improving learner adaptability, and providing real-time feedback (Chen Y. et al., 2024; Li P. et al., 2023). Additionally, integrating VR, the metaverse, and semantic knowledge graphs offers opportunities to foster creativity, engagement, and innovation in entrepreneurial education (Qiu, Isusi-Fagoaga, and García-Aracil, 2023; Yu H. et al., 2024).

Comparative studies across various cultural and institutional contexts would provide insights into how values, norms, and infrastructure shape learner readiness for digital entrepreneurial education (Hasan M. et al., 2024; Al-Housani, Al-Sada, and Koç, 2024; Syed, Alzahmi, and Tariq, 2024). Future research should also address how socio-economic factors influence receptivity to new technologies and pedagogies. Investigations focusing on marginalised communities, emerging economies, and diverse demographic groups can inform the development of culturally responsive and inclusive educational practices (Nano X. et al., 2024).

Long-term studies are needed to evaluate how digital tools and experiential learning approaches impact entrepreneurial skills over time and how learners apply these competencies in real-world scenarios, such as launching ventures or driving innovation within organisations (Chen J. et al., 2023; Munawar et al., 2023). These evaluations should consider the stability of support systems, the role of mentorship, and the evolving technological landscape. Such longitudinal research will equip policymakers and educators with the insights needed to sustain growth, update curricula, and ensure enduring entrepreneurial success (Oliver & Oliver, 2022; Inada, 2024).

6. Conclusion

This study explored the landscape of digital entrepreneurial education by identifying key themes related to technological integration, experiential pedagogies, socio-cultural dynamics, and forward-oriented strategies. Through a Bibliometric-Systematic Literature Review (B-SLR) of 261 articles, the research developed a conceptual framework that synthesises these dimensions into a coherent model of digital entrepreneurship education. The findings demonstrate that effective implementation depends not only on digital tools, but also on cultural relevance, educator competencies, inclusive practices, and supportive policy environments. This framework offers actionable insights for scholars, educators, and policymakers seeking to cultivate innovative, adaptable, and equitable learning ecosystems.

While the study provides a comprehensive overview, its scope was limited to English-language sources and selected databases, which may exclude other valuable perspectives. Future research should expand this scope to encompass diverse linguistic and cultural contexts, applying interdisciplinary and comparative approaches. Furthermore, future reviews may benefit from integrating non-English sources and grey literature to expand the representativeness of findings across global contexts. Continued development of theoretical models and longitudinal empirical studies is crucial for capturing the evolving interplay between digital innovation and entrepreneurship education. These efforts will help ensure that digital entrepreneurial learning remains inclusive, impactful, and responsive to global educational and economic challenges.

AI statement: No AI tools were used in the research, writing, or preparation of this manuscript.

Ethics statement: This study did not require ethics approval as it involved only the analysis of published literature.

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Evaluating Value Creation, Motivation, and Personal Experiences in a Game-Based Professional Learning Network for Computer Science Education

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Abstract: Gamification has emerged as a promising strategy to enhance student engagement and learning outcomes in computer science education. This study uses Wenger's Value Creation Framework to evaluate and design the gamification elements in the *Answers* platform, a Professional Learning Network (PLN) developed at TU Delft. Using a mixed-methods approach with 372 participants, this research examines the platform's impact on learning, motivation, and social interaction. Findings indicate that the platform significantly enhances academic engagement and applied value, as students actively use it for knowledge acquisition and problem-solving. However, social connectivity remains limited, as reflected in lower scores for relatedness and potential value. Qualitative insights reveal that students primarily engage with the platform for academic support rather than networking or peer collaboration. This study contributes to e-learning practice by offering design recommendations to integrate collaborative learning elements better and foster social interaction within gamified learning environments. Additionally, it advances theoretical discussions on gamified PLNs by illustrating how Wenger's framework can be operationalized to assess value creation in digital learning networks. The findings highlight the need for a more holistic approach to gamification that extends beyond point-based rewards to include community-driven engagement mechanisms. By addressing these gaps, this research provides actionable insights for educators, platform designers, and policymakers, supporting the development of more effective gamified learning environments that balance motivation, collaboration, and engagement in online education.

Keywords: Networked learning, Gamification, Value creation, Computer science education, Online

1. Introduction

1.1 Background and Context

Technology is evolving and changing every day. We face a rapid transition in how students in technical fields like computer science learn, interact, and work (Xu and Ouyang, 2022). They also need constant educational support to stay updated and solve their everyday problems effectively. Consequently, education and training providers play a crucial role in developing and delivering innovative learning solutions that meet these growing needs and ensure that learners are well-equipped to handle the challenges of a dynamic technological landscape. Students are expected to master complex concepts and skills, but maintaining motivation and engagement can be challenging. Many educational platforms need to implement a practical design that can satisfy students' demands, resulting in disengagement and suboptimal learning outcomes. Research has shown that while students may be proficient in using digital tools for entertainment and communication, this does not automatically translate into effective digital learning skills (Margaryan, Littlejohn and Vojt, 2011). The increasing reliance on technology in education, particularly in computer science, underscores the need for learning environments that scaffold meaningful engagement rather than assuming inherent technological fluency (Bennett & Maton, 2010). This study introduces "Answers," a novel Professional Learning Network(PLN) developed at TU Delft, aimed at redefining the educational landscape for computer science students.

Networked learning is an educational approach that uses digital and social networks to facilitate and enhance learning processes. It integrates technological tools and social connections to foster collaboration, resource sharing, and continuous learner interaction (Gourlay et al., 2021). PLNs are a representation of networked learning, where individuals engage in communities or networks to share knowledge, resources, and experiences for professional development (Poortman, Brown and Schildkamp, 2021). In higher education, particularly among computer science students, PLNs leverage platforms such as social media, online forums, and learning

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management systems to provide industry-relevant knowledge, peer support, and mentorship opportunities, thus embodying the principles of networked learning (Harding and Engelbrecht, 2015).

PLNs show promising results (Harding and Engelbrecht, 2015; Badoer, Hollings and Chester, 2020). In networked learning, gamification is increasingly recognized as a powerful tool for enhancing professional development (Saleem, Noori and Ozdamli, 2022; Li, Ma and Shi, 2023). Educators and trainers can significantly boost engagement and motivation among learners by incorporating game-like elements into networked learning environments. Amidst this transformation, gamification is a potent strategy to enhance learning experiences by combining game design elements into non-game contexts. Answers integrate gamification elements within a framework inspired by Wenger's theory of value creation (Wenger, Trayner, and De Laat, 2011). This integration seeks to engage students and deepen their learning and professional development through a networked learning environment.

1.2 Related Work

PLNs are dynamic ecosystems designed to meet the diverse professional needs of educators (Trust et al., 2016). They are structured online or offline communities where individuals actively share knowledge, skills, and best practices to achieve professional growth and development (Trust, 2012). They integrate people, spaces, and tools to facilitate ongoing professional development and knowledge exchange. The individuals within PLNs provide necessary feedback, support, and mentorship, enabling personal and professional growth (Trust, Krutka and Carpenter, 2016). While leveraging networks for learning is not novel (Tobin, 1998), the digital age has amplified their potential, transforming PLNs into powerful platforms for professional development. PLNs are particularly effective in fostering collaboration and innovation among educators, offering opportunities for reflection and the exchange of best practices (Cook et al., 2017).

We use the Value Creation Framework developed by Wenger, Trayner and De Laat (2011) to frame and evaluate the value generated through learning activities in our PLN. This framework identifies five cycles of value creation: immediate, potential, applied, realized, and transformative. Each cycle represents a distinct impact that network participation can have on individuals or groups (Dingyloudi, Strijbos and De Laat, 2019). Immediate value refers to the initial benefits participants gain from engaging with the gamified learning platform, such as gaining new knowledge and skills. Potential value encompasses expected benefits, including enhanced career prospects, increased confidence, and expanded social connections. Applied value is evident when learners apply the knowledge gained from the platform in their professional and personal lives, leading to, for example, actual improvements in job performance and the initiation of new projects. Realized value manifests as significant achievements in learners' careers or personal development, such as job promotions, entrepreneurial successes, and academic achievement. Finally, transformative value reflects profound, long-term changes in learners' perspectives and behaviors, fostering lifelong learning habits and a deeper appreciation for the benefits of the PLN. This framework is particularly effective in educational settings, where learning outcomes contain academic performance and the broader development of essential skills and capabilities in today's interconnected world.

Building on the principles of value creation and the collaborative nature of PLNs, the integration of gamification in these networks can further enhance the learning experience by adding motivational elements that drive engagement and participation. Gamified learning environments can engage students effectively through intrinsic and extrinsic motivators, boosting motivation and improving academic performance (Buckley and Doyle, 2016; Schöbel et al., 2019). By intrinsic motivation, we refer to engaging in activities driven by internal satisfaction, such as interest, enjoyment, and the inherent challenge of the task, rather than external rewards or pressures (Ryan and Deci, 2000). However, the impact of specific gamification mechanics on intrinsic motivation remains contested. While game elements such as badges, leaderboards, and point systems are often designed to foster motivation (Li et al., 2024), their effectiveness in promoting intrinsic motivation has been debated (Hanus and Fox, 2015). According to the Self-Determination Theory (Deci & Ryan, 1985), intrinsic motivation arises from autonomy, competence, and relatedness. However, research suggests that extrinsic motivators, such as points-based reward systems, may undermine intrinsic motivation if they shift students' focus away from meaningful engagement (Deci, Koestner, and Ryan, 2001).

Additionally, studies indicate that not all gamification strategies yield positive learning outcomes. Nicholson (2014) warns that superficial gamification, which relies primarily on pontification and extrinsic rewards, may fail to foster deep learning and long-term engagement. Furthermore, the effectiveness of gamification varies depending on curriculum design, student demographics, and instructional alignment (Dichev & Dicheva, 2017). Therefore, while gamification holds significant potential in professional learning networks, its impact is highly contextual and requires careful instructional design to ensure meaningful engagement rather than short-term compliance (Sailer & Homner, 2020).

However, the literature also highlights several other limitations. Many studies focus narrowly on specific game mechanics, often neglecting their long-term impact on learning outcomes or their integration with collaborative networks like PLNs. For example, Zhan et al. (2022) emphasize that the effectiveness of gamification varies significantly based on curriculum design and the thoughtful alignment of gamified elements with course objectives. Similarly, Videnovik et al. (2023) argue that while game-based learning enhances understanding and retention, its success depends on factors such as game design, curriculum integration, and student demographics. Additionally, prior research often lacks empirical data on how gamification affects social interaction and collaboration within learning networks (Li and Liu, 2023; Sailer and Homner, 2020).

To address these limitations and research gaps, our study critically examines the integration of gamification into professional learning networks (PLNs), evaluating both its benefits and limitations in fostering value creation, engagement, and intrinsic motivation within computer science education. By leveraging Wenger's Value Creation Framework and examining qualitative and quantitative data, this study addresses the ongoing discourse on gamification's effectiveness and challenges.

1.3 Research Objectives

The motivation behind this research stems from the observed need for more engaging and effective educational tools that can address the unique challenges of computer science education. Traditional learning platforms often need to improve in fostering motivation and deep engagement, which are critical components for mastering the complex concepts inherent in computer science (Videnovik et al., 2023).

The primary aim of this study is to evaluate how gamification within a PLN affects student engagement, intrinsic motivation, and the creation of immediate, potential, applied, realized, and transformative values. The research focuses on higher education, targeting computer science courses at the Bachelor's and Master's levels. By examining the integration of gamification elements with Wenger's Value Creation Framework, this study seeks to contribute to the growing body of knowledge on gamified learning environments and their effectiveness in fostering meaningful academic and professional development.

To achieve this aim, two key research questions guide this study: (1) How do learners perceive the gamified learning experience on the Answers platform? (2) How does the Answers system impact graduate students' value creation and intrinsic motivation? The findings provide insights into the design and implementation of gamified PLNs and their role in shaping student learning and engagement in technical education settings."

2. Methodology

This study aims to explore the impact of gamification on student engagement and learning outcomes within the "Answers" platform, a novel online learning environment developed for computer science education at TU Delft. The research addresses two primary questions: (1) How do learners perceive the gamified learning experience? (2) How does the "Answers" system impact value creation and intrinsic motivation?

We employed a mixed-methods approach, combining quantitative and qualitative data collection methods to comprehensively analyze the educational impact of the "Answers" platform. The mixed-methods design allows for integrating numerical data and in-depth personal experiences, providing a richer understanding of the research questions.

2.1 Participants

This study engaged 372 participants, including Bachelor and Master of Computer Science students, course instructors, and teaching assistants, who were actively involved with the Answers-EWI platform. This platform is freely available to all bachelor and master students, who can use it based on their preferences. This sample size is considered adequate for quantitative and qualitative analyses, as it meets the recommended thresholds for statistical power mixed-methods research (Creswell & Plano Clark, 2017). According to Cohen's (1992) guidelines for statistical power analysis, a sample size of over 300 is generally sufficient to detect medium to large effect sizes with a power of 0.80 at the 0.05 significance level in educational research. Eventually, 60 participants out of a total of 372 completed our questionnaires, and 10 participants were randomly invited for in-depth interviews.

2.2 Data Collection Methods

The methodology employed in this study involved multiple data collection methods to provide a comprehensive analysis of the educational impact of the "Answers" platform. The platform automatically generates log data that captures detailed information on user interactions, including the frequency and type of activities such as question posting, answering, and commenting. This log data provided quantitative metrics on engagement levels, enabling an analysis of how actively and in what ways students and instructors utilized the platform. Two questionnaires were administered to all participants, including course instructors, TAs, and students, to gather data on perceived value creation and intrinsic motivation.

Questionnaire 1. Value Creation Questionnaire (VCQ). Based on Wenger, Trayner and De Laat's (2011) five cycles of value creation, this questionnaire was designed to measure the different layers of value participants perceived as being created through their interaction with the platform. The items in the questionnaire corresponded to the immediate, potential, applied, realized, and reframing value. This Questionnaire has ten questions (five multiple choices and five open-ended questions). Each value creation cycle has one multiple-choice and one open-ended question. For example, the first question asks, “Participation changed me as a student (change in skills, attitudes, identity, self-confidence, feelings, etc.).” Participants need to answer on a scale between 1 to 6 (Strongly disagree to strongly agree, respectively). If they respond positively (strongly agree, agree, or slightly agree), they are asked to answer an open-ended question such as “Can you explain how participation changed you as a student?”. If they respond negatively (slightly disagree, disagree, and strongly disagree), the online questionnaire automatically asks: Can you explain why participation didn't change you as a student?

Questionnaire 2. Intrinsic Motivation Inventory (IMI) - 29-item Version by Ryan, Mims and Koestner, 1983.

To measure this construct in our research, we employed the Intrinsic Motivation Inventory (IMI), a multidimensional measurement tool designed to assess participants' subjective experience related to a target activity (Ryan, 1982). The IMI includes several subscales, including interest/enjoyment, perceived competence, effort, value/usefulness, felt pressure and tension, and perceived choice. Each subscale captures different dimensions of intrinsic motivation, providing a comprehensive overview of how engaged and motivated participants feel. Higher scores indicate greater intrinsic interest in the activity (McAuley, Duncan and Tammen, 1989). In our study, the IMI was used to evaluate how the gamified elements of the Answers platform influenced students' intrinsic motivation.

This comprehensive tool assessed participants' levels of intrinsic motivation concerning their platform use. It includes five subscales: relatedness, interest/enjoyment, perceived choice, pressure/tension, and effort. The IMI was administered to help us understand the motivational dynamics influenced by the gamified elements of the platform.

Additionally, ten participants were randomly selected for in-depth, semi-structured interviews to investigate value creation and the gamification experience further. Eight out of ten participants were students, and two were TAs. These interviews were designed to capture value-creation indicators, personal stories, and participants' experiences with the gamification elements of the "Answers" platform.

Each data collection method complemented the others, providing a rich, multi-faceted view of the platform's educational impact. Together, these methods enabled a robust analysis of both the measurable outcomes of gamification and the qualitative experiences of those engaged with the platform.

2.3 Procedure

Answers development and refinement started in 2022, and after approximately one academic year of iterative testing and feedback sessions, students could start using the platform. Participants were recruited through course announcements and email invitations from the start of the academic year in 2023 (September). Informed consent was obtained from all participants, ensuring confidentiality and voluntary participation. Log data were collected automatically by the platform, while the VCQ and IMI were administered online at the end of the semester (around February 2024). Interviews were conducted via video conferencing with the Microsoft Team, recorded, and then transcribed for analysis. These interviews were conducted around a month after the end of the semester in March 2024.

2.4 Description of the Intervention

The Answers platform was designed to enhance student engagement and collaborative learning by integrating game-based elements that promote participation, knowledge sharing, and peer interaction.

2.4.1 *Technical features*

The Answers platform uses Ruby on Rails with MySQL as the primary database. It is a modification of the open-source platform Qpixel by the Codidact organization (https://github.com/codidact/qpixel). User data is protected through end-to-end encryption and secure data storage practices. The platform complies with GDPR, ensuring that user privacy is maintained. User authentication is handled via the TU Delft single sign-on (SSO) mechanism. The source code is available at https://gitlab.ewi.tudelft.nl/eip/answers/qpixel. Figure 1 provides a snapshot of the platform and illustrate its core functionalities and user interface.

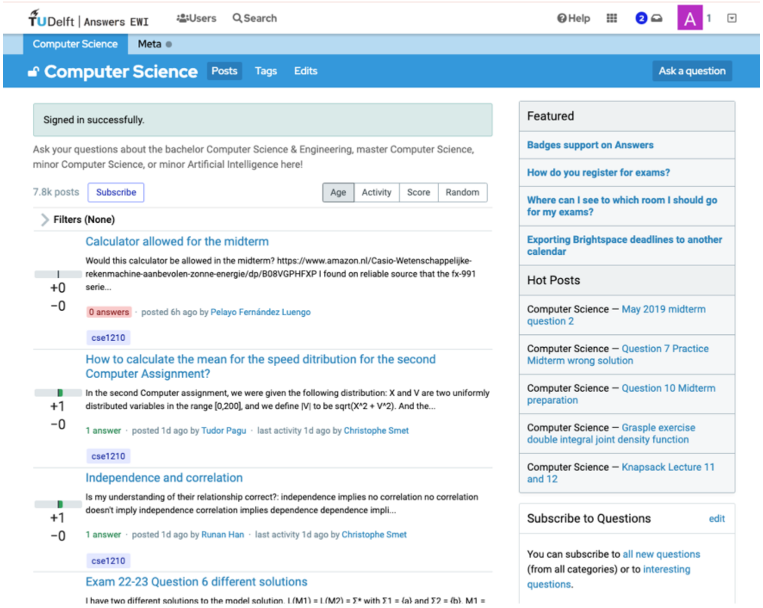

Figure 1: A Snapshot of Answers Platform

2.4.2 *Design principles*

Among the various gamification strategies available, we selected points and badges as our primary mechanisms, aligning them with the principles of Wenger's Value Creation Framework (Wenger-Trayner & Wenger-Trayner, 2020) to foster immediate, potential, and applied value within the learning network.

Points can serve as an immediate feedback mechanism, which could reinforce active participation by rewarding users for asking questions, answering queries, and engaging in discussions. Although several case studies showed the effectiveness of points in gamification (e.g., Huang and Hew, 2015; Ibànez, Di-Serio, and Delgado-Kloos, 2014), we should acknowledge the fact that "pontification" of education can sometimes lead to superficial engagement if not thoughtfully integrated into the learning design (Hellberg and Moll, 2023). Badges, on the other hand, were designed to recognize meaningful contributions and milestones. Also, they are designed to reflect individual achievements and community engagement (Aldemir, Celik and Kaplan, 2018). Table 1 provides an overview of badges and points designed for our platform.

Table 1: Description of Badges and Points

Badge	Description
Autobiographer	Complete your profile and upload a profile picture
First Question	Ask your first question
First Answer	Contribute your first answer
Self-Learner	Answer your own question with an answer that others find useful
Teacher	Help another community member with a good answer to their question
Top Contributor	Every two weeks the top contributor for of each course will be awarded this badge (if the course has sufficient contributions)

Badge based on points	
Great Question	Ask a question that many others are also interested in
Great Answer	Help the community by contributing a very helpful answer
Famous Question	Ask a question that many others look at

As mentioned earlier, these badges and points are inspired by the value creation framework (Wenger, Trayner, and De Laat, 2011). For example, one of the immediate value indicators is "participants bringing challenges they face for discussion" (Wenger-Trayner and Wenger-Trayner, 2020). We tried to encourage participants to ask questions on the Answers platform and bring the challenges they faced during the course by designing "First Question" and "Great Question" badges. Furthermore, one of the other typical indicators of potential value is the "Richness, diversity, and relevance of advice" (Wenger-Trayner and Wenger-Trayner, 2020) provided in the network. This inspired us to design "Great Answer" and "Top Contribution". Finally, one of the other Applied value indicators is "Stories from participants' context reporting innovations or newly discovered solutions or approaches" (Wenger-Trayner and Wenger-Trayner, 2020). This indicator helped us in designing the "Self-Learner" badge. Figure 2 illustrates an example of badges and recognitions, showcasing the types of achievements rewarded within the platform.

For the project's development, the teaching team of the computer science department initiated the concept of a system where students could exchange information, thereby building a knowledge base for future cohorts. Initial requirements were derived for posting questions and answers and ensuring the searchability of previously answered questions. After exploring existing solutions, Codidact/Qpixel, an open-source platform, was chosen as the foundation for the application. From this starting point, additional requirements were established to enhance the platform's suitability for educational purposes. Input was gathered from various stakeholders, including faculty and students, to understand their needs and expectations.

Two Computer Science students were tasked with implementing and integrating these features, adhering to an Agile development methodology to maintain flexibility and responsiveness to user feedback. User testing sessions were conducted throughout development to identify and address usability issues. Both quantitative and qualitative data were collected to inform design decisions. Features deemed generally applicable were contributed back to the Codidact project. After the initial deployment of the Answers platform, additional functionalities were added over time. Users were notified of new functionalities and instructed how they worked through the platform. Technical support was offered to address any emerging issues. Regular updates and feature enhancements were deployed based on user feedback. The platform's performance was continuously monitored through analytics, and feedback sessions were conducted with users to identify areas for improvement.

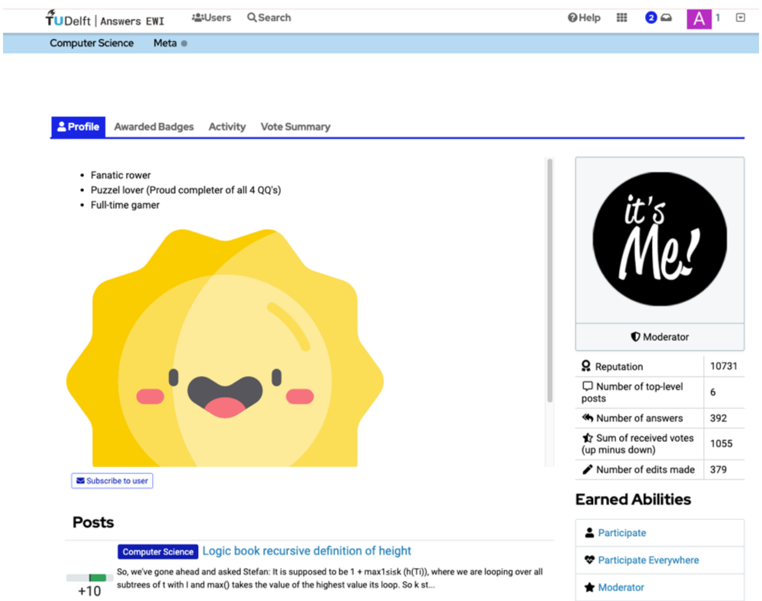

Figure 2: An example of Budges and Recognitions

2.4.3 *Engagement and interaction evaluation*

We expanded the platform's analytics capabilities to evaluate user engagement and interaction patterns. We track various metrics, such as the number of visits (tracks the frequency students visit the platform), activity frequency (counts the number of activities performed by the users, such as posting questions, answering questions, and commenting), and achievement and badges (monitors the badges users earn and their progress towards achieving specific milestones).

This intervention was introduced at the beginning of the academic year. It was available to all computer science students and faculty, providing a real-time, dynamic environment for enhancing educational experiences through gamified learning.

2.5 Data Analysis

The analysis of the collected data from the "Answers" platform involved a comprehensive approach, utilizing both quantitative and qualitative techniques to ensure a thorough understanding of the effects of gamification on learning outcomes and motivation.

The qualitative data collected from the Value Creation Questionnaire (Open-ended answers) and interviews were transcribed and analyzed using thematic analysis to identify recurring themes and patterns related to participants' perceptions of the gamification experience, value creation indicator, and stories. Qualitative data analysis software (Atlas ti) facilitated the coding of the data, which helped organize the data into meaningful categories based on the value creation framework. This method allowed for the in-depth exploration of how the gamification elements influenced learners' motivation, perceived value from the platform, and overall learning experience.

A mixed-methods data integration technique was used to integrate the quantitative and qualitative findings. This approach involved comparing and contrasting results from both data sets to draw comprehensive conclusions about the study's hypotheses. By triangulating the data, we aimed to validate the findings across different methods, enhancing the reliability and validity of the results.

3. Results

3.1 Quantitative Analysis

3.1.1 *Quantitative analysis of value creation questionnaire (VCQ)*

The methodology section explains that the VCQ has five multiple-choice and five open-ended questions. The first question explored the immediate value cycles and asked, “Participation changed me as a student (change in skills, attitudes, identity, self-confidence, feelings, etc.).” then the participant can choose between strongly agree, agree, slightly agree, slightly disagree, disagree, and strongly disagree. If they answered strongly agree, agree, and slightly agree, we asked them, "Can you explain how participation changed you as a student? And if they answered slightly disagree, disagree, and strongly disagree, they need to answer, "Can you explain why participation didn't change you as a student?". This procedure is repeated for questions regarding potential, applied, realized, and transformative value creation cycles. In this section, you can find the results of the first part of the questionnaire, and in section 3.2.1, we explain the results of the open-ended questions. Table 2 presents the descriptive statistics for the VCQ subcategories and summarizes the distribution of responses across the five value creation cycles.

Table 2: Descriptive results of VCQ

VCQ Components	Number of Positive Value Responses	Average	Std Dev	Median	Range (Min - Max)
Immediate Value	38/60	3.7	1.36	4	1-6
Potential Value	9/60	2.08	1.18	2	1-5
Applied Value	53/60	4.51	1.17	5	1-6
Realized Value	24/60	2.88	1.30	3	1-5
Reframing Value	19/60	2.71	1.40	2	1-6

Table 2 presents the descriptive statistics of the Value Creation Questionnaire (VCQ), which examines five cycles of value creation based on the framework proposed by Wenger, Trayner, and De Laat (2011). The VCQ assesses the impact of the Answers platform on participants across different dimensions of value creation.

Immediate Value: Out of 60 participants, 38 indicated that the Answers platform created positive immediate value for them. Specifically, these participants responded, "Strongly Agree," "Agree," or "Slightly Agree" to the statement: "Participation changed me as a student (change in skills, attitudes, identity, self-confidence, feelings, etc.)." This result suggests that a significant proportion of participants perceived an immediate enhancement in their personal and academic development due to their engagement with the platform.

Potential Value: The second component of the VCQ evaluates the potential value in terms of social connections with peers and other students. Interestingly, only 9 participants out of 60 responded positively to the statement: "Participation affected my social connections (change in the number, quality, frequency, emotions, etc.)." The average score for this dimension was 2.08, indicating a relatively low impact of the platform on social relationships.

Applied Value: The third component measures the applied value created by the platform. A majority, 53 out of 60 participants, responded positively to the statement: "Participation helped my practices as a student (get new ideas, insights, materials, procedures, etc.)." The average score for this dimension was 4.51, reflecting a high level of practical benefits derived from the platform.

Realized Value: The fourth part of the VCQ investigates the influence of the Answers platform on participants' ability to influence the world as students, such as enhancing their voice, contribution, status, and recognition. 24 out of 60 participants responded positively to this dimension, with an average score of 2.88. These results indicate a moderate impact on participants' perceived influence and recognition within their academic and social contexts.

Reframing Value: The final part assesses the reframing value, focusing on profound, long-term changes in participants' perspectives and behaviors. Nineteen participants responded positively to the statement: "Participation made me see my world differently (change in perspective, new understandings of the situation, redefine success, etc.)," with an average score of 2.71. This finding suggests that some participants experienced significant shifts in their worldview and understanding due to their involvement with the platform.

Figure 3 provides an overview of the average scores for each value creation cycle, illustrating the varying impacts of the Answers platform on different dimensions of value creation. The high average score for applied value highlights the platform's effectiveness in enhancing students' academic practices. In contrast, the lower scores for potential and reframing values underscore areas for improvement in fostering social connections and facilitating changes in perspectives.

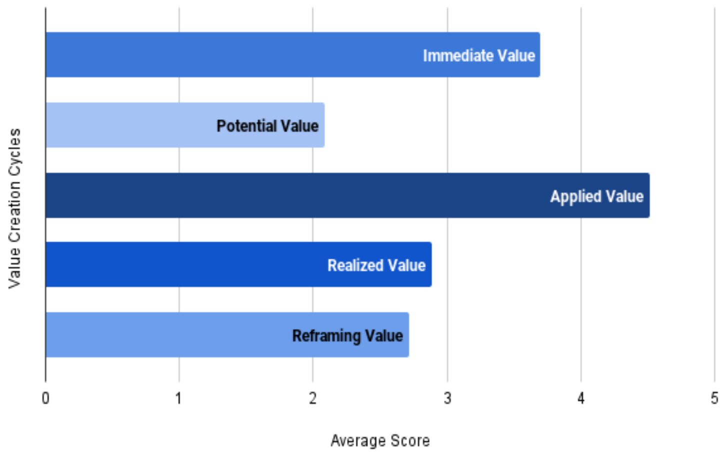

Figure 3: Average Score of Value Creation Cycles

3.1.2 Descriptive analysis of IMI

Table 3 presents the descriptive statistics of the Intrinsic Motivation Inventory (IMI) questionnaire, which measures various dimensions of intrinsic motivation on a scale from 1 (not at all true) to 7 (very true). The IMI assesses five subscales: relatedness, interest/enjoyment, perceived choice, pressure/tension, and effort, providing insights into participants' motivational dynamics when using the Answers platform. Figure 4 also presents the average scores for the IMI subscales and visualizes the variation across different motivational dimensions of IMI.

Table 3: Descriptive Analysis of IMI Subtests

IMI Subscale	Average	Std Dev
Relatedness	*0.30*	*0.59*
Interest/Enjoyment	*2.64*	*0.87*
Perceived choice	*0.82*	*0.78*
Pressure/Tension	*0.22*	*0.90*
Effort	*2.09*	*0.71*

The relatedness subscale explores the sense of connection between participants. As shown in Figure 4, scores for this subscale clustered around the lower end, indicating that participants did not feel significantly connected to others through the platform. For example, one of the questions in this subscale was, "I felt really distant from the other members of the network." These results suggest a need to enhance the social interaction features of the Answers platform to foster better connections among users.

The interest/enjoyment subscale scores were generally high, demonstrating that participants found the platform engaging and enjoyable. For instance, one of the questions in this subscale was, "While interacting with the other Answers-EWI members, I was thinking about how much I enjoyed it." The high scores indicate that gamification effectively enhanced user engagement and enjoyment.

The perceived choice subscale examines participants' sense of autonomy in networking and communicating with other Answers platform users. For example, one of the questions was, "I felt like I had a choice about interacting with the other network members." The results for this subscale showed mixed feelings among participants regarding their sense of control over their interactions and use of the platform. Therefore, it suggests that while some users felt autonomous, others did not perceive a strong sense of choice in their interactions.

The low average score for the pressure/tension subscale indicates that most participants did not experience pressure or tension when interacting with the platform or other members. An example question from this subscale was, "I did not feel nervous about interacting with the other network members." These results highlight that the platform's design effectively minimized stress and anxiety among users, creating a comfortable environment for interaction.

The effort subscale had a high average score, indicating that participants actively tried to maximize their experience and interactions within the network. For example, one of the questions in this subscale was, "I tried hard to have a good interaction with the other network members." This implies that users were willing to invest significant effort to benefit from the platform, reflecting a high level of engagement and commitment.

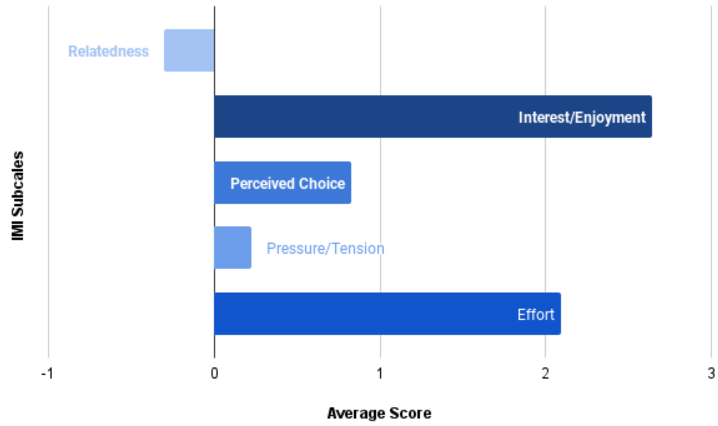

Figure 4: Average scores of IMI Subscales

3.1.3 Descriptive analysis of engagement and interaction analysis

The analytics module of the Answers platform provided detailed insights into user engagement and interaction. Our key findings include visit frequency, activity Frequency, and number of badges earned. The average number of weekly visits was 347, indicating regular engagement with the platform. As Figure 5 shows, participants constantly visit the Answers Platform, but we also see significant drops during holidays in weeks 8 and 14.

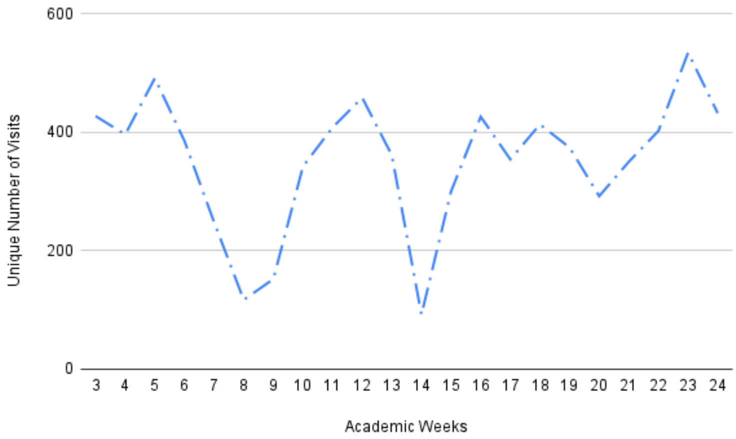

Figure 5: Visit Frequency

Activity Frequency analysis indicates that, in total, our platform users raised 616 questions, answered 608 times, and left comments 395 times. Most interactions were questions (38%), followed by direct answers (37%) and commenting (25%). An overview of these findings is illustrated in Figure 6.

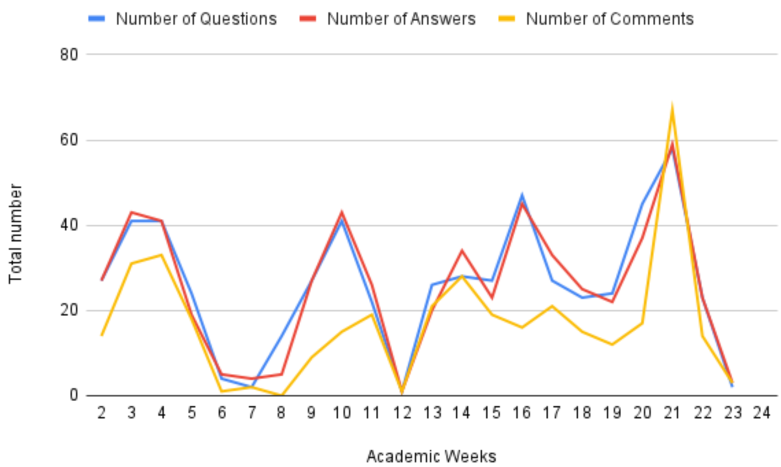

Figure 6: Activity Frequency of Answers Users

Answers' users earned 428 badges during the study period, reflecting their achievements and milestones. Figure 7 shows the patterns of users' peak activity during exam periods.

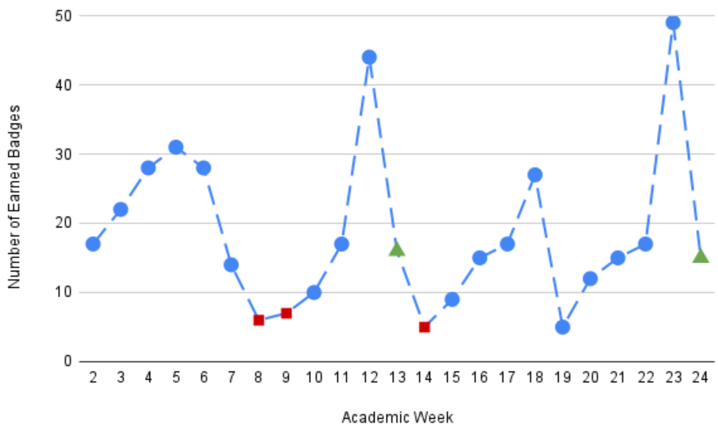

Figure 7: Total number of budges earned by Answers' users. Red squares indicate holiday weeks, and green triangles indicate exam weeks

In conclusion, our quantitative analysis results indicate that while the immediate value perceived by participants is relatively high, this value is more personal than social. This can be supported by the low potential value and the relatedness subscale scores of IMI, which reflect limited social engagement and connection among users. This pattern suggests that students find the Answers platform valuable for individual learning but must utilize it to fully build social connections or collaborative learning.

Moreover, the engagement data, such as the frequency of visits and the number of questions asked, supports this interpretation. While students actively use the platform, the low relatedness scores suggest that these interactions are more transactional than community-building. This trend aligns with the qualitative analysis, where students expressed that they primarily use the platform for academic purposes rather than socializing.

These findings are consistent with Wenger, Trayner, and De Laat's (2011) value creation framework, which claims that personal value may only translate into potential value with intentional design efforts to foster social connections. The following qualitative analysis section will explore these patterns further, providing more context and depth to these quantitative findings.

3.2 Qualitative Analysis

3.2.1 Qualitative analysis of open-ended answers of VCQ

In VCQ, participants were asked multiple-choice and open-ended questions that explored the five value creation cycles: immediate, potential, applied, realized, and transformative. While the multiple-choice questions allowed participants to express their "level of agreement" with the provided statements related to these cycles, the open-ended questions provided more profound insights into the reasons behind their responses.

Participants who agreed with the statements for each cycle were asked to elaborate on how their participation influenced them, such as "Can you explain how participation changed you as a student?" Contrariwise, those who disagreed were prompted to explain why the participation did not have an impact, with questions like "Can you explain why participation did not change you as a student?" The responses to these open-ended questions were subjected to initial coding, which enabled us to group the data into different themes. This thematic analysis provided a richer understanding of the various dimensions of value creation experienced by the participants beyond what could be captured through the multiple-choice responses alone. A summary of these findings is presented in Table 4.

Table 4: Result of Qualitative Analysis of Open-ended Response of VCQ

Value Creation Cycle	Positive and negative value	Theme	Occurrence	Example Quotes
Immediate	Positive	Knowledge Acquisition	15	"I became more familiar with material."
		Improved Communication	7	"It is nice to be able to ask questions and having people respond. It helps with

Value Creation Cycle	Positive and negative value	Theme	Occurrence	Example Quotes
				communication skills and understanding of the material."
		Problem Solving	7	"Solved questions I had."
		Peer Learning and Interaction	7	"I can see what type of problems others also struggle with, and it's very informative."
	Negative	Low Usage	6	"I didn't really participate and have not really used Answers.ewi that much"
		Utility-Driven	5	"It did not change my way of studying, just the way I sought out help"
		No Significant Impact	4	"It was not that much of an effect on me, I just received help when needed
		Challenges in Participation and availability of alternative support	5	"I feel like I would still be able to ask questions to my peers, or TAs during labs, without posting them on Answers"
Potential	Positive	New and Improved Social Connections	3	"Participation affected my social connections in a good way because I had the opportunity to make new friends."
		Increased Closeness and Unity	2	"It creates union between students."
		Professional and Peer Recognition	2	"It helped me recognize dedicated colleagues. It also made me a bit more confident in my skills, and made me dedicate more to cooperation."
	Negative	Educational Utility and Focus	18	"The people I interact with on Answers-EWI I either already know or I did not start interacting with them more."
		Lack of Social Interaction	17	"I only look at the answers."
		Low Engagement and Usage	6	"I didn't participate much for that to happen."
		Preference for Other Platforms and Methods	5	"While I do agree that it gives a positive emotion when someone took the time to answer your questions, I feel like other (unofficial) platforms give more social interactions. (Such as the WhatsApp groups)."
Applied	Positive	New Ideas and Approaches	9	"Provided innovative ideas and clear explanation of certain concepts."
		Problem-Solving and Insights	7	"I've gotten valuable answers from it that helped me with studying."
		Peer Learning and Perspectives	8	"It gives good extra views on topics by other students, lecturers and TAs."
		Additional Learning Support	20	"In the rare case that someone had the same problem that I did, it boosted my confidence because I wasn't the only person struggling."
	Negative	Low or No Usage	3	"I haven't really felt it was necessary to use it."
		Preference for Traditional Resources	2	"I guess, but getting that info from either course staff or course material would have helped a lot more."
		Lack of Useful Outcomes	2	"So far nothing useful has come of trying to use the platform."

Value Creation Cycle	Positive and negative value	Theme	Occurrence	Example Quotes
Realized	Positive	Recognition and Confidence	4	"By answering questions, mostly in-person, I could make an impact in my study group. Moreover, I feel like it raised my level of confidence."
		Peer Interaction and Contribution	4	"The network makes it easy for a student to talk to other students about similar topics, so I think it has a big impact on students."
		Influence on Course and Problem-Solving	5	"It is an accessible way to bring possible problems forward to course staff."
		Potential and Limitations	4	"Personally it has not influenced me as a student, but I have seen posts where students help each other, and therefore the student that is helping is usually very appreciated."
	Negative	No Effect or Impact	7	"Not using the network has had no effect on me as far as I'm aware."
		Low Usage and Contribution	6	"I have not participated on EWI answers enough to feel like I was an influence there."
		Educational Utility and Question-Focused	5	"I only used answers to ask questions so it did not change my view of the world or influence or anything."
		Low Impact and Recognition Issues	5	"It's not that deep."
Transformative	Positive	Varying Perspectives and Changed Views	7	"It made me see the world differently in some area in which I changed my view after seeing an answer/asking a question."
		Shared Struggles and Supportive Environment	3	"It's very nice to see previous students / teachers helping out with students' questions, it's a very supportive environment."
		Self-Understanding and Inspiration	4	"Now I have a much more in-depth perspective of this field."
		Low Usefulness and Mixed Impact	4	"It is good that I see people help each other without any form of compensation."
	Negative	No Significant Impact	12	"No significant impact."
		Educational Utility	7	"It's just a help, it doesn't change world views."
		Low Usage	5	"I have not used answers.ewi that much so idk a lot of things do not apply to me."
		Question-Focused	5	"It helps me when I do not know what to do, but that is all I use it for."

Several patterns emerge that align with and expand upon the quantitative results presented earlier by reviewing the qualitative findings from the open-ended questions. The themes of 'knowledge acquisition' and 'improved communication' are frequently mentioned in the immediate value cycle, which aligns with the relatively high scores for perceived usefulness and engagement in the quantitative data. This finding suggests that while students benefit from the Answers platform regarding individual learning and skill development, their interactions could be more collaborative, as evidenced by the low relatedness scores in the IMI.

Another pattern observed is the frequent mention of 'lack of social interaction' in the potential value cycle, which corresponds with the low scores in the relatedness subscale of the IMI. These findings indicate a consistent challenge in fostering a sense of community and social connectedness on PLN platforms. Despite the platform's success in facilitating academic support, it fails to promote deeper social interactions among users.

Moreover, the recurring theme of 'preference for traditional resources' in both the applied and transformative value cycles provides additional context to the mixed feelings of autonomy and choice reported in the IMI. While the platform offers valuable resources, students may still rely on more traditional forms of support, such as direct interaction with course staff or peers, potentially limiting the platform's impact on broader educational outcomes.

Finally, these patterns reveal a complex interaction between the platform's design, its intended outcomes, and the actual experiences of its users. By contrasting these qualitative insights with the quantitative data, it becomes clear that while the platform is effective in certain areas, there are opportunities to enhance its social and collaborative dimensions to realize its full potential.

3.2.2 Qualitative analysis of in-depth interviews

This section presents the insights derived from ten in-depth interviews conducted with students and TAs who used the Answers platform. The interviews aimed to explore students' and TAs' experiences, motivations, value creation, and the platform's impact on their learning practices. The analysis revealed several key themes: awareness and communication of gamification features, expectations and experience, social connections and platform usage, instructors' and mediators' influence, platform benefits, technology comparison, and trust and reliability. We briefly explain each of these themes in detail as follows.

Theme 1. Awareness and Communication of Gamification Features.

Nine out of ten interviewed participants noticed the gamification elements like badges. However, they needed to engage more deeply with them, indicating a need for better communication about these features. For instance, Participant Eight mentioned, "I didn't really notice a lot of change, *but I haven't used answers in a while either.*" Similarly, Participant Four said, "*I've noticed the badges, but I don't notice the points or other gamification elements on it*."

Effective communication strategies are essential to ensure students understand and utilize new features. This includes targeted notifications and clear explanations about the benefits and functionalities of the gamification elements.

Theme 2. Expectations and Experience

Students expected the platform to be a resource for finding answers and sharing knowledge, and it met these expectations. However, engagement with gamification elements could have been higher. Participant One stated, "*I kind of expected it to be what it is. It's an answer platform. If you ask questions, people can see your questions and respond.*" she added, "*It was nice because there were answers and questions from the year before, which is very useful for general questions about course material*." These findings raise the importance of providing clear guidance on the platform's benefits and capabilities, which could enhance student participation and engagement with gamification features.

Theme 3. Social Connections and Platform Usage

The platform was primarily used for academic purposes, with limited impact on fostering social connections. Many students preferred alternative, informal communication methods, such as WhatsApp and Discord, for social engagement and quick exchanges. Participant Two noted, *"I don't really see it very much as a social platform."* Similarly, Participant Four stated, *"There are obviously WhatsApp groups or Discord servers made by students for networking."*

Low engagement with the platform was largely attributed to the availability of alternative platforms that students found more efficient for networking and discussions. Participant Eight mentioned, *"We mainly use WhatsApp for communication."* These findings suggest that integrating the platform with existing student-preferred communication tools could improve engagement and enhance social interactions.

Theme 4. Instructors' and mediators' Influence

Instructor recommendations played a significant role in how students used the platform. Instructors' active involvement can enhance the platform's perceived value and encourage more frequent use. Participant Two mentioned, "*It was great to get in touch with the lecturer through the platform*." Similarly, Participant Eight said, "*Some teachers use the forums actively, which is very helpful*." Promotion of the platform during lectures and instructor participation can significantly increase its usage and effectiveness.

Theme 5. Platform Benefits and Technology Comparison

The platform provided valuable records of past discussions and immediate access to information, which benefited students. Participant Four, for example, mentioned, "It really helps to see previous questions and answers." Participant Nine added, "Having access to past discussions is very helpful." While AI tools like ChatGPT offer quick answers, students trust human responses for accuracy and context. Participant Ten stated, "I don't fully trust ChatGPT because I've seen what it can spit out, and it's not always smart." Ensuring the accuracy and reliability of the information delivered on the platform is critical.

Theme 6. Trust and Reliability

Students prefer human responses over AI-generated ones due to their reliability and accuracy despite the longer response time. Participant Four highlighted, "When I see someone answer your question, I look at the votes and see if I know the person already." Factors such as upvotes, the credibility of responders, and personal experience influenced trust in the platform. Ensuring the trustworthiness of the information provided is essential for the platform's success.

4. Discussion

4.1 Perceptions of the Gamified Learning Experience

The first research question explored how learners perceive the gamified learning experience on the *Answers* platform. The quantitative results indicated that most students perceived the platform positively, particularly in terms of its academic utility. The qualitative data supported this perspective, with students appreciating the Answer's role in accessing learning materials, answering questions, and understanding peers' challenges. However, engagement with gamification elements, such as badges and points, was mixed. While some participants reported feeling motivated by progress-based rewards, others found these elements unnecessary or unnoticeable. Previous research on gamification in education suggests that the effectiveness of game elements depends on individual preferences, perceived relevance, and alignment with intrinsic learning goals (Hamari, Koivisto, & Sarsa, 2014; Sailer & Homner, 2020). To increase engagement, system designers and instructors could enhance awareness and visibility of gamification mechanics, try to satisfy the psychological needs of their participants (e.g., autonomy, competence, and relatedness)(Suh, Wagner, and Liu, 2016), integrate more meaningful incentives, and provide peer recognition for contributions.

4.2 Impact of Answers Platform on Value Creation and Intrinsic Motivation

Our second research question focused on how the platform impacts value creation and intrinsic motivation. The VCQ results highlighted strong applied value, with 88.3 percent of participants agreeing that the platform helped their academic practices. Interview responses confirmed this, as students noted that exposure to different problem-solving approaches enhanced their learning. This finding is consistent with Wenger's applied value cycle, where learners integrate new knowledge into their existing skill sets (Wenger, Trayner, & De Laat, 2011).

However, findings From IMI indicated low scores in the relatedness subscale, which suggests that students did not feel socially connected through the platform. This challenge in gamified learning environments, where game elements alone may not be sufficient to foster collaborative or social learning experiences, has also been emphasized in another research (Kraut et al., 2008). Our qualitative analysis supports this, as students frequently mentioned relying on external communication tools (e.g., WhatsApp, Discord) for peer interaction.

4.3 Social Connections and Community Building

The platform's impact on social connections could have been more pronounced, with only 9 out of 60 participants reporting positive effects on their social interactions. Many students indicated that they primarily used the platform for academics rather than socializing. This finding shows the importance of informal learning networks and their roles in promoting professional development (Nijland, Van Amersfoort, Schreurs, and De Laat, 2018; De Laat, Schreurs, and Sie, 2014).

Researchers have identified several limitations in how gamification fosters social interaction. A key concern is that game mechanics can sometimes encourage superficial or competitive behavior rather than deep, meaningful collaboration. For instance, if poorly implemented, gamification with points might push students into *"destructive competition"* where they feel pressured or controlled by the game (Bovee, Jernejcic, and El-Gayar, 2020). A 2024 review similarly warns that gamification can over-emphasize competition at the expense of collaboration (Wulan, 2024). When students focus too much on winning or rankings, true community-building may suffer.

There are also social and emotional considerations. Gamification can introduce social comparison that is not always healthy. A recent study on the "dark side" of gamified communities found that intense use of game elements can lead to stress, anxiety, or interpersonal conflicts (e.g., feelings of inequity or jealousy) if not moderated (Srivastava et al., 2022). In summary, gamification may encourage quantity over quality without careful design, foster unhealthy competition, or not engage students as intended.

However, one solution to maximize the social benefits of gamification while mitigating its drawbacks can be designed for cooperation, not just competition. Many studies emphasize collaborative gamification to foster meaningful peer interaction. This means structuring game elements so students work together (in teams or as a class) toward goals instead of solely competing against each other. Cooperative or team-based challenges can satisfy students' need for social connectedness and shared purpose. An (2021) has found that *social gamification* (integrating social networking and teamwork into the game) tends to outperform purely individual gamification in terms of student interaction and even academic performance. Also, Dindar, Ren, and Järvenoja (2021) compared gamified cooperation vs. competition and found no loss in achievement or motivation but significantly higher social relatedness in the cooperative condition. In practice, we can encourage community building using team points or group leaderboards instead of individual rankings. By making peers depend on each other for success, gamification can encourage help-seeking, communication, and a supportive learning community.

4.4 Engagement and Interaction

Descriptive analytics of engagement and interaction highlighted the platform's effectiveness in maintaining regular student involvement. The average number of weekly visits was 347, demonstrating consistent engagement. Moreover, users actively participated by raising 616 questions, providing 608 answers, and leaving 395 comments. This high level of activity aligns with existing literature on the positive impact of gamification on student engagement (Rivera and Garden, 2021; Alsadoon, 2023). However, our findings align with studies that argue that engagement metrics alone do not reflect deeper cognitive involvement or collaboration (Dillenbourg, 2021). Future studies should measure student-generated content depth, response quality, and long-term knowledge retention to provide a more comprehensive understanding of engagement.

4.5 Influence on Student Voice and Perspective

The realized and transformative value scores were moderate, with 40% of participants feeling that their ability to influence their learning environment improved. However, in follow-up interviews, some students expressed that *Answers* had enabled them to raise their academic concerns in ways that were not previously possible. This finding suggests that while the immediate transformative value may be unpretentious, the platform might contribute to a longer-term shift in student agency and participation. A potential area for future research is exploring how gamified platforms can promote more structured student-led initiatives. An example could be developing feedback loops between students and instructors to address learning challenges or co-designing gamification elements to reflect student needs.

4.6 Practical Implications and Recommendations

Our findings have a few practical implications for designing gamified learning platforms. First, we aim to improve social interaction by integrating discussion-based features and collaborative activities, which can foster a stronger sense of relatedness. Second, educators need to enhance motivation mechanisms by moving beyond points and badges. To achieve this goal, platforms can integrate peer recognition systems, narrative-based progression, or personalized incentives. Finally, reinforcing engagement beyond task completion. Future studies should investigate how to sustain long-term engagement through adaptive game mechanics, explore interventions to improve social connectivity and measure long-term learning retention.

5. Conclusion

This study explores two main research questions. First, how do learners perceive the gamified learning experience on the Answers platform? Second, how does the Answers system impact graduate students' value creation and intrinsic motivation? The findings indicate that while the platform successfully enhances learning practices and engagement, its impact on social connections and broader perspectives is less pronounced. Points and badges have limitations in sustaining engagement; alternative motivational designs should be explored. Future research should focus on strategies to increase active participation and foster a sense of community, ensuring the platform's content remains relevant and challenging. Also, Wenger's Value Creation Framework provides a powerful lens for evaluating multi-dimensional learning outcomes in gamified environments.

Platforms like *Answers* can maximize their impact on student learning and professional development by refining game design elements and fostering community-driven participation.

AI statement: No AI tools were used in this research to generate the text, data, or any type of information.

Ethics statement: Participation in this study was voluntary, and all students signed an informed consent form acknowledging their understanding and agreement to participate. No further ethics approval is required.

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Systematic Review: How Technology Supports Collaborative Writing Learning in Higher Education

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Abstract: Technology-enhanced collaborative academic writing (TECAW) in higher education has gained increasing attention due to its potential to enhance students' academic writing skills through interaction, shared authorship, and structured pedagogical support. Framing collaborative academic writing (CAW) as a pedagogical process, this systematic literature review explores how digital technologies and instructional strategies have been utilised to support students' engagement across the writing phases. A total of 27 peer-reviewed empirical studies, published between 2014 and 2024 and indexed in the Scopus database, were analysed using the PRISMA 2020 framework to ensure methodological rigour and transparency. The findings identified twenty types of technologies applied across the three phases of CAW including prewriting, in-writing, and post-writing. These technologies were categorised into five groups: collaborative study tools, classroom-based technologies, cloud-based word processors and shared documents, network-based social computing, and supporting tools. Frequently utilised platforms, including Google Docs, Moodle, Zoom, and WhatsApp, functioned either as interactive collaborative spaces that foster communication and idea co-construction or as task-supporting tools that facilitate drafting, feedback, and revision activities.In parallel, six core instructional strategies were identified: prewriting activities, scaffolding, peer review and feedback, collaborative revising and editing, reflective tasks, and collaborative note-taking. These strategies were systematically mapped across the writing phases, supporting not only the technical aspects of writing but also promoting collaborative interaction, critical thinking, and reflective learning practices. Importantly, the review highlights that successful TECAW implementation requires the intentional orchestration of technologies and instructional designs to align with the pedagogical goals at each stage of collaborative writing. The review emphasises that the effective integration of technology in CAW must be intentionally aligned with the pedagogical objectives at each stage of writing, ensuring that tools not only enhance task performance but also strengthen students' collaborative engagement and academic writing development. Overall, this study offers valuable insights for educators and researchers seeking to design student-centred, technology-supported writing instruction that reflects evolving digital pedagogies in higher education.

Keywords: Scientific writing, Collaborative writing, Technology-enhanced collaborative academic writing learning

1. Introduction

In recent years, academic writing has emerged as a critical competency for university students, who are expected to engage with disciplinary knowledge, present evidence-based arguments, and communicate ideas with clarity and coherence (López-Pellisa, Rotger and Rodríguez-Gallego, 2021; Li *et al.*, 2024). However, mastering academic writing is a cognitively demanding process that involves continuous practice, feedback, and reflection (Li *et al.*, 2024). Recognizing the limitations of traditional, individual-centred writing instruction, many educators have turned to Collaborative Academic Writing (CAW) as an alternative pedagogical approach. In this study, CAW is conceptualised not simply as co-authorship, but as a structured and intentional learning process that facilitates the development of academic writing skills through social interaction, peer feedback, and mutual responsibility (Storch, 2013; Li, 2018).

CAW engages students in all stages of the writing process (planning, drafting, revising, and reflecting) while fostering negotiation of meaning, shared decision-making, and reciprocal learning (Hsu, 2019; Lingard, 2021). This process encourages students to actively construct knowledge, sharpen their arguments, and gain a deeper understanding of academic conventions. Positioning CAW as a learning process emphasises its potential to support students' development of writing skills through iterative collaboration, consistent with constructivist theories of learning (Vygotsky and Cole, 1978). The inherently social nature of CAW helps students become more conscious of audience, clarity, and structure, while also cultivating communication, teamwork, and

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metacognitive awareness. By engaging in collaborative writing tasks, students are encouraged to reflect on their contributions, critically evaluate peer input, and revise their work accordingly (Storch, 2013, 2017).

At the same time, the integration of technology-enhanced learning (TEL) has revolutionised how CAW is facilitated in higher education. In this study, TEL refers to the use of digital platforms, tools, and applications to support, mediate, and enhance the learning process involved in collaborative writing. Technology can enhance this collaborative process by providing tools and platforms that facilitate communication, coordination, and access to information. The use of technology such as Google Docs allows students to collaborate in real-time, share documents, comment, and edit writing together without having to meet face-to-face (Jeong, 2016; Costley and Fanguy, 2021; H. Zhang *et al.*, 2022; Kaur and Chowdhury, 2022; Kitjaroonchai and Phutikettrkit, 2022; Alhazmi and Elamin, 2023; Burris-Melville and Burris, 2023; Fanguy, Costley, *et al.*, 2023). Online discussion forums and learning management applications such as Google Classroom, Moodle, and Microsoft Teams allow students to discuss, plan assignments, and organise work more effectively (Miftah and Cahyono, 2022; Burris-Melville and Burris, 2023; Sundari and Febriyanti, 2023; Hati and Bhattacharyya, 2024; Jusslin and Hilli, 2024). In addition, technology also overcomes geographical boundaries, allowing students from different locations to work together and share knowledge (Kaur and Chowdhury, 2022). Technology also indirectly supports the development of critical thinking skills in academic writing by mediating the activities of reflection, analysis, and continuous evaluation of academic writing (H. Zhang *et al.*, 2022; Malik *et al.*, 2023).

Despite the proliferation of digital tools in higher education, it remains unclear how technology and instructional strategies are integrated into CAW as a learning process. Existing studies often highlight either the benefits of collaboration or the usefulness of individual tools, but offer limited insight into how digital technologies actively support students' progression through the phases of academic writing, from prewriting to post-task reflection (Storch, 2019; Zhang and Zou, 2022). Moreover, the alignment between technological affordances and pedagogical goals have a significant impact on the quality of students' academic writing (Cahyono *et al.*, 2023; Herdianto *et al.*, 2024). But it is not always made explicit, leaving a practical gap in guiding educators to effectively design technology-supported collaborative writing instruction.

To respond to the increasing interest in integrating technology into writing pedagogy, this article aims to provide a structured synthesis of empirical studies that examine how technology supports collaborative academic writing (CAW) as a pedagogical process in higher education. In doing so, it contributes to a deeper understanding of how specific technologies and instructional strategies are applied across different phases of CAW, and how these tools mediate learning outcomes. By synthesising recent findings, this review aims to provide educators, instructional designers, and researchers with evidence-based insights for developing effective, student-centered, and technology-integrated writing practices in higher education.

In particular, the objective of this review is to systematically analyse and categorise the types of technologies used and instructional strategies implemented to support CAW in tertiary education settings. To achieve this objective, the following research questions were formulated:

RQ1. What types of digital technologies have been implemented to support collaborative academic writing as a pedagogical approach in higher education?

RQ2. What instructional strategies have been employed to facilitate technology-enhanced collaborative academic writing across different stages of the learning process?

2. Literature Review

2.1 Collaborative Academic Writing as Pedagogical Learning Approach

Academic writing in higher education demands a complex combination of cognitive, linguistic, and disciplinary knowledge. Students are required to construct evidence-based arguments, structure coherent texts, and engage with scholarly literature using discipline-specific conventions (Hyland, 2013). Academic writing involves critical thinking, problem solving, and justification, as students must evaluate sources, synthesise ideas, and organise arguments to meet academic expectations (Suyitno, 2012; Marni *et al.*, 2019; Chuang and Yan, 2023). In this context, collaborative academic writing (CAW) plays a crucial role. It enables students to co-construct knowledge, engage in scholarly discourse, and build essential skills such as reasoning, audience awareness, and communication. Studies show that CAW enhances students' ability to comprehend academic content, articulate ideas clearly, and produce more sophisticated written work (MacArthur and Graham, 2016; Li *et al.*, 2024). These collaborative practices are particularly relevant as higher education increasingly emphasises interdisciplinary work, teamwork, and real-world writing scenarios.

Within this context, Collaborative Academic Writing (CAW) emerges not only as a learning outcome but also a pedagogical approach that fosters academic writing learning through co-construction, interaction, and reflection. Rooted in constructivist learning theory, particularly Vygotsky's concept of the Zone of Proximal Development (ZPD) (1978), CAW provides an environment where learners develop their writing skills through meaningful social interaction and negotiation of meaning. Learning occurs within the ZPD, as peers scaffold each other's understanding of content and writing conventions. Meaningful learning can occur at the ZPD, which is described as the gap between the current level of development of learners' capacities and their developmental potential.

CAW involves distinct stages—brainstorming, conceptualising, outlining, drafting, reviewing, revising, and editing—each requiring collaboration, shared responsibility, and continuous communication (Ede and Lunsford, 1992; Li, 2018). These stages support not only writing competence but also higher-order skills such as critical thinking, teamwork, and metacognitive reflection (Storch, 2017; Ramadhanti *et al.*, 2019). As such, CAW aligns closely with pedagogical goals of active, student-centered learning that develops both academic literacy and 21st-century competencies.

2.2 Technology-Enhanced Collaborative Writing

With the evolution of digital learning environments, a growing number of digital tools have been incorporated into collaborative writing practices in educational settings since 2009 (Storch, 2019; Chen and Hapgood, 2021). Li (2018), through a systematic review of 21 studies published between 2008 and 2017, highlighted computer technologies, wikis, and Google Docs as the most commonly utilised tools in Technology-Enhanced Collaborative Writing (TECW). Similarly, Storch (2019), after analysing significant studies on collaborative writing from 1997 to 2017, noted that most TECW implementations were grounded in the use of computer-based and online technologies. Zhang and Zou (2021) identified six widely used tools in TECW activities: wikis, Google Docs, chat platforms, Facebook, online forums, and offline word processors.

The integration of new technologies has had a generally positive influence on learners' engagement and perceived benefits in collaborative writing (Li, 2018; Zhang and Zou, 2022). These tools promote peer interaction, facilitate self-assessment and error recognition, enhance motivation and confidence, simplify the writing and editing process, and contribute to a more engaging and enjoyable learning environment (Zhang and Zou, 2022). However, the success of TECW is not guaranteed, especially when learners struggle with unfamiliar technology or group collaboration (Zhang and Zou, 2022). Additional factors, such as task type, tool selection, language proficiency, and group dynamics, can also significantly impact TECW outcomes (Storch, 2011).

2.3 Limitation of Previous Review Studies

Although the application of technology in collaborative academic writing has been investigated, systematic reviews in this domain remain limited. Several existing reviews highlight important trends but are either focused on different educational levels or broader writing skills, not specifically academic writing at the higher education level.

For instance, Williams and Beam (2019) systematically reviewed studies on technologies used to mediate writing instruction and writing tasks. The use of technology motivates student engagement and participation in writing tasks and enhances social interaction and peer collaboration. However, the study concentrated on writing development at the early childhood, elementary, middle, junior high, and high school levels. Furthermore, Akhtar et al., (2019) provided a systematic literature review on academic writing studies that focused on investigating students' academic writing challenges and solutions. This literature review concluded the need for strategies that help improve students' writing skills. However, the articles reviewed were also limited to ESL students in Malaysia as the research context. While Zhang and Zou (2022) reviewed 34 empirical research articles and identified various technologies that can enhance the collaborative writing process. The integration of technology in writing instruction encourages group interaction, helps students reflect on their work and identify errors and weaknesses, increases learner motivation and confidence, facilitates writing, encourages students to learn from others, and makes the learning process fun. However, the systematic literature review also only focused on ESL students.

Thus, to date, no systematic literature review has comprehensively explored technology-supported collaborative academic writing at the tertiary level, despite the distinctive complexity and expectations associated with academic discourse in higher education (Hyland, 2013). This review aims to fill that gap by synthesizing how digital technologies and instructional strategies are utilized to support CAW learning in university settings.

3. Methodology

The objective of this review is to identify and analyse the technologies and instructional strategies that support the process of collaborative academic writing in higher education.This study is a Systematic Literature Review that carries out a credible review process based on the PRISMA framework (Page *et al.*, 2021) (see Figure 1) to ensure transparency and rigour in identifying, selecting, and analysing relevant literature. The review focused on studies exploring the use of digital technologies and instructional strategies in collaborative academic writing (CAW) as a pedagogical process in higher education.

3.1 Review Protocol

The review process followed a structured protocol consisting of four phases: identification, screening, eligibility, and inclusion. The process and results are illustrated in the updated PRISMA 2020 flow diagram, and all reporting criteria have been aligned with the PRISMA framework, including details on inclusion criteria, search strategy, study selection, data extraction, and synthesis.

3.2 Data Source and Search Strategy

The literature search was conducted using the Scopus database, chosen for its extensive coverage of peer-reviewed and high-quality academic publications across disciplines. In response to reviewer feedback, especially those reporting empirical findings in the fields of education, instructional technology, and digital learning. The keywords used were (a) "collaborative" or "collaborative writing" or "write collaboratively" or "collaboratively write" or "collaboratively written" or "collaborative written text" or "learn collaboratively through writing" or "collaborative learning" and (b) "academic writing" or "academic text" or "scientific writing"; using AND connectors.

3.3 Inclusion and Exclusion Criteria

The articles were then selected based on the inclusion criteria. Studies were included if they:

- Were published between 2014 and 2024,
- Were written in English,
- Document type is an article
- Available in full text
- Relate to the research objectives, by focusing on technology-enhanced collaborative language learning (TECLL) within academic writing contexts.
- Reported empirical findings related to technology-supported collaborative academic writing in higher education,

Studies were excluded if they:

- Weren't written in English
- The type of document is book chapter, conference paper, review, and book
- No full text available
- Not focus on TECLL in academic writing context
- Not reported empirical findings related to technology-supported collaborative academic writing in higher education

From the search results, 316 articles were publishe between 2014-2024. Only articles that used English were selected, leaving 296 articles. The type of article document that will be analysed is only the type of research article. Document types such as book chapters, conference papers, reviews, and books were not included in the analysis so 206 articles were obtained. Of the remaining articles, only 95 articles were selected because of open access and continued in the title and abstract screening process. From the screening of titles and abstracts, 52 articles were obtained that were relevant to the research objectives. Furthermore, 25 articles were excluded because they did not have empirical data and were not in the context of collaborative academic writing learning in higher education. Thus, the screening ended with 27 articles to analyse.

3.4 Data Selection and Data Analysis

After applying the inclusion criteria and removing duplicates, titles and abstracts were screened. Full texts of the remaining articles were assessed for eligibility. To ensure inter-rater reliability, the coding process involved multiple stages. First, five articles were jointly selected by all reviewers to serve as a calibration set, representing a range of publication years, methodologies, and technology types. These articles were discussed collectively to develop a shared understanding of the coding categories and thematic structure. In this stage, representative samples are chosen to align researchers on a consistent interpretation of the coding framework. A satisfactory agreement was reached at the end of the coding (Pearson's $r = 0.85$).

After this calibration phase, the remaining studies were independently coded by two researchers. Discrepancies were documented and discussed in regular review meetings, and consensus was reached through negotiated agreement. When needed, a third researcher served as an adjudicator. This iterative process enhanced the reliability and transparency of the data analysis. The final set of studies was analysed using thematic coding to identify recurring patterns in the use of technologies and instructional strategies across different phases of the collaborative academic writing process.

The synthesis focused on the pedagogical roles of technology in CAW, categorised by its function as an interactive collaborative space or as a task-supporting tool, and mapped to stages of the writing process. This analytic lens allows the review to offer insights into how technology and pedagogy intersect to support collaborative academic writing in higher education. To address the research questions, the 27 articles were analysed from two perspectives.

a. Technology in implementing technology-enhanced collaborative academic writing learning

This category concerns the types and use of technologies, platforms, digital tools, or online systems that teachers/researchers have used to support their implementation of collaborative academic writing learning activities. Technology included collaborative study tools, classroom-based technology, cloud-based word processors and shared documents, network-based social computing, and supporting tools. The categorisation of technologies and software for collaborative writing was adapted from Zhang et al., (2022) and Loncar et al., (2021).

b. Strategy used in implementing technology-enhanced collaborative academic writing learning

Collaborative writing can be systematically organised into three pedagogical phases: pre-collaborative writing, in-collaborative writing, and post-collaborative writing, each encompassing specific instructional practices designed to support the development of both writing and collaboration skills (R. Zhang *et al.*, 2022). The pre-collaborative writing phase focuses on building readiness by ensuring that students are cognitively and socially prepared to engage in the collaborative writing process. The in-collaborative writing phase involves the actual implementation of writing tasks, emphasising active communication, negotiation of meaning, and the establishment of shared responsibility among group members. Finally, the post-collaborative writing phase centers on evaluation and reflection, aiming to assess the collaborative process, the quality of the written product, and areas for future improvement. In this study, instructional strategies were identified and categorised based on these three phases of collaborative academic writing as outlined by previous research.

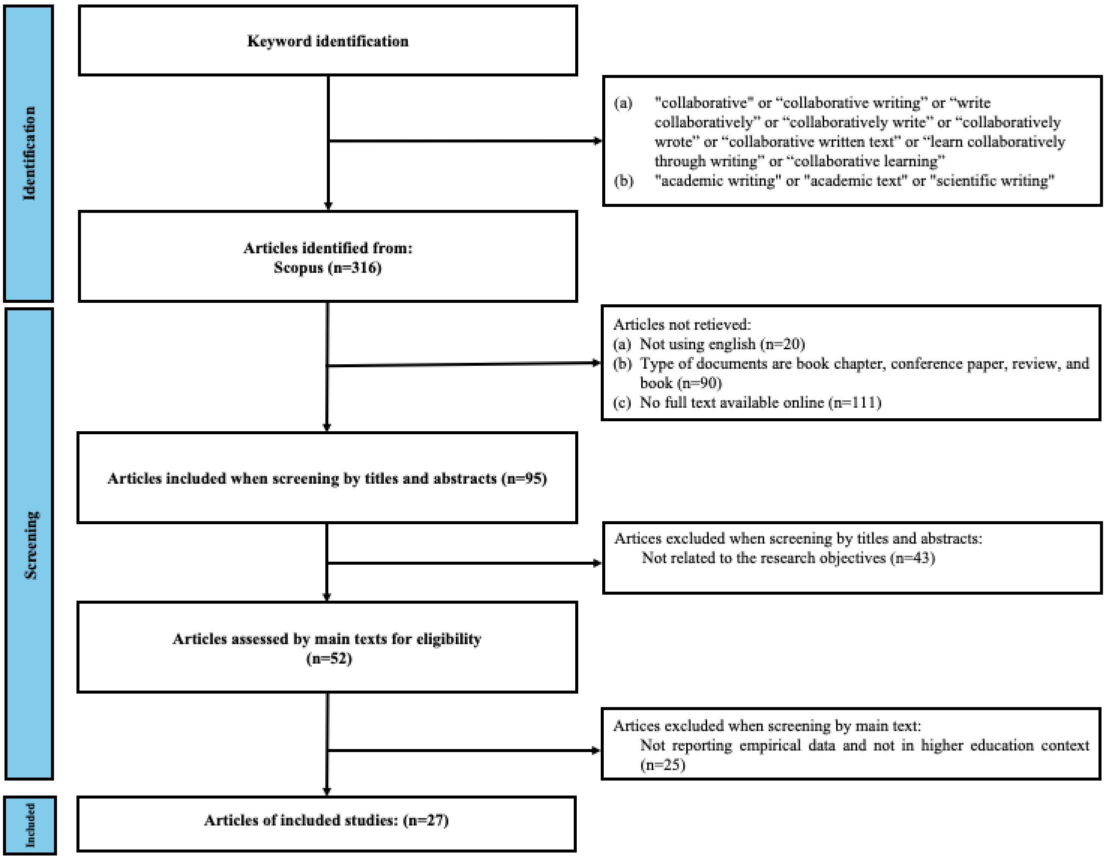

Figure 1: Process and method data search, selection, and collection

4. Findings and Discussion

4.1 Technologies that Supports Collaborative Academic Writing Learning

Based on the analysis of the selected research articles, 20 types of technology applied in collaborative academic writing learning can be identified (see Appendix A). Figure 2 shows the various technologies used in collaborative academic writing learning and Figure 3 shows the number of studies implemented technologies in CAW per year.

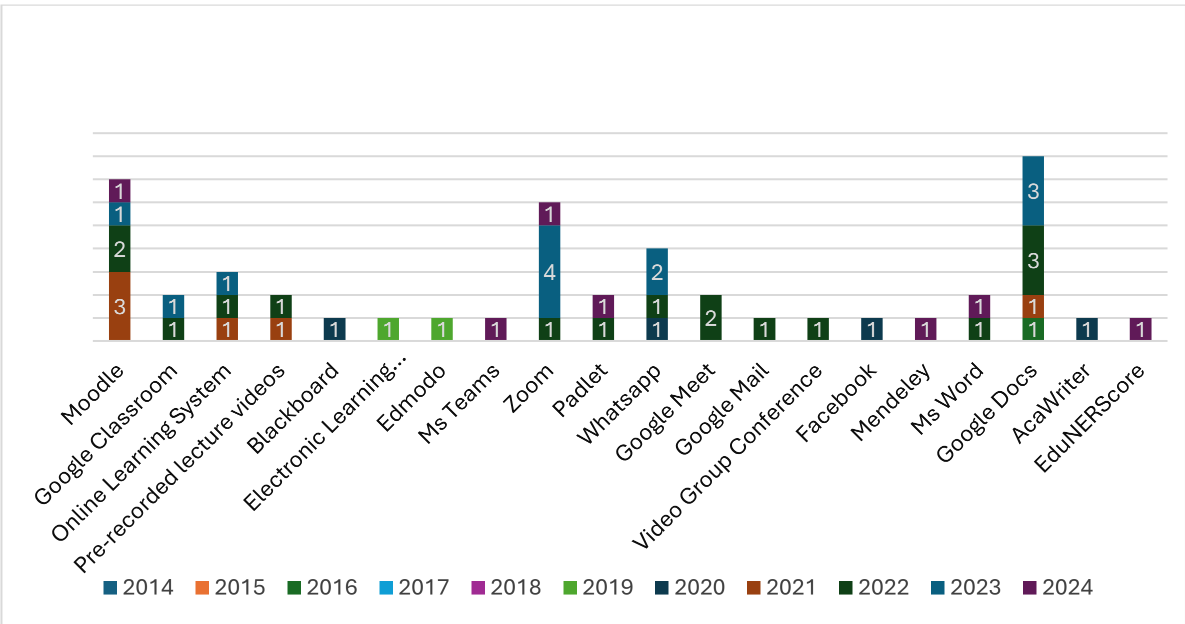

Figure 2: Numbers of Technology for Collaborative Academic Writing Learning Implemented in Studies

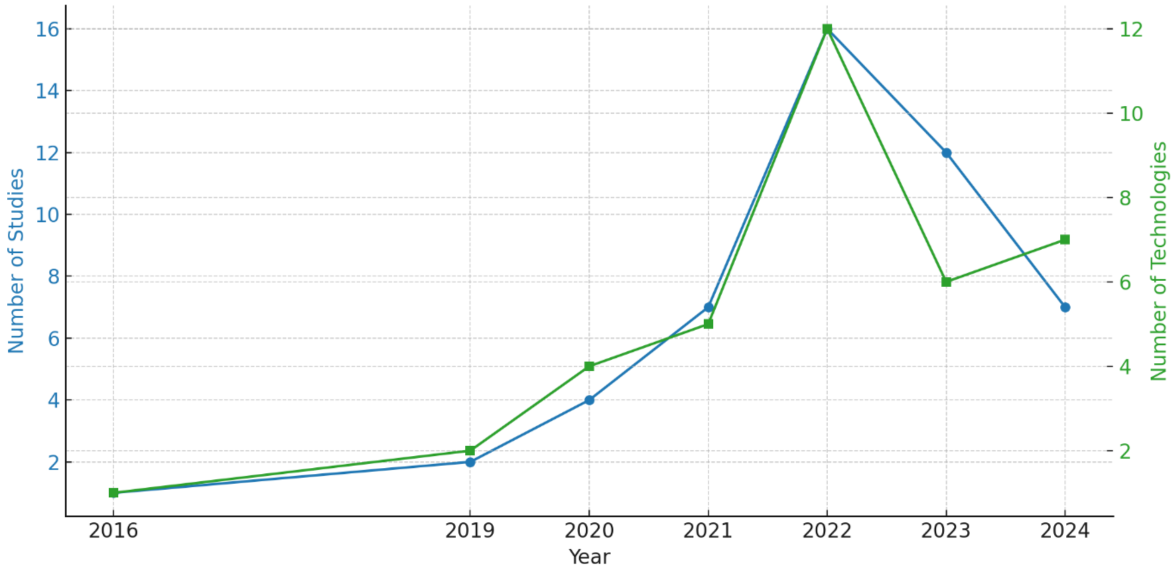

Figure 3: Technology Used in Collaborative Academic Writing Learning per Year

The analysis of technology use across publication years reveals a significant temporal trend in the integration of digital tools for collaborative academic writing (CAW). The year 2022 marks a peak in both frequency (16 studies) and diversity (12 technologies) of technologies adopted in CAW studies. This notable surge aligns with the global shift towards online and hybrid learning environments prompted by the COVID-19 pandemic, which compelled institutions to rapidly adopt digital platforms such as Google Docs, Zoom, and Moodle to sustain academic writing collaboration. The pandemic acted as a catalyst, not only accelerating technology adoption out of necessity but also expanding educators' and researchers' familiarity with a broader range of digital tools.

From 2019 onwards, a steady increase in the application of technology is observable, indicating growing scholarly engagement with technology-enhanced CAW. In contrast, the earlier part of the review window (2014–2018) reflects relatively limited activity, suggesting a lack of focus on technologically mediated CAW during that period. Although a slight decline is noted in 2023 in both the frequency and diversity of technologies, the continued presence of six or more distinct platforms suggests a sustained momentum. The trend continues into 2024, with seven technologies mentioned and increased reference to recently developed platforms, highlighting an ongoing post-pandemic shift towards digital adaptation and innovation in CAW practices.

Overall, this upward trajectory reflects not only the circumstantial influence of the pandemic but also a broader pedagogical transformation. The integration of digital tools into CAW appears to have evolved from a reactive response to a proactive, intentional strategy that underscores the pedagogical value of technology in supporting collaborative writing in higher education.

Based on the identification results, the technology applied in collaborative academic learning can be categorised based on its use which is shown in Table 1 as follow:

Table 1: The Type of Technology

Type of Technology	Technologies
Collaborative Study Tools	Padlet, Gmail, Zoom, Google Meet, Microsoft Teams, and Video Group Conference
Classroom-based Technology	Moodle, Google Classroom, Blackboard, Online Learning Systems, Electronic Learning Environment, Edmodo, Pre-recorded lecture videos
Cloud-based Word Processors and Shared Documents	Google Docs, Microsoft Teams
Networks-based Social Computing	Facebook, Whatsapp
Supporting Tools	Microsoft Word, AcaWriter, and EduNERScore, Mendeley

A single technology may fall into multiple categories depending on its functional use in the collaborative writing process. For example, Microsoft Teams can serve as a video conferencing platform as well as a collaborative document editing tool. Accordingly, it was categorised simultaneously as both a Collaborative Study Tool and a Cloud-Based Word Processor to reflect its multifunctional role.

The purpose of using these various technologies is described as follows.

a. Collaborative Study Tools

Collaborative study tools were applied in eleven studies, consist of Padlet, Whatsapp, Facebook, Gmail, Zoom, Google Meet, Microsoft Teams, and Video Group Conference. One of the functions of using these technologies is to facilitate group discussions. Collaborative learning cannot be separated from group discussion activities. These technologies support both asynchronous and synchronous discussion processes.

Research has also found technology to be very helpful for collaborative discussion processes. Chatting in Zoom has excellent potential for synchronous written dialogue (Jusslin and Hilli, 2024). In addition, synchronous discussion written in Padlet showed a positive relationship with student collaboration (Jusslin & Hilli, 2024). As described by Kaur and Chowdhury (2022), students were satisfied with the discussion process through the WhatsApp platform because the work became easier and could be done at any time.

b. Classroom-based Technology

Fifteen studies applied classroom-based technology in the collaborative academic writing learning. Research conducted by Jusslin and Hilli (2024) showed that Moodle can serve as an asynchronous hybrid learning space that students can access as needed and also used synchronously through screen sharing for materials on the platform. Mulyati and Hadianto (2023) also found that using the Integrated Online Learning System as virtual learning environment could facilitate students in receiving and providing detailed feedback, which improved the quality of argumentative essays, feedback, and domain-specific knowledge.

In collaborative academic writing learning, teachers can manage learning synchronously or asynchronously using LMS (Jusslin and Hilli, 2024). Teachers can manage the learning flow through the LMS, and students can asynchronously manage the materials they want to access (Duin and Tham, 2020; Jusslin and Hilli, 2024). Several features like discussion forums, project groups, and cloud-based collaborative writing tools in the LMS promote students' socio-cognitive development and encourage process-based writing. These features create a social learning space that allows students to find topics of investigation together, define the problems together, and seek solutions (Duin and Tham, 2020). However, Jusslin and Hilli (2024) added that various collaborative and individualised spaces are needed to support students' academic writing.

c. Cloud-based Word Processors and Shared Documents

Nine studies were utilised Cloud-based Word Processors and Shared Documents in collaborative academic writing, including Google Docs and Micrososft Teams. Google Docs is one of the platforms that help the collaborative writing process. *Google Docs* is a web-based word-processing tool that allows multiple writers to collaborate and edit their writing synchronously in real-time or asynchronously. Technologies such as Google Docs and Microsoft Teams allow students to work together in real-time, share documents, provide comments, and track changes made by group members (Jeong, 2016; Costley and Fanguy, 2021; H. Zhang *et al.*, 2022; Kaur and Chowdhury, 2022; Kitjaroonchai and Phutikettrkit, 2022; Alhazmi and Elamin, 2023; Burris-Melville and Burris, 2023; Fanguy, Costley, *et al.*, 2023; Hati and Bhattacharyya, 2024) These tools not only facilitate better communication but also improve the coordination and effectiveness of teamwork (Burris-Melville and Burris, 2023). These tools allow collaborators to create texts at their preferred time and independent of space while using built-in chat or comment windows to interact with other team members and revisit their revision history to edit or revise the text they shared. Collaborating on web-based tools such as Google Docs can provide opportunities for learners to negotiate tasks, share linguistic resources, conceptualised lexical units and grammar rules, and further enhance cognitive advantages that affect knowledge acquisition at an individual level (Alghasab, Hardman and Handley, 2019; Chen, 2019). The use of web-based collaborative tools motivates learner engagement and participation in group writing, enhances peer interaction, and helps students to correct each other's mistakes (H. Zhang *et al.*, 2022; Kitjaroonchai and Phutikettrkit, 2022).

d. Networks-based Social Computing

Four studies employed Facebook and WhatsApp as network-based social computing tools in collaborative academic writing. WhatsApp, on the other hand, is a mobile-first messaging application that facilitates real-time communication through text, voice messages, and multimedia sharing. While Facebook supports academic collaboration through features such as groups, threaded discussions, commenting, and file sharing, allowing students to engage in discussions, provide feedback, and coordinate writing tasks asynchronously. Facebook and WhatsApp function as network-based social computing tools that support group cohesion, encourage reflection through peer interaction (Banegas *et al.*, 2020; Kaur and Chowdhury, 2022; Sundari and Febriyanti, 2023; Yuniarti *et al.*, 2023). As described by Kaur and Chowdhury (2022), students were satisfied with the discussion process through the WhatsApp platform because the work became easier and could be done at any time.

e. Supporting Tools

Some technologies greatly support the academic writing process. Software specifically designed to support the scientific writing process, such as Microsoft Word, AcaWriter, and EduNERScore, help students in various aspects of writing, such as drafting paper, managing references, and grammar and plagiarism checking (Knight *et al.*, 2020; Susilo, Mufanti and Fitriani, 2021; Kitjaroonchai and Phutikettrkit, 2022; Jusslin and Hilli, 2024; Li *et al.*, 2024). AcaWriter and EduNERScore are examples of Natural Language Processing (NLP), technology that can recognise sentences that communicate specific rhetorical functions and thus generate automated feedback on writing (Knight *et al.*, 2020; Li *et al.*, 2024). The main functions of this technology are to improve the quality of writing through error detection, provision of corrective suggestions, and ensuring academic honesty. EduNERScore is not merely an individual assessment tool; it is explicitly designed to support and enhance the collaborative process in academic writing, particularly during the peer commenting and group reflection phases. These technologies can reduce plagiarism, improve writing skills, and help students develop a more professional and scholarly writing style.

4.2 Highlighted Instructional Strategies in Technology-enhanced Collaborative Academic Writing Learning

The results of the systematic literature review, presented in Figure 4 below, highlight some strategies as critical features that support students in learning academic writing collaboratively supported by technology (see Appendix B). These strategies become features of collaborative academic writing learning that play roles in the learning process.

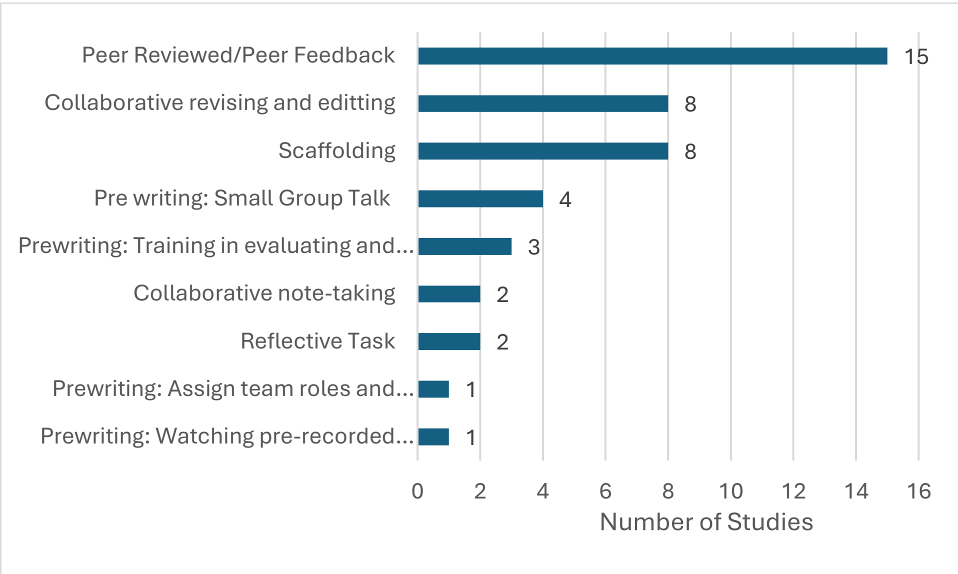

Figure 4: Numbers of Studies Reporting Different Strategies for Technology-enhanced Collaborative Academic Writing Learning

Almost all the types of technology described in this review mediate the instructional strategies employed in collaborative academic writing learning. The identified strategies serve as critical pedagogical anchors across each phase of Technology-Enhanced Collaborative Academic Writing (TECAW) in learning. Importantly, almost all types of technology identified in this review play a mediating role in supporting these instructional strategies in TECAW.

a) Prewriting Phase

Strategies such as assigning team roles, watching pre-lecture videos, and conducting mini-lessons are typically implemented during the pre-collaborative writing stage to build students' preparedness. Classroom-based technologies such as Moodle, Google Classroom, and pre-recorded lecture videos are widely used to deliver writing instruction asynchronously, share learning materials, assign team roles, and introduce writing tasks (H. Zhang *et al.*, 2022; Burris-Melville and Burris, 2023; Yuniarti *et al.*, 2023). The strategies play a pivotal role in activating students' prior knowledge, establishing shared cognitive frameworks, and preparing students for effective group interaction.

Furthermore, collaborative note-taking was found as a strategy that can enhance pre-academic writing learning. This strategy involves several students recording information together. Collaborative note-taking can enrich the quality of notes produced by students. Students can complement and improve their notes by collaborating, resulting in more comprehensive and detailed notes. The research found that students who take notes collaboratively can produce more complete information than those who take notes individually (Fanguy, Baldwin, *et al.*, 2023). So they tend to generate more new ideas and information, which helps develop students' academic writing skills.

Furthermore, the prewriting stage is sufficient to determine the success of academic writing learning. Implementing prewriting strategies, particularly within small groups composed of peers with varying language proficiency levels, has been found to enhance the quality of students' essays. Such structured prewriting activities help students focus more effectively on the writing task, especially when facilitated through writing prompts that aid in maintaining topic relevance and guiding discussions (Tatiana, 2021). By facilitating early peer negotiation and idea sharing, prewriting strategies ensure that all group members enter the writing phase with aligned understandings, clear purposes, and a collaborative mindset. This cognitive activation in the prewriting stage is fundamental because it lays the groundwork for the higher-order thinking processes required during drafting and revising.

b) In-Writing Phase

The in-collaborative writing stage marks the phase where students begin to construct the initial draft of the manuscript, engaging in real-time collaboration, content development, and iterative refinement of their ideas. Cloud-based word processors, particularly Google Docs and Microsoft Teams, are central to enabling collaborative drafting in real time (Alhazmi and Elamin, 2023; Burris-Melville and Burris, 2023; Fanguy, Costley, *et al.*, 2023; Hati and Bhattacharyya, 2024). Peer drafting and revising activities foster co-construction of knowledge by encouraging group members to provide immediate feedback, challenge each other's ideas, and jointly refine the textual output. This dynamic interaction strengthens critical reasoning and academic argumentation skills while simultaneously nurturing social negotiation and consensus-building as key competencies for academic collaboration (Andheska *et al.*, 2020; Leng, Yi and Gu, 2021; Wang, Zhang and Cooper, 2025). Collaborative study tools such as Padlet and WhatsApp support peer discussion, planning, and negotiation of ideas in synchronous and asynchronous context (Smith, 2022; Yuniarti *et al.*, 2023; Jusslin and Hilli, 2024). Meanwhile, supporting tools such as Microsoft Word and Mendeley assist with drafting in offline settings and managing collaborative citation libraries, respectively (Kitjaroonchai and Phutikettrkit, 2022; Hati and Bhattacharyya, 2024).

In this stage, strategies including providing scaffolding, peer review, and collaborative revising and editing are commonly employed to support active engagement in the writing task. Scaffolding, such as the use of metacognitive prompts, helps students navigate the complexities of academic writing by offering structured guidance (Teng, 2021). These prompts facilitate students' ability to use what they know, transform what they know for academic communication, and structure what they know for the benefit of peers. For instance, giving scaffolding can help students navigate complex writing tasks by offering structured support and guidance throughout the collaborative process. An example of applied scaffolding was using metacognitive prompts (Teng, 2021). Metacognitive prompts in collaborative writing facilitate students' ability to use what they know, transform what they know for academic communication, and structure what they know for the benefit of peers.

c) Post-writing Phase

In the post-collaborative writing stage, reflective tasks are often used to encourage metacognitive thinking and evaluation of both the writing product and the collaborative process. Reflective tasks, including writing reflective logs or group-based self-assessments to evaluate collaboration, writing quality, and individual contributions. Supporting tools like AcaWriter and EduNERScore (based on NLP) provide automated feedback to help students revise and reflect critically on their work (Knight *et al.*, 2020; Li *et al.*, 2024). These activities prompt students to evaluate the quality of their written products, reflect on the collaborative dynamics, and assess their individual contributions to the group effort. Beyond mere correction of writing errors, reflection fosters metacognitive awareness, allowing students to internalise effective writing strategies and collaborative practices that can be transferred to future academic tasks.

These findings strongly resonate with Vygotsky's (1978). sociocultural theory of learning, which emphasises that knowledge is constructed through social interaction within the Zone of Proximal Development (ZPD). In the context of Technology-Enhanced Collaborative Academic Writing (TECAW), digital platforms and structured instructional strategies provide collaborative spaces where learners can scaffold each other's understanding, co-construct academic knowledge, and progressively develop higher-order writing skills. The integration of technologies and pedagogical approaches, aligned with different phases of the writing process, reflects the principles of collaborative learning envisioned by Vygotsky, affirming that meaningful academic writing development is best achieved through socially mediated activities supported by appropriate technological tools.

The use of technology underscores the imperative for an intentional and pedagogically informed alignment between digital tools, writing phases, and instructional strategies. Rather than adopting a one-size-fits-all approach, educators must strategically curate technologies based on their specific affordances and their ability to support distinct cognitive, social, and metacognitive goals at each writing stage. Such strategic alignment is not merely beneficial, it is essential for cultivating meaningful collaboration, enhancing writing quality, and empowering students to engage deeply in the co-construction of academic writing.

4.3 Limitations and Suggestions

This review has several limitations. The study exclusively collected articles indexed in the Scopus database, which may have limited the diversity of technologies identified and resulted in gaps during the early years of the review period (e.g., 2014, 2015, and 2017). As a consequence, certain emerging technologies or earlier studies published in other reputable databases may not have been captured. Additionally, the review focuses primarily on studies in higher education contexts, which may not fully reflect technological practices in other academic levels or informal learning environments. Based on these limitations, future research is recommended to expand the scope of literature to include multiple databases to capture a broader spectrum of technologies and practices and explore the integration of emerging technologies, particularly artificial intelligence and adaptive learning systems, to better understand their potential in facilitating collaborative writing processes. Furthermore, future investigations should pay closer attention to the design of instructional frameworks that systematically align technologies with the distinct cognitive, social, and metacognitive dimensions of each phase of collaborative academic writing.

5. Conclusion

This systematic literature review highlights the evolving role of technology in supporting collaborative academic writing (CAW) within higher education contexts. The analysis demonstrates that the integration of digital tools is not merely incidental, but rather pedagogically purposeful, aligning closely with instructional strategies that target the cognitive, social, and metacognitive dimensions of student learning.

The findings reveal that technologies such as Google Docs, Moodle, Zoom, WhatsApp, and Microsoft Teams have been extensively utilized to facilitate collaborative writing processes, particularly following the global shift toward online and hybrid learning in 2020. The temporal analysis shows a notable increase in both the frequency and diversity of technologies applied since 2019, reflecting a growing maturity in the methodological and instructional design of Technology-Enhanced Collaborative Academic Writing (TECAW).

Crucially, the review identifies that instructional strategies — including prewriting activities, scaffolding, peer drafting-revising-editing, and reflective tasks — are systematically integrated across the different phases of collaborative writing (prewriting, in-writing, and post-writing). These strategies leverage technology not only as a communication medium but also as an interactive collaborative space and a task-supporting tool, collectively nurturing students' critical thinking, peer negotiation, and self-regulated learning. When technologies are intentionally aligned with these instructional strategies, they significantly enhance the collaborative learning experience and foster deeper engagement with academic writing practices. In conclusion, technology-enhanced collaborative academic writing learning is most effective when technologies, writing phases, and instructional strategies are strategically and pedagogically orchestrated.

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Appendix A

Table 2: Technology-enhanced collaborative academic writing learning

Platform	Authors
Moodle	(Jusslin and Hilli, 2024), (Burris-Melville and Burris, 2023), (Pourdana, 2022), (Kitjaroonchai and Phutikettrkit, 2022), (Arroyo González, Fernández Lancho and De la Hoz Ruiz, 2021), (Tatiana, 2021), (Teng, 2021)
Google Classroom	(Sundari and Febriyanti, 2023), (Kaur and Chowdhury, 2022)
Online Learning System	(Mulyati and Hadianto, 2023), (H. Zhang *et al.*, 2022), (Costley and Fanguy, 2021)

Platform	Authors
Pre-recorded lecture videos	(H. Zhang *et al.*, 2022), (Costley and Fanguy, 2021)
Blackboard	(Motlhaka, 2020)
Electronic Learning Environment (ELO)	(Van Blankenstein *et al.*, 2019)
Edmodo Mobile Application	(Hosseınpour, Bırıa and Rezvanı, 2019)
Microsoft Teams	(Hati and Bhattacharyya, 2024)
Zoom	(Jusslin and Hilli, 2024), (Burris-Melville and Burris, 2023), (Alhazmi and Elamin, 2023), (Fanguy, Costley, *et al.*, 2023), (Sundari and Febriyanti, 2023), (H. Zhang *et al.*, 2022)
Padlet	(Jusslin and Hilli, 2024), (Smith, 2022)
Whatsapp	(Yuniarti *et al.*, 2023), (Sundari and Febriyanti, 2023), (Kaur and Chowdhury, 2022), (Banegas *et al.*, 2020)
Google Meet	(Kaur and Chowdhury, 2022), (Pourdana, 2022)
Google Mail	(Kaur and Chowdhury, 2022)
Video Group Conference	(Thirakunkovit and Boonyaprakob, 2022)
Facebook	(Banegas *et al.*, 2020)
Mendeley	(Hati and Bhattacharyya, 2024)
Microsoft Word	(Jusslin and Hilli, 2024), (Kitjaroonchai and Phutikettrkit, 2022), (Susilo, Mufanti and Fitriani, 2021)
Google Docs	(Burris-Melville and Burris, 2023), (Alhazmi and Elamin, 2023), (Fanguy, Costley, *et al.*, 2023), (Kaur and Chowdhury, 2022), (H. Zhang *et al.*, 2022), (Kitjaroonchai and Phutikettrkit, 2022), (Costley and Fanguy, 2021), (Jeong, 2016)
AcaWriter	(Knight *et al.*, 2020)
EduNERScore	(Li *et al.*, 2024)

Appendix B

Table 3: Strategies in technology-enhanced collaborative academic writing learning

Strategy	Authors
Prewriting: Training in evaluating and decoding information or mini lesson	(Hati and Bhattacharyya, 2024), (Alhazmi and Elamin, 2023), (Thirakunkovit and Boonyaprakob, 2022)
Prewriting: Watching pre-recorded lecture videos	(H. Zhang *et al.*, 2022)
Pre writing: Small Group Talk	(Burris-Melville and Burris, 2023), (Yuniarti *et al.*, 2023), (Sundari and Febriyanti, 2023), (Shayakhmetova *et al.*, 2020)
Prewriting: Assign team roles and responsbilities	(Burris-Melville and Burris, 2023)
Scaffolding	(Yuniarti *et al.*, 2023), (Sundari and Febriyanti, 2023), (Mulyati and Hadianto, 2023),(Kitjaroonchai and Phutikettrkit, 2022), (Susilo, Mufanti and Fitriani, 2021), (Teng, 2021), (Knight *et al.*, 2020), (Van Blankenstein *et al.*, 2019)
Peer Reviewed/Peer Feedback	(Hati and Bhattacharyya, 2024), (Jusslin and Hilli, 2024), (Burris-Melville and Burris, 2023), (Alhazmi and Elamin, 2023), (Sundari and Febriyanti, 2023), (Mulyati and Hadianto, 2023), (Kaur and Chowdhury, 2022), (Pourdana, 2022), (H. Zhang *et al.*, 2022), (Smith, 2022), (Banegas *et al.*, 2020), (Motlhaka, 2020), (Van Blankenstein *et al.*, 2019), (Hosseınpour, Bırıa and Rezvanı, 2019), (Jeong, 2016)
Collaborative revising and editting	(Hati and Bhattacharyya, 2024), (Sundari and Febriyanti, 2023), (Kaur and Chowdhury, 2022), (H. Zhang *et al.*, 2022), (Kitjaroonchai and Phutikettrkit, 2022), (Susilo, Mufanti and Fitriani, 2021), (Knight *et al.*, 2020), (Jeong, 2016).
Reflective Task	(Pourdana, 2022),(Thirakunkovit and Boonyaprakob, 2022)
Collaborative note-taking	(Costley and Fanguy, 2021), (Susilo, Mufanti and Fitriani, 2021).

Avatars vs. Video Presence: Effects of Instructor Presence on Cognitive Load in Video-Based Learning

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Abstract: This study examines the impact of instructor presence on cognitive load and learning outcomes in video-based learning environments, addressing a significant gap in optimising instructional design for digital education. Utilising eye-tracking technology to measure pupil dilation, a reliable proxy for cognitive load, this research compares three experimental conditions: no instructor presence, physical instructor presence, and avatar-based instructor presence. Thirty-three undergraduate participants engaged with educational videos, and their cognitive load was assessed through pupil dilation while learning gains were evaluated using pre- and post-tests. Findings indicate that physical instructor presence induces the highest extraneous cognitive load due to non-verbal distractions, negatively affecting learning outcomes. Conversely, avatar-based instructor presence effectively balances cognitive demands by reducing extraneous load and fostering germane cognitive processing, enhancing learning outcomes. The absence of an instructor minimises distractions and moderates cognitive load but results in only moderate learning gains, highlighting the importance of instructor presence in video-based learning, particularly for complex materials requiring contextual support and guided instruction. This research underscores the potential of avatars as a scalable and efficient instructional tool, especially in remote and asynchronous learning contexts. By simplifying visual cues and employing purposeful gestures, avatars mitigate extraneous distractions while maintaining instructional presence. These findings suggest that avatars can bridge the gap between the absence of an instructor and the potential overload associated with physical instructors. The study also demonstrates the value of integrating physiological measures like eye tracking into educational research to refine instructional designs further. This approach offers real-time insights into cognitive processing and learner responses, reducing biases inherent in self-reported measures. This work contributes actionable insights into designing scalable, effective educational technologies that optimise cognitive load and improve learning outcomes, paving the way for innovative approaches in modern e-learning.

Keywords: Cognitive load, Video-Based learning, Eye-Tracking, Avatar, Educational technology

1. Introduction

Effective learning materials, delivery methods, and environments are crucial in helping students meet their educational goals. Learning materials can be presented in various formats, with video emerging as a particularly impactful medium. Video-Based Learning (VBL) allows learners to control their pace by pausing, rewinding, or replaying content. By integrating audiovisual content, videos have proven to be an excellent tool for improving understanding and retention of information, surpassing traditional methods like reading or listening to lectures. (Sablić et al., 2021) (Gómez-Ortega et al., 2023). Examples include lecture videos in online courses and tutorial videos on platforms like YouTube or Coursera.

Massive Open Online Courses (MOOCs) have accelerated VBL adoption by providing scalable, interactive, and globally accessible education (Bettiol, Psereckis & MacIntyre 2022). These platforms make abstract concepts more tangible through animations, demonstrations, and real-world case studies. VBL has recently seen an increase in adoption, with many students participating in online courses.

Several studies have shown that videos, when designed according to multimedia learning principles, enhance retention and understanding more effectively than reading alone (Tarchi, Zaccoletti & Mason 2021; Alhazmi 2024). Compared to text or audio-only lectures, video-based learning is more engaging and compelling, promoting deeper learning by leveraging multisensory inputs to enhance cognitive processes (Lackmann et al. 2021). This aligns with Mayer's Cognitive Theory of Multimedia Learning, highlighting how well-designed videos reduce cognitive load and improve comprehension (Mayer 2009).

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Cognitive load refers to the demand for working memory resources, which decreases as processing capacity increases (Lang 2006; Chen & Epps 2014). Cognitive Load Theory (CLT) guides effective teaching methods by addressing learning challenges through instructional design (Sweller & Chandler 1994). Cognitive Load (CL) consists of three domains: intrinsic CL, extraneous CL, and germane CL (Brünken, Seufert & Paas 2010). Intrinsic CL (Sweller & Chandler 1994) refers to the innate complexity of information and content that must be comprehended and learned. Extraneous CL is created by additional requirements that result from poor instructional design and are not directly related to the task (Sweller, Van Merrienboer & Paas 1998). Germane CL entails storing new information in long-term memory, allowing individuals to focus more on activity execution (Zhang et al. 2020). CLT highlights the need for instructional strategies that minimise extraneous load, optimise intrinsic load, and foster germane load to enhance learning, particularly in technology-driven education (Leppink et al. 2014). By aligning instructional design with cognitive capacity, CLT helps create more effective learning environments.

Some researchers use questionnaires to assess cognitive load, which can be subjective. More objective methods should be employed to evaluate the effects of various instructional designs on cognitive load. According to (Souchet et al. 2021), eye tracking is an effective method for measuring cognitive load, offering real-time, high-validity assessments. However, despite the growth in physiological signals measurement tools such as electroencephalography, eye tracking, and heart rate variability, research on their application in education is still sparse, with few studies exploring eye-tracking in learning contexts (Lim, Mountstephens & Teo 2020). This technology records eye positions, gaze patterns, fixations (where the eyes stop to focus), saccades (quick eye movement between points), and pupil dilation (how wide the pupil opens), which is particularly useful for evaluating cognitive load (Zagermann, Pfeil & Reiterer 2016; Bourguet et al. 2020).

(Negi & Mitra 2020) found that fixation duration can be an indicator for measuring cognition and attention. Nevertheless, fixation duration does not always indicate cognitive load, as other factors, such as visual salience, can also cause participants to fixate on a particular area. In this study, we focus on using pupil dilation as the indicator of cognitive load. Pupil dilation correlates with cognitive effort: a larger dilation indicates a higher cognitive load, while a smaller dilation suggests a lower strain (Peysakhovich, Dehais & Causse 2015; Zheng et al. 2022). The sympathetic nervous system controls pupil dilation, typically during mentally demanding or emotional activities. Baseline pupil size can also influence cognitive performance, as larger baselines are linked to reduced task-related dilation (Gilzenrat et al. 2010). Fixation duration, measured in milliseconds, indicates time spent viewing an “Area of Interest”, helping researchers understand cognitive load distribution (Zagermann et al. 2016). Areas of Interest (AOIs) help analyse visual attention by mapping eye movements to specific stimuli (Hessels et al. 2018). The accuracy of AOI definitions depends on eye-tracking precision. In this study, AOIs are used to examine how participants allocate attention in instructional videos, assessing the correlation between fixation transitions and pupil size increases. Incorporating such tools can provide insights into learner responses and inform the use of different learning delivery methods in distance education, especially VBL.

Instructional design plays a crucial role in VBL effectiveness. Optimising VBL implementation is essential to maximise learning outcomes. For example, the effects of different video lecture presentation formats on learning outcomes have not been thoroughly examined. Research on how "presence" in video content affects cognitive load remains limited. While prior studies have explored the role of physical instructors in increasing cognitive load (Polat 2023), few have systematically compared this with avatar-based representations and their potential to balance intrinsic and extraneous cognitive loads in digital environments (Pignatiello et al. 2019).

"Presence" in educational videos refers to an instructor’s perceived involvement in the learning material(Beege et al. 2023). The different types of presence in VBL are: physical instructor presence, where the real lecturer appears in the video with natural gestures and expressions; avatar presence, a simplified computer-generated representation of the lecturer using minimal, purposeful gestures; and no lecturer presence, which features only slides and voice-over without any visual representation of the instructor. Each mode influences cognitive load and learning effectiveness differently. A physical instructor can enhance motivation, but may increase cognitive load due to additional stimuli such as spontaneous gestures (Heidig et al. 2024). In contrast, avatars offer simplified, controlled visuals and balance cognitive demands more effectively (Ayres & Paas 2007). The absence of a lecturer removes social cues, allowing full attention to content, but might hinder learning motivation (Chi 2023). Gestures serve as non-verbal cues that clarify concepts, direct attention, and reinforce learning (Wakefield et al. 2018). Effective gestures reduce cognitive load by aiding comprehension, while excessive or irrelevant gestures can distract learners (Rohrer, Delais-Roussarie & Prieto 2020). In VBL, simplified, purposeful gestures (whether from an instructor or an avatar) enhance comprehension without overwhelming learners (Dargue, Sweller & Jones 2019).

Our research investigates how different types of instructor presence in videos, such as non-lecturer presence, physical presence, or presence as an avatar, affect learners' cognitive load and learning gain. Understanding these differences is key to designing effective VBL environments. Despite the increasing use of VBL, it remains unclear how different types of instructor presence affect learners' cognitive processing and learning outcomes. Previous studies have concentrated on a single form of instructor presence, highlighting a significant design gap, specifically, the limit of lecturer presence variation. Moreover, cultural differences in communication preferences may modulate how learners perceive and process instructional presence, potentially influencing cognitive load and learning outcomes. Addressing these gaps, the current study seeks to broaden the scope of previous research by empirically examining multiple types of instructor presence. To achieve this, it employs physiological measures to assess cognitive and learning effects, providing actionable insights for improving VBL instructional design. Accordingly, this study investigates the interplay between instructor presence, cognitive load, and learning gain, where learning gain refers to improved learners' knowledge or understanding after studying activities, measured by comparing pre- and post-test scores. The learning gain reflects how much the learner has learned due to educational intervention.

Our study is guided by the following research questions: How does the instructor's presence influence the learner's cognitive load? (RQ1); and What is the relationship between cognitive load and learning gain in VBL? (RQ2). By advancing our understanding of how lecturer presence influences cognitive processing and learning outcomes, this research contributes to developing scalable and effective digital education solutions across diverse learning environments in higher education and professional training. The findings of this study are expected to offer practical insights, such as guiding instructional designers to adopt avatar-based instructors in video learning environments, which may help reduce extraneous cognitive load while maintaining instructional presence.

2. Methodology

2.1 Experimental Design

This study employed a 3×1 within-subject design, where all 33 participants experienced three conditions of instructor presence (physical instructor, avatar, and no lecturer), serving as their own control group. This design minimises individual differences by comparing each participant's performance across all conditions. The experiment design had the following conditions regarding lecturer presence as the independent variable.

- Non-lecturer presence in the video: The learning material is presented asynchronously (accompanied by the researcher) with voice-over slides, but the lecturer is not visible.
- Lecturer's physical presence in the video: The learning material is presented asynchronously, including the lecturer's physical presence, capturing their face and upper body.
- Lecturer's presence as an avatar in the video: This format is similar to the lecturer's physical presence, but the avatar represents the lecturer. The avatar appears simple and realistic with a static facial expression (no movement of eyes or mouth) and is dressed in formal clothing. The avatar performs basic gestures, such as raising a hand, pointing a finger, and looking downward, which are inspired by the physical presence of the lecturer. The avatar's appearance in the learning video is shown in Figure 1.

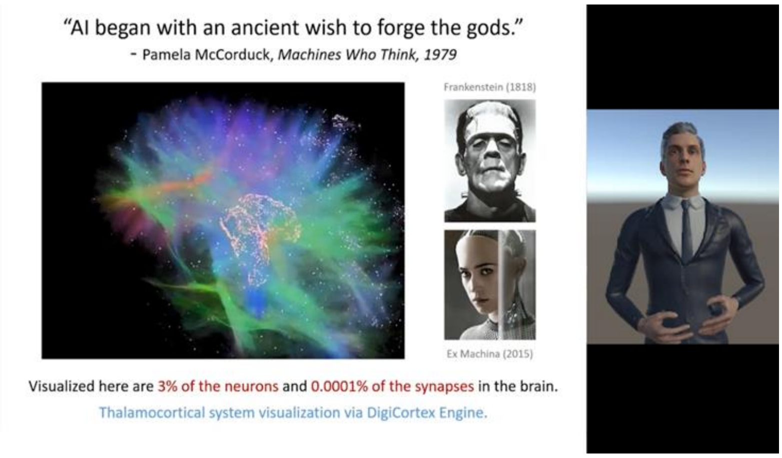

Figure 1: The appearance of the Avatar in the Video

The dependent variables were cognitive load, measured by the pupil diameter size increase or pupil dilation events and learning gain from pre- and post-test results. The total number of trials was 99 (=33 participants x 3 conditions).

The videos in this study were delivered asynchronously to avoid direct live interaction between participants and the instructor. This approach ensured that each participant received a consistent and controlled classroom experience. While synchronous settings might introduce richer social dynamics, they could also lead to inconsistencies in delivery, making it harder to isolate the effects of instructor presence on cognitive load.

2.2 Procedure and Video Stimuli

In this study, eye movements and pupil size were recorded from participants using eye-tracking technology under controlled conditions, including consistent lighting, environment, and timing. This experimental design ensured that pupil diameter measurements could be compared reliably across the different experimental conditions. The experiment took place in a university laboratory.

Three learning video stimuli were used, each lasting approximately 5 minutes. The videos were adapted from Lex Fridman's YouTube video on "Deep Learning" (www.youtube.com/watch?v=O5xeyoRL95U), chosen for its relevance to the participant's field of study. Additionally, the video layout, with the lecturer separate from the slides, allowed for seamless modification, enabling the controlled replacement of the instructor with an avatar and the deletion of the real lecturer. Overall, each participant spent about 60-75 minutes on the experiment. The visual timeline of the process is illustrated in Figure 2.

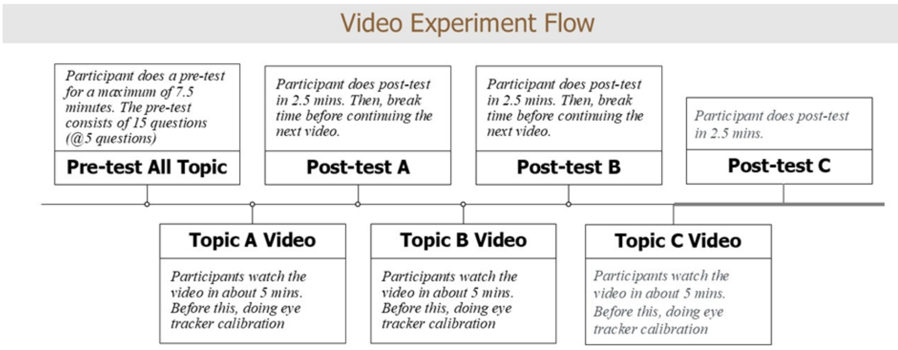

Figure 2: The Flow of Video Experiment

Before viewing the videos, participants completed a knowledge test of multiple-choice questions related to the content (pre-test). After watching the videos, they took a second knowledge test (post-test) to assess their learning gain.

The experiment began with 10 minutes of preparation and instruction, followed by a 7.5-minute pre-test (15 questions). Participants then underwent 5 minutes of eye-tracking calibration before watching a 5-minute video on Topic A ("Deep Learning Basics"), followed by a 2.5-minute post-test (same five questions from the pre-test).

After a 5-minute break, participants completed another 4-minute calibration and watched a 5-minute video on Topic B ("Representation Learning"), followed by another 2.5-minute post-test. A second 5-minute break preceded a final 4-minute calibration before watching a 5-minute video on Topic C ("The Challenge of Deep Learning"), concluding with a 2.5-minute post-test (same last five questions from the pre-test).

2.3 Participants

This study involved 33 participants. The sample size was determined based on a priori power analysis to ensure sufficient statistical power (80%) to detect medium effect sizes (Cohen's d = 0.5) with a significance level of 0.05 (Serdar et al. 2021). This is consistent with prior studies on cognitive load using eye-tracking technology in educational settings (Sáiz-Manzanares et al. 2024).

Participants were third-year undergraduate students majoring in Electronic Engineering and Computer Science, aged 20–23 years (M = 21.5, SD = 0.8). The same educational background guarantees that all participants have similar prior knowledge of the videos' topics. All individuals had either normal vision or vision corrected to normal, and no prior history of neurological disorders. Those specific criteria limited the number of participants. Nevertheless, the sample size was sufficient for the intended statistical analyses.

This experiment was conducted by the ethical guidelines. Detailed information for participants was provided in the advertisement email before they came to the study site. They had the right to withdraw at any time without explanation. Participants were asked to read and fill out the consent form at the beginning of the study.

Before the experiment, participants were briefed on the study's objectives and design in the laboratory. Study details were emailed beforehand, and participation was voluntary, allowing withdrawal at any time. No expenses were incurred by the participants in this research. Participants received £20-25, depending on their test scores, as compensation. This token of appreciation was given after the completion of the experiment.

2.4 Apparatus

Participants' eye movements and visual attention during video-based learning were recorded using eye-tracking technology. The collected data were analysed statistically to examine how different experimental conditions affect fixations and pupil dilation, which reflect visual attention and cognitive load. The eye-tracking device used was a 120 Hz core eyeglasses model from Pupil Labs (see Figure 3). Calibration was conducted before each session using a standard five-point calibration method to ensure accuracy. Data with a confidence level below 0.6 were excluded from the analysis.

Two laptops and an external monitor were used for the experiment. The primary laptop managed the setup, calibrated the eye-tracking system, and played video stimuli. A second laptop was assigned for participants to complete pre- and post-tests, ensuring independence from the investigator's control. The external monitor provided real-time eye-tracking data, allowing immediate accuracy verification and troubleshooting.

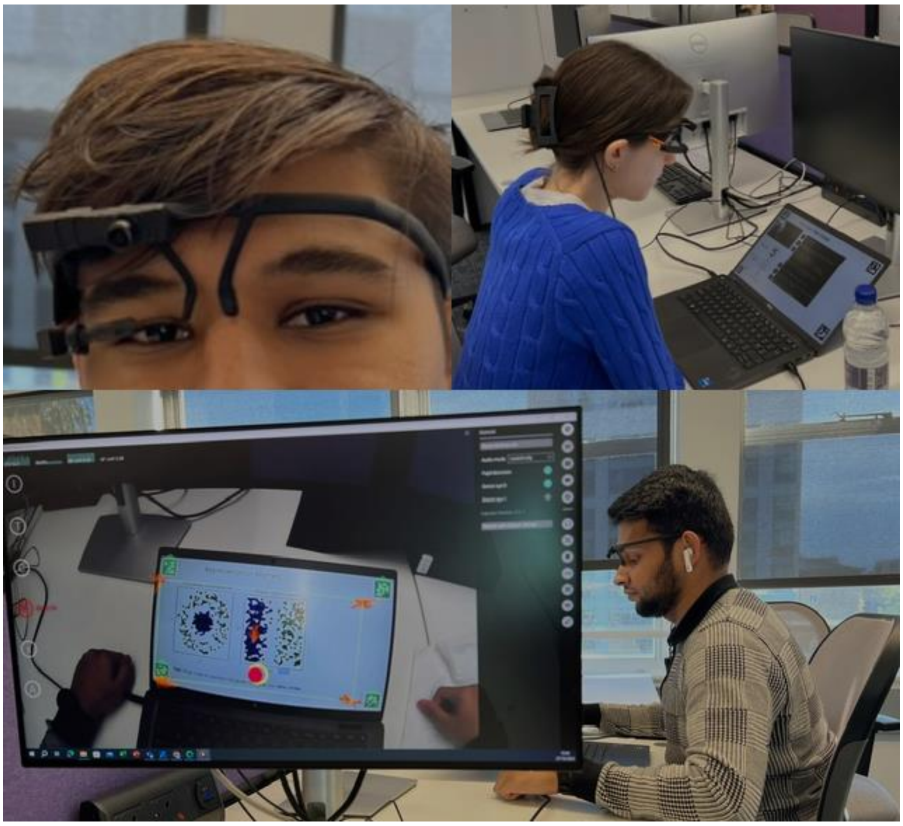

Figure 3: Experimental Tools (images used with authorisation from the study participants)

3. Results

3.1 Pupil Dilation Across Conditions

Pupil diameter was measured for each participant across the three experimental conditions. We assumed that an increase in pupil diameter, i.e., pupil dilation, corresponds to an increase in cognitive load. Subsequently, statistical analyses were performed to determine whether there were significant differences in pupil diameter changes across the three video stimuli.

Before processing the pupil diameter data, we first cleaned the raw data through several steps: (1) replacing blank diameter_3d values with the nearest non-blank value; (2) substituting data with low confidence (< 0.6) with the nearest high-confidence value; and (3) detecting outlier data using the z-score method and replacing them with the nearest non-outlier value.

Figure 4 illustrates the actual pupil diameter size. It plots the distribution of pupil diameter sizes for the 33 participants under the three experimental conditions: no lecturer presence, lecturer's physical presence, and lecturer present as an avatar. 14 people had a bigger pupil diameter with no lecturer presence, 14 people with a lecturer's physical presence, and 5 people with an avatar presence.

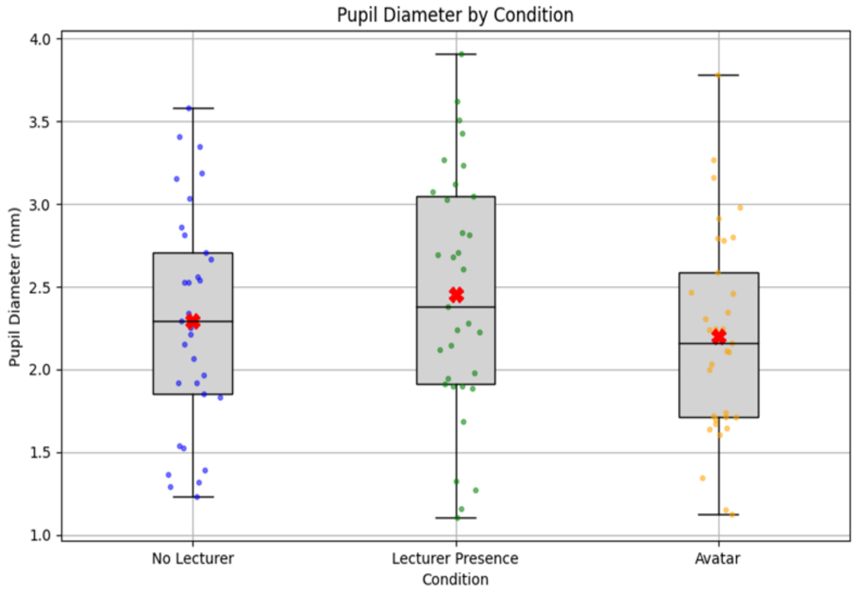

Figure 4: Pupil Diameter from all Participants across Conditions

Furthermore, to investigate the cognitive load experienced by participants across different experimental conditions, pupil dilation was measured, which was associated with the highest levels of cognitive load. To quantify pupil dilation, we first established a baseline by calculating the mean pupil diameter [1] and its variability through the standard deviation [2]. Significant pupil dilation was identified as any instance where the pupil diameter exceeded the baseline by more than one standard deviation [3], and the mean of significant dilation was computed [4]. A sample visualisation illustrating changes in pupil dilation over time for a single participant is presented in Figure 5.

$$\text{Baseline/Mean } (\bar{d}) = \frac{1}{N}\sum_{i=1}^{N} d_i \tag{1}$$

$$\text{Standard Deviation } (\sigma) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_i - \bar{d})^2} \tag{2}$$

$$\text{Dilation Threshold } = \bar{d} + \sigma \tag{3}$$

$$\text{Significant Dilation (Mean)} = \frac{\sum_{i=1}^{N}[d_i > (\bar{d}+\sigma)]}{N_{\text{significant}}} \tag{4}$$

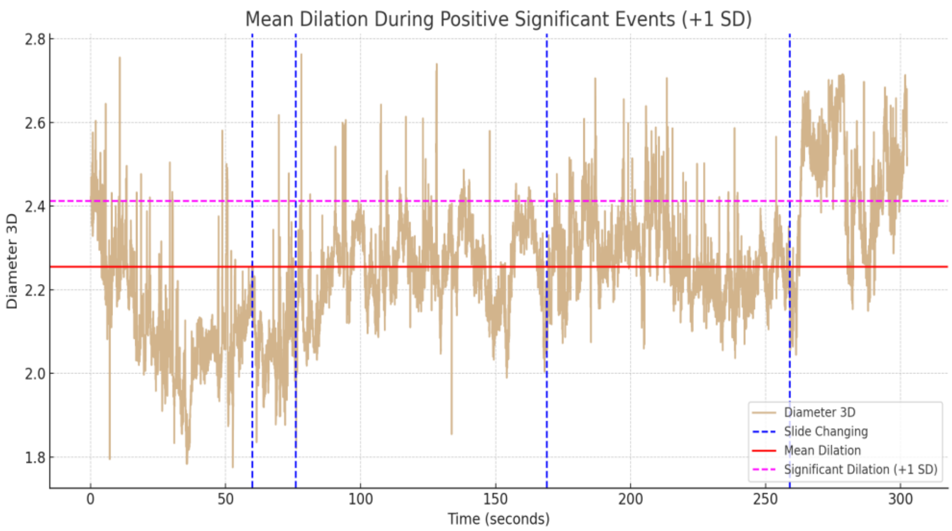

Figure 5: Example of Significant Pupil Dilation from One Participant

To see the statistical difference between lecturer conditions, we enriched the dataset by slicing it into slides on the videos. Using the within-subject design from 33 participants, topic A video had 4 slides, topic B had 6, and topic C had 5. Table 1 provides the slide design summary of each topic.

The mean significant dilation per slide for the non-lecturer presence is 2.31 mm; for the physical presence of the lecturer, it is 2.40 mm; and for the avatar lecturer, it is 2.01 mm. Initially, the Shapiro-Wilk test was performed to determine the normality of the data for each condition. The results indicated significant deviations from normality for all three conditions: no lecturer ($W = 0.893$, $p < 0.001$, $N = 165$), lecturer presence ($W = 0.895$, $p < 0.001$, $N = 165$), and an avatar lecturer ($W = 0.885$, $p < 0.001$, $N = 165$). These findings suggest that the data in all conditions are not normally distributed, justifying the use of non-parametric statistical methods for subsequent analyses.

Table 1: Topic Slide Design

Topic Video	Duration (min)	Number of Slides	
A	5	4	
B	5	6	
C	5	5	

Furthermore, we conducted the test comparing the significant pupil dilation between no lecturer and lecturer physical presence. We found that the p-value for a paired t-test indicates no significant difference between those conditions ($W = 5895.0$, $p = 0.687$, $N = 165$), with a small effect size ($r = -0.12$). Subsequently, we compared the conditions for no lecturer and the avatar. The test indicated a significant difference between those conditions ($W = 4983.0$, $p = 0.018$, $N = 165$), with a small to medium effect size ($r = -0.24$).

Finally, we examined the difference in significant pupil dilation between the physical presence of the lecturer and the avatar condition, which resulted ($W = 4756.0$, $p = 0.008$, $N = 165$), with a medium effect size ($r = -0.26$). To examine the effect of cognitive load in various forms of lecturer presence more closely, it is interesting to explore the correlation between pupil dilation and learning gain.

3.2 Correlation between Pupil Dilation and Learning Gain

Knowledge assessments were conducted before and after exposure to the instructional video stimuli to evaluate learning gains. These assessments included 15 multiple-choice questions to measure participants' understanding at each stage. Learning gains were calculated following the method described in (Marx & Cummings 2007). Specifically, when the post-test score was higher than the pre-test score, the difference was divided by the maximum possible score minus the pre-test score, as shown in (5). Conversely, if the post-test score was lower, the difference was divided by the pre-test score (6). Cases where the pre-test and post-test scores were identical and represented either the maximum or minimum score were excluded from the analysis(7). For instances where the pre-test and post-test scores matched but were not at extremes, the learning gain was set to 0 (8).

$\frac{post-pre}{Max.-pre}$, if $post > pre$ (5)

$\frac{post-pre}{pre}$, if $post < pre$ (6)

exclude, if $post = pre =$ maximum or minimum (7)

0, if $post = pre$ (8)

Table 2 presents the mean pupil dilation (in mm) and mean learning gain (in percentage) along with their respective standard deviations (SD) for each experimental condition. We first assessed the normality of significant pupil dilation data per condition and learning gain using the Shapiro-Wilk test to determine the appropriate correlation test.

Table 2: Mean Pupil Dilation and Learning Gains Across Conditions

Condition	Mean Pupil Dilation (mm)	SD	Mean Learning Gain (%)	SD
No Lecturer	2.3090	1.2142	45.6061	43.9080
Physical Lecturer	2.3986	1.4259	36.1616	44.7449
Avatar Lecturer	2.0073	1.3508	47.9293	39.2051

The assumption of normality for all variables was tested using the Shapiro-Wilk test. The results indicated that some variables deviated significantly from normality: learning gain of no lecturer presence ($W = 0.884, p = 0.002$), learning gain from the lecturer's physical presence ($W = 0.909, p = 0.009$), and learning gains from the avatar lecturer ($W = 0.921, p = 0.020$). Conversely, all pupil dilation variables were found to be normally distributed: pupil dilation of no lecturer ($W = 0.970, p = 0.488$), pupil dilation of the lecturer's physical presence ($W = 0.985, p = 0.921$), and pupil dilation of the avatar lecturer ($W = 0.966, p = 0.375$).

Given the significant deviations from normality in the learning gain variables, Spearman's rank-order correlation was employed to examine the relationship between learning gain and pupil dilation across conditions. The analysis yielded the following results:

- Learning Gain and Pupil Dilation in no lecturer presence: A small positive correlation was observed ($r_s = 0.132, p = 0.463$). This suggests that minimal instructional presence may require learners to engage their cognitive resources independently, though the weak correlation indicates a limited impact on learning outcomes.
- Learning Gain and Pupil Dilation in lecturer's physical presence: A moderate negative correlation was observed ($r_s = -0.335, p = 0.057$), which approached statistical significance. This finding suggests that the physical presence of a lecturer may introduce extraneous cognitive load through non-verbal cues and visual complexity.
- Learning Gain and Pupil Dilation in avatar lecturer: A small-to-moderate positive correlation was observed ($r_s = 0.224, p = 0.211$). This suggests that avatars help optimise germane cognitive load by providing sufficient instructional presence while minimising extraneous distractions, thus enhancing learning outcomes.

The findings suggest potential trends in the relationships between pupil dilation and learning gain. These results align with the study's hypotheses that different forms of instructor presence impact pupil dilation and learning gain differently. The correlations between learning gain and pupil dilation across the different conditions can be seen in Figure 6.

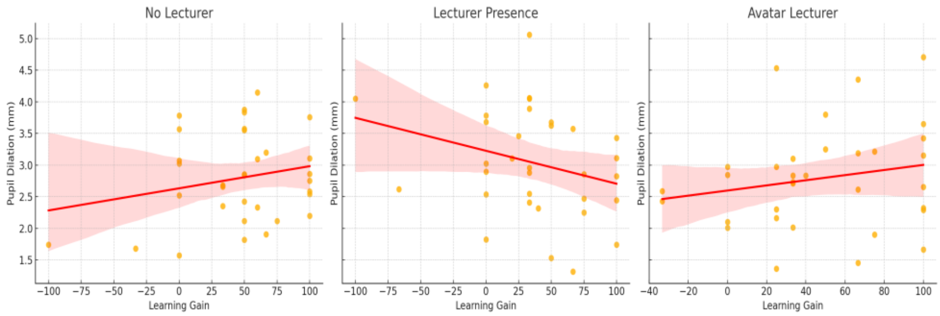

Figure 6: Correlation Between Pupil Dilation and Learning Gain from All Participants

3.3 Pupil Dilation Comparison Between High and Low Learning Gain Participant Groups

We categorised participants in each experimental condition into two groups based on their learning outcomes: high versus low learning gain. We compare the pupil dilation between high- and low-level learning gain in each condition to see if there is a relationship between high and low learning gain on pupil dilation in different presence conditions.

With 33 participants per condition, we ranked the participants based on the test's learning gain and time duration. We assigned the top 16 performers to the "high learning gain" group, eliminating 1 median participant, and the remaining 16 belonged to the "low learning gain" group. We enriched the data by measuring pupil dilation at intervals of 1 minute to strengthen the statistical calculation. Thus, each group has 80 data points (16 x 5).

None of the data points were normally distributed after performing a normality test on all the data points. Hence, the Wilcoxon signed-rank test was used to see the difference in pupil dilation size between high and low performers across three different presence conditions.

Firstly, we compared the pupil dilation between high and low learning gain groups in the no lecturer condition. The results indicated no significant difference in pupil dilation between those learning levels $W = 1527.0$, $p = 0.796$ ($N = 80$). This indicates that the absence of a lecturer results in a similar cognitive load across both high and low-learning gain groups, suggesting that learners rely on their intrinsic cognitive effort equally. Next, we analysed the lecturer's physical presence condition. We found a significant difference in pupil dilation between the high and low-learning gain groups $W = 947.0$, $p = 0.012$ ($N = 80$), indicating that excessive cognitive load may disproportionately hinder learners with lower initial performance levels. Interestingly, the low learning gain group exhibited a higher pupil dilation. Lastly, we examined pupil dilation when the lecturer was present as an avatar. The results revealed no significant difference $W = 1389.0$, $p = 0.702$ ($N = 80$). This suggests that the simplified and controlled representation of the avatar maintains a balanced cognitive load, benefiting both high and low-learning gain groups similarly.

3.4 Correlation Between Number of Transitions Between AOIs and Pupil Dilation

We explored the correlation between the number of fixation transitions and pupil diameter increase in the lecturer presence and avatar experimental conditions for all the participants (n = 33). Transition refers to switching visual attention from AOI 1 (slide) to AOI 2 (lecturer area); see Figure 1. This analysis aimed to determine whether frequent shifts in attention across different areas of stimuli contributed to pupil dilation. The scanpath shows an example of the transition from one participant, as seen in Figure 7.

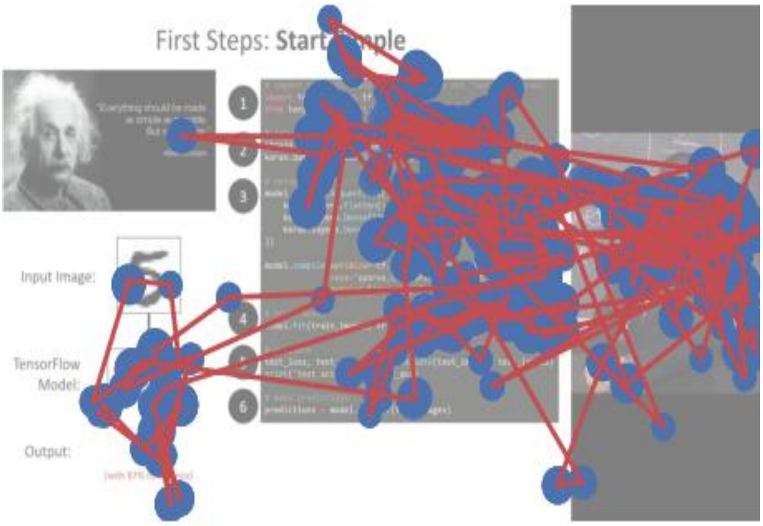

Figure 7: Example of Scanpath from One Participant

A Shapiro-Wilk test was conducted to evaluate normality. The results showed that the Transition in the lecturer's physical presence significantly deviates from normality ($W = 0.915, p = 0.014$), while Pupil Dilation of the lecturer's physical presence ($W = 0.985, p = 0.921$), Transition in the avatar lecturer ($W = 0.967, p = 0.401$), and Pupil Dilation of the avatar lecturer ($W = 0.966, p = 0.375$) followed normal distributions ($N = 33$ For all columns).

Based on these results, a Spearman correlation was used for Pupil Dilation and Transition in lecturer presence, yielding a small negative monotonic relationship ($r_s = -0.168, p = 0.351$). A Pearson correlation was used for Pupil Dilation and Transition in the avatar lecturer, indicating a small positive linear relationship ($r = 0.156, p = 0.385$).

4. Discussion

4.1 Effect of Instructor's Presence on Cognitive Load

The comparative analysis of pupil dilation distributions across the three conditions (no lecturer, lecturer presence, and avatar) suggests different levels of cognitive burden. The findings indicate that the physical presence of a lecturer is associated with the highest levels of cognitive load, as evidenced by the largest mean pupil dilation.

- Lecturer Physical Presence vs. No Lecturer: The comparison between a lecturer's physical presence and a no lecturer's presence highlights the cognitive challenges posed by having a visible instructor. The results showed no significant difference in pupil dilation, suggesting that added visual stimuli do not universally increase cognitive load. However, the physical lecturer condition had a slightly higher mean pupil dilation, implying that processing non-verbal cues and instructional content may be more mentally demanding. This aligns with cognitive load theory, which states that extraneous cognitive load, such as processing non-essential visual elements, can interfere with learning (Sweller 2010).
- Lecturer Physical Presence vs. Avatar: The physical lecturer condition resulted in a significantly higher cognitive load than the avatar condition, underscoring the benefits of using avatars in video-based learning. Avatars do not increase cognitive load like physical instructors because they use simplified, purposeful gestures and lack dynamic facial expressions, reducing visual distractions. A physical lecturer's dynamic and complex visual cues increase cognitive effort, potentially distracting from the content. Conversely, avatars provide a simplified, controlled representation, reducing extraneous cognitive load and allowing more focus on learning (Alemdag 2022).
- No Lecturer vs. Avatar: A significant difference was found, with no lecturer presence leading to higher pupil dilation. The lack of instructional presence may impose extra cognitive demands due to missing guidance. In contrast, avatars provide a structured instructional presence while maintaining low visual complexity, helping mitigate cognitive load. Their simplified representation shifts cognitive load towards germane processing, enhancing learning outcomes (Sweller 2020). This supports findings that avatars lower unnecessary cognitive strain, which is vital in online education (Schöbel, Janson & Mishra 2019).
- Fixation Transition: The analysis of pupil dilation and attention shifts between instructional content (slides) and instructor presence suggests a nuanced effect on cognitive load (Kolnes, Uusberg & Nieuwenhuis 2024). With a physical lecturer, a small negative correlation suggests frequent attention shifts may help distribute cognitive effort, reducing strain. However, this pattern was absent in the avatar condition, where a small positive correlation suggests that transitions slightly increased cognitive load.

The findings highlight distinct effects of instructor presence on cognitive load. A physical lecturer induces the highest extraneous cognitive load, likely due to complex visual and non-verbal cues. In contrast, avatars reduce distractions, maintaining instructional presence while promoting germane cognitive load, which enhances learning. The absence of an instructor lowers cognitive load but limits learning gains, emphasising the need for an instructional presence in video-based learning, especially for complex materials.

Fixation transitions between slides and instructor presence varied by condition. With a physical lecturer, frequent transitions helped distribute cognitive effort, reducing cognitive strain. In contrast, in the avatar condition, transitions slightly increased cognitive load but also contributed to germane processing by aiding content assimilation. The findings confirm that instructor presence significantly influences cognitive load, with physical lecturers inducing the highest extraneous load, while avatars provide a more balanced learning experience (RQ1).

4.2 Relationship Between Cognitive Load and Learning Gain

The relationship between cognitive load and learning gain in video-based learning (VBL) is complex and context-dependent, as shown by pupil dilation analyses. The correlation between pupil dilation (a proxy for cognitive load) and learning gain varied across experimental conditions, suggesting that the instructor's presence influences how cognitive load affects learning outcomes.

In the no lecturer condition, a small positive correlation suggests that the absence of a presenter allows learners to allocate more resources to processing, enabling focused interaction with content and better learning outcomes. However, (Rodemer, Karch & Bernholt 2023) noted that the lack of instructional guidance might hinder comprehension of complex material due to missing social and contextual cues.

The physical presence of a lecturer showed a moderate negative correlation between pupil dilation and learning gain, indicating that a higher cognitive load may detract from learning. Processing visual and non-verbal cues can overwhelm learners, creating extraneous cognitive load, especially with challenging topics. This highlights the drawbacks of excessive cognitive load, as noted by (van der Wel & van Steenbergen 2018).

In the avatar condition, a small to moderate positive correlation suggests that avatars provide instructional presence while minimising extraneous demands. Simplified visual stimuli encourage optimal germane cognitive effort, positively influencing learning outcomes. Avatars can also capture attention and support learning by eliciting physiological responses (Ricou et al. 2024).

Comparing high and low-learning gain groups supports these findings. Low-performing learners in the physical lecturer condition exhibited higher pupil dilation, indicating that excessive cognitive load hindered information retention. No significant differences were found between high and low performers in the no-lecturer or avatar conditions, suggesting that both maintain cognitive load at manageable levels.

The findings show that cognitive load and learning gain are closely tied to instructor presence, with avatars striking a balance by reducing unnecessary strain while maintaining instructional cues. These results highlight the importance of instructional design in moderating cognitive load for effective digital education. Excessive cognitive load (e.g., physical lecturer presence) hinders learning, while balanced cognitive load (e.g., avatar presence) enhances outcomes (RQ2).

Avatars likely shift cognitive processing towards germane load, helping learners focus on content over distractions. This aligns with cognitive load theory, which emphasises optimising instructional design. Avatars should feature simple, non-distracting designs, avoiding dynamic elements that increase cognitive demands. Purposeful gestures, such as pointing, can direct attention to critical information and complement verbal content. Synchronising avatar behaviours with instructional material ensures coherence and reduces cognitive effort. Slower gestures and speech patterns can improve comprehension of complex topics. Subtle social presence, like consistent eye contact, fosters connection without overwhelming learners. These design considerations align with the study's findings, emphasising avatars' potential to balance cognitive load and instructional presence, providing an effective alternative to physical lecturers in VBL environments. In light of these findings, the study carries important implications for designing digital instructional environments, particularly as video-based learning becomes a standard in higher education and professional training. The evidence that avatar-based instructors can reduce extraneous cognitive load while maintaining learning effectiveness suggests a promising direction for scalable and cost-effective online education.

4.3 Limitations

While this study provides valuable insights into the relationship between instructor presence and cognitive load in video-based learning, several limitations should be acknowledged. While this study used pupil dilation as a proxy for cognitive load, it is important to acknowledge that other factors beyond cognitive effort can influence this measure. Emotional states, such as stress, can also cause pupil dilation (Heimerl et al. 2022), potentially confounding interpretations related solely to cognitive processing. Additionally, individual biological differences, including baseline pupil size or sensitivity to light, may affect how pupil responses manifest across participants. However, a within-subjects design helps control some of these variations.

Furthermore, using a single eye-tracking measure without triangulation from other physiological data may limit the comprehensiveness of cognitive load assessment. Future studies could integrate additional indicators such as heart rate variability or EEG to strengthen validity.

5. Conclusion

This study provided insights into the impact of instructor presence, including no lecturer, physical lecturer, and avatar, on cognitive load and learning outcomes in video-based learning. Eye-tracking in this study provided objective and real-time insights into the cognitive load, reducing the biases often inherent in self-reported measures. Eye-tracking data revealed that a physical lecturer increased extraneous cognitive load, negatively affecting lower-performing learners. In contrast, avatars balanced cognitive load by reducing distractions and enhancing germane cognitive processing. The absence of an instructor moderated cognitive load but limited learning gains, highlighting the importance of instructional presence for complex materials. These findings support avatars as an effective alternative, particularly in remote and asynchronous education.

Avatars offer a scalable and cost-effective solution for video-based learning, especially in MOOCs and remote settings. Their controlled gestures and visual design enhance germane processing and improve learning outcomes. To implement avatars effectively in diverse educational contexts, designers should prioritise simplicity, clarity, and alignment with instructional goals. Avatars should use minimal yet purposeful gestures and maintain a consistent visual presence without overwhelming motion.

By integrating the principles of Cognitive Load Theory, this research contributes to developing scalable, inclusive, and impactful e-learning technologies. Continued efforts to explore innovative design strategies and broaden the investigation's scope will help fully realise the potential of avatars and other digital tools in improving learning experiences across diverse educational contexts. Further research should explore dynamic avatars and integrate additional physiological measures like heart rate variability or electroencephalography to deepen the understanding of cognitive, emotional, and biological influences on learning.

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Ethics Statement: This study adhered to the ethical guidelines of Queen Mary University of London (approval number: QMERC20.565.DSEECS23.036). Participants provided informed consent, and data were pseudonymised.

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Educators' Self-Efficacy, Work Engagement, and Mental Health in the Transition to On-Line or Remote Work During the COVID-19 Pandemic

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Abstract: The COVID-19 pandemic had a significant impact on all sectors of education globally, but the full extent of that impact is yet to be understood. To build our understanding of the effects of the pandemic and its associated lockdowns on educators, this study set out to examine educators perceived self-efficacy, work engagement and mental health during the period when classes were transitioned to an online, away-from-school or off-campus mode of delivery. Data were collected through an online survey, distributed via social media and a snowball approach. The study found that the levels of self-efficacy, work engagement and mental health during on-line and remote work differed between educational sectors and between genders. The paper concludes by considering implications for educational institutions in times of crisis.

Keywords: Self-Efficacy, Work engagement, Mental health, COVID-19, Education workforce

1. Introduction

Globally, COVID-19 and the associated stay-at-home measures meant that workers had to adopt and adapt to new ways of conducting their everyday work activities (Jetten et al., 2020). Educators were no exception to this. With education facilities closed, they had to deal with the rapid transition of their teaching to home environments, as a way of providing opportunities for student learning, while ensuring that staff and students were safe "from a public health emergency that [was] moving fast and not well understood" (Hodges et al., 2020, para. 2). Ziebell et al. (2020) found that teachers worked more hours during the pandemic restrictions, while MacIntyre et al. (2020) indicated that teachers experienced more stress than during their usual teaching activities. Increased workloads came from expectations that educators would seamlessly move to online and blended learning, even though this was a relatively new field of practice in many teaching contexts (Hu et al., 2019).

Given educators were faced with the swift transformation of their teaching and learning environments, this study set out to investigate the mental state and self-efficacy of educators from a broad range of contexts, including early childhood, primary and secondary schools, technical colleges, and higher education. During this time, social distancing measures were in place and educators were having to manage complex educational environments. The authors hypothesized that teachers would show indicators of emotional disturbance and distress and that this would impact on their teaching self-efficacy.

The "emergency remote teaching" (Hodges, 2020, para. 1) that occurred as a result of the COVID-19 lockdowns meant that emerging technologies were thrust into educators' working lives. Without warning, they were required to engage with what Popchev and Orozova (2020) called the Fourth Industrial Revolution: "the integration of the physical and virtual world, as well as of social communities" (p. 116). Hodges et al. (2020) highlighted that it is important to distinguish between situations of forced online teaching—in this case, "a temporary shift of instructional delivery to an alternate delivery mode due to crisis circumstances" (para. 14)—and prepared and planned integration. Forced online teaching put educators into a space of high expectations and required them to instigate such teaching, even if they were without adequate resources and the support and careful online design processes that forge success (Hodges et al., 2020).

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Work engagement is conceptualised as a fulfilling and positive state of mind, characterised by high levels of energy, resilience, and persistence, with educators seeing themselves as able to deal with the demands of the job (Schaufeli & Bakker, 2004). However, there is evidence that educator stress impacts their efficacy and long-term outcomes of the education process, such as job satisfaction (Collie, Perry & Martin, 2017). They. argue that teachers' stress is triggered by three main sources: the level of work pressure or demands, emotional or behavioural responses, and stress as a transaction between work demands and the resources to manage those demands. Indeed, teachers' intention to quit is predicted by their levels of exhaustion (Granziera, Collie, & Martin, 2022), burnout and, conversely, job satisfaction (Madigan & Kim, 2021). Furthermore, teachers' levels of self-efficacy are reflected in their levels of disengagement (Perera et al., 2021). It would appear that all of these may have been intensified by sudden transition to school closures and online learning induced by COVID-19 pandemic. What remains unclear in the literature, in terms of a transactional model (Collie, Perry & Martin, 2017), are the relations among teachers' engagement, self-efficacy, and mental health during the lockdowns,specifically with regards to environmental demands and cognitive stressors.

Thinking along these lines, Luthar and Skyler (2020) concluded that schools need a "trauma informed approach" (p. 154) that is systemically supported by policymakers through the provision of dedicated social, emotional and behavioural resources. There is also evidence that educators require mentoring and support, and that their work environments have an impact on attrition rates within the profession (Borman & Dowling, 2008).

The current research presents a clinical approach to measuring educator psychological distress, work engagement and self-efficacy, to investigate how educators were impacted by COVID-19 and to consider whether this impact requires increased support and possibly clinical intervention. This paper describes the data that emerged from an online survey for considering ongoing policy and support of educators across educational sectors, and creates a base line for further research. The aim of the study was to examine educators' self-reports of self-efficacy for teaching, engagement in their work, and mental health, during the period in which classes were transitioned to an online, off-campus mode of delivery across educational sectors. Three specific research questions were posed:

RQ1: In what ways has COVID-19 impacted on teaching self-efficacy?

RQ2: How has COVID-19 altered educators' work engagement?

RQ3: To what extent has COVID-19 had an impact on educators' anxiety and stress?

2. Method

Ethics approval (#H20REA103) was received from the host university prior to recruitment and data collection. Participation was voluntary, and participants could exit the survey at any stage. There were no financial incentives for participation. The data were completely anonymous, with no identifiable details collected (e.g., name, IP address). The online survey included an informed consent button for participants to consent.

2.1.1 Participants

Potential participants were invited to complete a survey hosted on the Lime Survey platform. The participants comprised a convenience sample (Kelley et al., 2003) of educators who were recruited through email contacts and the researchers' personal social media accounts, including Facebook, LinkedIn, and Twitter. Additional recruitment occurred through snowballing, when social media users shared the survey details with others. Potential participants were advised that the survey was in English language. Whilst the invitation to participate extended to all education settings (e.g., sector, country), teachers employed by the Queensland Department of Education in Australia were excluded from the survey, due to their employer's embargo on research activities in response to the COVID-19 pandemic.

Recruitment resulted in 420 respondents: 342 females (81.4%) and 78 males (18.6%), with a combined average age of 43.72 years (SD = 10.42, Mdn = 45). The survey respondents worked in various education sectors: early childhood (n = 18, 4.3%), elementary/primary (n = 173, 41.4%), secondary/high school (n = 113, 27%), vocational education and training (n = 10, 2.4%), higher education (n = 103, 24.6%), and corporate training (n = 1, .20%). Two participants did not indicate a sector.

The participants were working in 30 countries: Australia (n = 300, 71.6%), Indonesia (n = 24, 5.7%), the Philippines (n = 19, 4.5%), USA (n = 14, 3.3%), Canada (n = 10, 2.4%), Papua New Guinea (n = 9, 2.1%), South Africa (n = 6, 1.4%), United Kingdom (n = 6, 1.4%), New Zealand (n = 4, 1.0%), Ireland (n = 3, 0.7%), Israel (n = 3, 0.7%), Japan (n = 3, 0.7%), Thailand (n = 2, 0.5%), and the remainder (n = 17) from multiple other countries with one respondent from each. Their qualifications included postgraduate masters and doctoral degrees (n = 223, 53.1%), undergraduate/bachelor degrees (n = 182, 43.3%), and lower certificates (n = 15, 3.6%).

2.1.2 The measures

Participants responded to an online survey comprising demographic questions and psychometric measures of self-efficacy, work engagement, and psychological distress. The survey introductory information included a statement to contextualize its aim: "This survey aims to investigate the impact of the disruptions and challenges of COVID-19 on educators." Each measure was preceded with the statement: "How I have been feeling and thinking about myself and my work as an educator?"

Teaching Self-Efficacy

The 12-item version of the Teacher Self-Efficacy Scale [TSES] (Tschannen-Moran & Woolfolk Hoy, 2001) was used to measure participants' self-efficacy on three sub-scales: Instructional Strategies, Classroom Management, and Student Engagement. The TSES has been used widely in different countries (Klassen et al., 2009). Participants responded to the items on a scale of 1 (none at all) to 5 (a great deal). Examples of items are:

> *For the Classroom Management sub-scale: "How much can you do to control disruptive behaviour in the classroom?"*
>
> *For the Student Engagement sub-scale: "How much can you do to motivate students, who show low interest in schoolwork?"*

Using Cronbach's alpha, the measures' internal consistency estimates were: Instructional Strategies α = .83, Classroom Management α = .88, and Student Engagement α = .76.

Work Engagement

The 9-item Utrecht Work Engagement Scale [UWES] (Schaufeli, Bakker, & Salanova, 2006) was used to measure participants' work engagement, including vigour, dedication, and absorption. They demonstrated that the UWES has utility in different international contexts. Participants responded to the items on a scale of 1 (never) to 6 (always). Example items are:

> *For vigour : "At my work, I feel bursting with energy."*
>
> *For dedication: "I am proud of the work that I do."*
>
> *For absorption: "I am immersed in my work."*

Using Cronbach's alpha, the measures' internal consistency estimates were: Vigour α = .84, Dedication α = .88, and Absorption α = .76.

Psychological Distress

The 10-item Kessler Psychological Distress Scale [K10] (Andrews & Slade, 2001) was used to measure participants' psychological distress, based on questions about anxiety and depressive symptoms, such as "feeling tired out for no good reason" and "sad and depressed." The K10 has been extensively tested in different counties and languages other than English (National Comorbidity Survey, 2005). Items were responded to using a 5-point scale from 1 (*none of the time*) to 5 (*all of the time*). The sum of these scores yields a minimum possible score of 10 and a maximum possible score of 50, with the higher scores indicating higher levels of psychological distress. Participants with scores under 20 are likely to be well; scores of 20 to 24 are indicative of a mild mental disorder; scores of 25 to 29 are indicative of a moderate mental disorder; and scores of 30 and above indicate a severe mental disorder. Internal consistency in this sample was Cronbach's α = .91.

Data Screening and Analysis

The raw data set was screened prior to analysis. This process deleted 221 non-responses generated by potential participants who entered the survey site's landing page but did not progress into the survey. There were no surveys with missing responses for the TSES, UWES, and K10. Because of the low numbers of participants in some sectors, the analyses focused on the primary, secondary and higher education sectors. Participants' gender was also considered.

2.2 Results

Table 1 presents the TSES, UWES, and K10 measures' mean scores, skewness, kurtosis, and their intercorrelations. The measures' distributions of skewness and kurtosis were within acceptable limits.

Table 1: Measures' Descriptive Statistics, Skewness, Kurtosis, and Scale Score Correlations (N = 420)

Measure	SE-CM	SE-IS	SE-Seng	WE-V	WE-D	WE-A	WE-tot	K10	Age
SE-CM	—								
SE-IS	.65**	—							
SE-Seng	.72**	.66**	—						
WE-V	.26**	.28**	.37**	—					
WE-D	.26**	.25**	.37**	.77**	—				
WE-A	.30**	.29**	.36**	.61**	.66**	—			
WE-tot	.31**	.31**	.41**	.90**	.92**	.84**	—		
K10	-.20**	-.31**	-.22**	-.39**	-.32**	-.22**	-.35**	—	
Age	.05	.15**	.01	.15**	.10*	.13*	.14**	-.34**	—
M (*SD*)	3.63 (.83)	3.77 (.76)	3.50 (.71)	4.61 (1.04)	5.44 (1.02)	5.32 (.93)	5.12 (.88)	22.47 (7.41)	43.72 (10.42)
Skewness	-.41	-.54	-.06	-.22	-.37	-.42	-.31	.39	.025
Kurtosis	-.16	.20	-.25	-.13	-.30	.82	.03	-.57	-.45

Note. SE-CM = Self-Efficacy Classroom Management, SE-IS = Self-Efficacy Instructional Strategies, SE-Seng = Self-Efficacy Student Engagement, WE-V = Work-Vigour, WE-D = Work Engagement Dedication, WE-A = Work Engagement Absorption, WE-tot = Work Engagement Total, K10 = Kessler 10. * $p < .05$, ** $p < .01$

2.3 Self-Efficacy

Females' and males' levels of self-efficacy measured by the TSES (on a 1–5 scale) did not differ for the three subscales: Classroom Management (females: M = 3.62, SD = .85; males: M = 3.69, SD = .73), Instructional Strategies (females: M = 3.74, SD = .77; males: M = 3.91, SD = .70), and Student Engagement (females: M = 3.51, SD = .72; males: M = 3.42, SD = .65). We explored mean levels of self-efficacy across the primary school, secondary/high school, and higher education sectors, but did not include the other sectors due to their relatively small numbers of participants.

For Classroom Management, a one-way ANOVA revealed no statistically significant differences across the three sectors: primary, M = 3.64, SD = .84; secondary, M = 3.71, SD = .82; higher education, M = 3.57, SD = .77 [F(2, 386) = .79, p = .45]. There were statistically significant differences for mean levels of Instructional Strategies across the sectors (primary, M = 3.62, SD = .78; secondary, M = 3.87, SD = .71; higher education, M = 3.96, SD = .67) [F(2, 386) = .8.13, p < .001]. Post hoc analysis using the Bonferroni test indicated that teachers in the primary school sector had lower mean levels of self-efficacy for Instructional Strategies than those in the Secondary (M_{diff} = -.25, CI95% LL = -.46, UL = -.04) and Higher Education (M_{diff} = -.34, CI95% LL = -.56, UL = 5.95) sectors. The effect size for the differences was small, eta^2 = .04. For Student Engagement, there were no statistically significant differences across the three sectors: primary, M = 3.53, SD = .71; secondary, M = 3.54, SD = .74; higher education, M = 3.37, SD = .62 [F(2, 386) = .1.85, p = .16]. A two-way ANOVA revealed no interaction effects across gender and sector for all measures of self-efficacy.

2.4 Work Engagement

Females' and males' mean scores for total work engagement differed (on a 1 – 6 scale) (females: M = 5.10, SD = .89; males: M = 5.33, SD = .84) [t = 2.28, df = 418, p = .02, M_{diff} = .25, CI95% LL = .03, UL = .47]. Likewise, their levels of Vigour differed (females: M = 4.54, SD = 1.05.; males: M = 4.90, SD = .93.) [t = 2.70, df = 418, p < .01, M_{diff} = .35, CI95% LL = .13, UL = .60]. The effects sizes for the differences were relatively small for total engagement (*r* = .11) and Vigour (*r* = .13). Differences between females' and males' means scores for Dedication (females: *M* = 5.40, *SD* = .1.03; males: *M* = 5.62, *SD* = .98), and Absorption (females: *M* = 5.29, *SD* = .92; males: *M* = 5.47, *SD* = .98) were not statistically significant.

We explored levels of work engagement across the primary, secondary, and higher education sectors, using a one-way ANOVA. The other sectors were not included in the analysis due to their relatively small sample sizes.

Mean levels were significantly different for Dedication (primary: *M* = 5.36, *SD* = 1.00; secondary: *M* = 5.36, *SD* = .10; higher education: *M* = 5.67, *SD* = .96), [*F*(2, 386) = 3.61, *p* = .03], but not for work Engagement (primary: *M* = 5.07, *SD* = .87; secondary: *M* = 5.06, *SD* = .92; higher education: *M* = 5.31, *SD* = .81), Absorption (primary: *M* = 5.31, *SD* = .86; secondary: *M* = 5.22, *SD* = 1.03; higher education: *M* = 5.50, *SD* = .89), and Engagement (primary: *M* = 5.36, *SD* = 1.00; secondary: *M* = 5.36, *SD* = 1.06; higher education: *M* = 5.67, *SD* = .95). The effect size for Dedication's differences was small, $eta^2 = .02$.

The Bonferroni test revealed Dedication's mean difference to be lower for the primary sector compared to higher education (CI95% LL = .-.61, UL = -.01), but not in comparison to the secondary sector. Mean differences for Dedication for the secondary and higher education sectors were not statistically significant. A two-way ANOVA revealed no interaction effects across gender and sector for all measures of engagement.

2.5 Psychological Distress

The distribution of scores (on a 1 – 5 scale) revealed that 54.5% of the participants had scores 20 and higher (*M* = 22.47, *SD* = 7.41). This is a reason for concern, given that scores of 20 or above are indicative of mental disorder: 20–24 mild; 25–29 moderate, and higher than 30 severe (Andrews & Slade, 2001). There were *n* = 174 (41.4%) participants with scores in the well category, *n* = 85 (20.2%) in the mild category, *n* = 81 (19.2%) in the moderate category, and *n* = 80 (19.3%) in the severe category (19%).

The difference between females' mean level of distress (*M* = 23.12, *SD* = 7.32) and males' (*M* = 19.61, *SD* = 7.18) was statistically significant, *t* = -3.83, df = 418, *p* < .01, M_{diff} = -3.50, CI95% LL = -5.30, UL = -1.70. Although the effect size of the difference was small (*r* = .18), females' mean score fell above the cut-off score of 20 for moderate mental disorder, whereas the males' fellow below the cut-off score.

We explored differences across primary (*M* = 24.56, *SD* = 7.14), secondary/high school (*M* = 22.33, *SD* = 7.01), which were above the 20 cut-off, and higher education sectors (*M* = 18.70, *SD* = 6.98), but did not include the other sectors due to their relatively small numbers. Using a one-way ANOVA, differences among the three sectors were statistically significant, *F*(2, 386) = 22.26, *p* < .01, with $eta^2 = .10$ indicating a moderate to strong effect size. Post hoc analysis using a Bonferroni test revealed each sectors' respective means score differences were statistically significant. Thus, teachers in the primary school sector had higher levels of distress than those in the secondary sector (CI95% LL = .18, UL = 4.29) who, in turn, had higher levels than those in the higher education sector (CI95% LL = 1.32, UL = 5.95).

Table 2 presents the raw number and percentage of cases in each K10 distress category across the primary, secondary, and higher education sectors. The proportions were statistically different, $\chi^2 = 34.75$, *p* < .001, with the primary school sector having the highest rates of mild, moderate, and severe psychological distress. A two-way ANOVA revealed no interaction effect across gender and sector.

Table 2: Number and Percentage of Cases in each K10 Distress Category

	K10 Distress Category			
Sector	Well	Mild	Moderate	Severe
Primary school	50 (30.5%)	37 (46.8%)	44 (59.5%)	42 (58.3%)
High school	49 (29.9%)	24 (30.4%)	19 (25.7%)	21 (29.2%)
Higher education	65 (39.6%)	18 (22.8%)	11 (14.9%)	9 (12.5%)
Total per category	164 (42.2%)	79 (20.3%)	74 (19.0%)	72 (18.5%)

Note. Total indicates the n per category and % of total *N* = 389 cases

2.6 Correlational Analysis

All measures correlation coefficients were statistically significant. As would be expected, the subscale measures of self-efficacy have stronger correlations with one another than with the subscales of work engagement, and vice versa, providing evidence of the measures' validity. Furthermore, all self-efficacy and work engagement subscales' correlations were negatively correlated with psychological distress. Thus, higher levels of self-efficacy and work engagement were associated with lower levels of distress, and vice versa. Psychological distress was negatively correlated with age, with relative peaks evident in distress levels for those in their mid-20s and mid-40s.

3. Discussion

This study aimed to examine educators' self-reports of self-efficacy for teaching, engagement in work, and mental health, during the period in which classes across educational sectors were transitioned to an online, or remote, mode of delivery. This section will answer the three specific research questions posed.

3.1 RQ1: In What ways has COVID-19 Impacted on Teaching Self-Efficacy?

Teacher self-efficacy is a significant predictor of ability to cope with job-related stress and is part of a multifactorial phenomenon (Katsantonis, 2020). This study has examined teaching self-efficacy and self-efficacy in general terms during the response to COVID-19 and builds on recent interest in this topic (Zee & Koomen, 2016). The limited gender difference found in our study contrasts with the findings of Ehrish et al. (2020), who found females to have higher levels of teacher efficacy and higher levels of interpersonal/communication skills.

Our results are contrasted by the differences for instructional strategies between sectors with primary teachers indicating higher levels of teacher self-efficacy than both secondary and higher education teachers. Primary teachers' Psychological distress was also concerningly higher than in the secondary and higher education sectors, which suggests there is a strong link between the two areas and a need for policy makers to address this sector and its ability to cope during trauma-based events, such as the COVID-19 pandemic.

3.2 RQ2: How has COVID-19 Altered Educators' Work Engagement?

Although educators were required to move quickly to emergency remote teaching, the educators in this study still felt highly engaged with work. With the total work engagement averages above five (on a six-point scale), educators were positive and identified with their work (Ruiz-Frutosab, 2021). When compared to women, men showed slightly increased levels of vigour, dedication, and absorption, indicating higher resilience and persistence in the face of difficulties (Schaufeli, Bakker, & Salanova, 2006).

Work engagement across sectors differed, with higher dedication in the primary sector compared to the secondary and higher education sectors. It is likely that specific contexts and the demands across the different sectors may have contributed to varied levels of work engagement. In the primary sector, for example, educators typically have a commitment and dedication to one class of students for the whole day; whereas other sectors do not.

3.3 RQ3: To What Extent has COVID-19 had an Impact on Educators' Anxiety and Stress?

Concerningly, just over half of the participants had scores on the K10, indicating they were experiencing some degree of distress (Andrews & Slade, 2001). Perhaps this is not surprising given the outcomes of COVID-19, including high death rates across the world and lockdowns to try to halt transmission. We assume participants were concerned about personal matters (e.g., the well-being of family members, finances), and work (e.g., the remote work transition).

Our study also showed differences in distress levels between genders, with females experiencing greater distress. Perhaps this can be attributed to the multiple demands experienced by female participants, including the home-schooling of educators' own children during the time of the survey. Indeed, Power (2020) highlighted that research prior to COVID-19 had suggested that females globally managed 75% of the day-to-day demands of family life, including caring responsibilities for children, elderly parents, friends or family members with a disability or health condition, and this has been exacerbated during the pandemic. Our results also mirror concerns reported by mental health providers that demand for mental health support services increased during COVID-19 stay-at-home restrictions (Lifeline, 2020).

Remote working environments have long been associated with stressful working conditions, including the intensification of labor and longer working hours (DeFilippis et al., 2020), and changes to ways of working have been found to significantly contribute to increased stress levels (Taylor, 2020). For teachers in Australia, stress related to remote teaching may have been intensified on an already high level of stress. Indeed, according to the 2018 Teaching and Learning International Survey (TALIS) (Organisation for Economic Cooperation and Development, 2018), 58% of Australian teachers reported feeling quite a bit or a lot of stress in their jobs compared to the international average of 49%. In relation to our study, this could mean that individuals' work-life balance was not manageable, or even that boundaries between work and home were more ambiguous during the transition to remote work. For example, if educators were working longer hours to manage their workload during the transition, this may have been exacerbated by the need to allow time through their day for managing their own children. Moretti et al. (2020) found that one-third of remote workers were less stressed and one-third experienced increased stress.

In our study, there were also significant differences in distress depending on the work environment of the participants, for example, primary school, secondary school or university. Although this could reflect the nature of their work, it is also likely that university educators were more familiar with teaching in online environments and working remotely. If this was the case, we would expect less distress experienced by educators working in the university sector. In addition, primary teachers spend all day with the same students, so the stress may be cumulative over the same day, whereas secondary and university educators work with the multiple groups of students within a day.

3.4 Conclusion

The overall sample size of our study is sufficient for the statistical analyses used to address the research questions and comparisons of mean levels of self-efficacy, work engagement, and mental health among three educational sectors (viz. primary, secondary, and higher education). However, these findings should be interpreted with caution considering the convenience sample used in the study limits the generalisability of the findings. Whilst the measures had appropriate levels of internal consistency as evidence of reliability, consistent with other research, we were unable to test the three measures' invariance across the sectors.

This study examined the self-reports of self-efficacy for teaching, engagement in work, and the mental health of educators from different educational contexts, when classes were pivoting to online or other hybrid off-campus teaching modes. The findings of this study suggest several implications. Firstly, educational institutions (especially primary schools) need to consider the provision of mental health/psychological support for their staff when traumatic or crisis events occur. This is particularly important given the psychological distress reported by primary educators suggesting a need for sector-specific interventions and trauma-informed support systems. Secondly, employers should consider the additional burden put on females in multiple caring roles. This finding aligns with broader gender equality concerns and suggests policies such as flexible work arrangements and other targeted support is important for staff with caregiving responsibilities. Finally, educational institutions need to consider items which impact on work intensification, such as working hours, workload, place and pace of work. Practical strategies to address this could include workload audits, time-use studies and boundaries for remote work to prevent burnout. This study found that there were different outcomes for self-efficacy, work engagement and mental health in different sectors. There were also gender differences in work engagement and stress related to additional work hours and caring duties falling to females during this time.

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Beyond the One-Size-Fits-All: A Systematic Review of Personalized and Gamified e-Learning for Neurodivergent Learners

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Abstract: Traditional education, characterized by rigid curricula and inflexible teaching methods, often fails to accommodate the diverse cognitive profiles of neurodivergent learners, including those with Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), and dyslexia. Although e-Learning has introduced greater flexibility and interactivity into education, many existing platforms continue to adopt a one-size-fits-all approach, primarily catering to neurotypical learners, often overlooking the diverse cognitive and behavioral needs of neurodivergent students. The neurodivergent students frequently encounter challenges related to attention regulation, sensory processing, and retention of information, and these factors are rarely addressed in the design of conventional digital learning environments. While gamification and intelligent technologies have shown promise in enhancing learner engagement and personalization, their application in neurodiverse contexts remains limited and insufficiently customized. This systematic literature review investigates the potential of gamified e-Learning platforms, enhanced by advanced intelligent technologies, to create personalized and inclusive educational experiences for neurodivergent students. Following the PRISMA protocol, this study analyzed 82 studies published between 2020 and 2024 from Scopus, Web of Science, and Google Scholar databases, focusing on gamification in e-Learning and its effectiveness for neurodivergent learners. The findings suggest that traditional e-Learning platforms lack the adaptability and personalization required to engage neurodivergent students effectively. However, emerging approaches—such as adaptive gamification, multisensory content delivery, personalized feedback, and AI-driven analytics—show promise in improving engagement and learning outcomes. Technologies like reinforcement learning and generative AI offer further potential for dynamic content customization. The study identified the pressing need for future research focusing on developing inclusive, personalized, adaptive e-Learning systems and pedagogical models; conducting longitudinal studies on their efficacy; exploring sensory overload and accessibility barriers; evaluating the effectiveness of generative AI and immersive technologies; addressing the digital divide; and ensuring ethical AI-driven personalization.

Keywords: e-Learning, Gamification, Engagement, Knowledge retention, Learning outcome, Adaptive, Neurodivergent

1. Introduction

Education has always been centered on rigid curricula and inflexible modes of learning without considering the fact that people are different. In a classroom filled with unique cognitive styles, fostering success requires embracing neurodiversity and creating inclusive learning environments (Lynch, Singal, and Francis, 2024). Neurodiversity refers to a wide range of neurological variations, not limited to autism spectrum disorder (ASD), attention deficit hyperactivity disorder (ADHD), dyslexia, and other sensory processing challenges. These individuals often exhibit unique cognitive, sensory, and social-emotional profiles that can pose challenges in traditional educational settings. Recognizing and accommodating these differences is crucial to ensure equal access to quality education and to foster an inclusive learning environment (Sofiadin and Azuddin, 2021).

As the world embraces digital transformation, e-Learning has emerged as a powerful tool to enhance accessibility and personalization in education. E-Learning technologies encompass a broad spectrum of tools and platforms designed to facilitate digital learning experiences (Blezu and Popa, 2008). Most e-Learning platforms are not designed with the needs of neurodivergent learners in mind, limiting their accessibility and adoption. The literature recommends combining e-Learning with gamification as a promising direction to overcome this challenge. Gamification is an approach that uses game elements such as points, badges, leaderboards, awards, etc., in non-game contexts like e-Learning to engage and motivate neurodivergent learners (Deterding et al., 2011). While gamification is known to benefit e-Learning, existing implementations are seldom tailored to the varied learning styles and neurocognitive needs of neurodivergent learners, highlighting the need for more customized and inclusive design strategies. The learner's behavior, learning style (LS), goals, and motivation are to be considered when developing the learning approach. AI-driven personalization and intelligent tutoring systems are growing, but their role in enhancing learning outcomes

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remains underexplored. To the best of our knowledge, there has not been any systematic work that reviews the current state of literature addressing the extent to which e-Learning systems and pedagogical models support neurodivergent learners, the ways in which gamification can be customized to suit their diverse learning styles, and the role of intelligent technologies in enhancing personalized learning for this population. Therefore, this study aims to address this research gap by attempting to answer the following research questions (RQs).

RQ 1. How do different e-Learning systems and pedagogical models impact engagement, knowledge retention, and learning outcomes among neurodivergent learners?

RQ 2. How can gamification approaches be customized to address the diverse learning styles of neurodivergent students?

RQ 3. What impact does the integration of advanced intelligent technologies have on enhancing student performance in personalized e-Learning platforms?

The selection of the RQs is based on the fundamental goal of e-Learning platforms: to support effective learning, best measured through learner engagement, knowledge retention (KR), and learning outcomes (LOs). Neurodivergent learners, due to their distinct cognitive profiles, often experience e-Learning environments differently from neurotypical learners, particularly in the absence of real-time teacher support. RQ1 examines the effects of various pedagogical models and e-Learning system designs on the efficacy of learning for neurodivergent students. One persistent challenge in e-Learning is sustaining learner engagement and improving LOs and KR. Gamification has emerged as a promising strategy to address this issue. Therefore, RQ2 focuses on how gamification can be tailored to align with the diverse learning styles of neurodivergent individuals. Finally, RQ3 explores how advanced intelligent technologies can be used to personalize learning experiences and improve performance for this diverse learner group.

The remainder of this manuscript is organized as follows: Section 2 provides an overview of the background and comparative study of prior reviews and other empirical and conceptual studies within the gamified e-Learning domain. Section 3 outlines the research methodology and details the approach adopted for the retrieval and analysis of the literature. Section 4 presents the findings of the review, addressing the research questions formulated in this study. Section 5 discusses the findings from the reviewed articles based on the research questions. Section 6 provides the practical and research implications of the findings, future research directions, and conclusions of the study, along with a summary of contributions and limitations.

2. Literature Review

Traditional learning, a teacher-centered mode of instruction based on face-to-face interactions in classrooms, relies on standardized teaching methods, assuming uniform learning styles and pacing, typically a one-size-fits-all approach (OSFA) (Buzzi et al., 2019). Neurodivergent students face barriers in such settings due to limited flexibility, lack of multisensory experiences, and emotional challenges from classroom interactions (Chugh, Vyas and Shukla, 2022). The COVID-19 pandemic accelerated e-Learning adoption, enabling remote access to education but exposing challenges in inclusivity, engagement, and accessibility (Fabriz, Mendzheritskaya and Stehle, 2021). Studies document how educators integrated digital tools into classrooms post-pandemic, but issues remain, especially for marginalized groups (Adedoyin and Soykan, 2023; Maatuk et al., 2022). Research has explored assistive technology in traditional classrooms, with gamified applications to improve motivation and learning for students with disabilities (Al-Dababneh and Al-Zboon, 2022; Sulaimani and Bagadood, 2023; Alkhawaldeh and Saleem, 2024). Gamification, defined as the integration of game design elements in non-game settings, gained prominence in the educational domain as a strategy to enhance learner motivation and engagement in digital learning environments. Early implementations focused on points, badges, and leaderboards to encourage learner involvement and maintain engagement in digital learning (Rincón-Flores, Mena and Montoya, 2020). With the advancement of e-Learning platforms, particularly the widespread adoption of Massive Open Online Courses (MOOCs) and Learning Management Systems (LMS), gamification has progressively shifted toward adaptive and personalized approaches (Raju et al., 2021). It is now recognized not merely as a motivational tool but as a comprehensive framework for delivering inclusive, learner-centered, and effective educational experiences. However, limited studies focus on e-Learning accessibility for neurodivergent learners (Cinquin, Guitton and Sauzéon, 2023). Studies have indicated that gamification has improved motivation, engagement, and learning outcomes attainment in e-Learning (Awad, Salameh and Al Redhaei, 2023), but its impact on neurodivergent learners remains significantly under-researched (Lampropoulos and Sidiropoulos, 2024). Equitable e-Learning requires addressing digital accessibility disparities (Park and Kim, 2021), ensuring assistive technology compatibility, and accommodating diverse learning styles. Hence, there is a need for research in e-Learning ecosystems to create recommendations to ensure accessibility and adaptability for neurodivergent individuals.

2.1 Related Works

Recent advancements in gamified e-Learning systems have shown promise in enhancing learner engagement and motivation. However, most studies continue to focus on generic personalization strategies, often overlooking the diverse cognitive needs of neurodivergent learners. This section synthesizes the most relevant prior works, highlighting key trends, limitations, and research gaps.

2.1.1 Prior reviews

This section briefly reviews some of the relevant systematic literature reviews on gamification in e-Learning related to the topic of our systematic review. Many existing reviews highlight the importance of gamification in education, from early childhood to higher education, as a tool for next-generation education. Table 1 summarizes the primary focus of the existing systematic review studies and their limitations.

These studies explored gamification in e-Learning across various contexts such as MOOCs (Jarnac de Freitas and Mira da Silva, 2023; Major and Mira da Silva, 2023; Rohan, Pal and Funilkul, 2020; Saputra, Hidayanto and Prabowo, 2021; Karsen, Masrek and Safawi, 2022), LMS platforms (Saleem, Noori and Ozdamli, 2022; Sabri, Fakhri and Moumen, 2022), and higher education (Alalgawi and Sadkhan, 2022; Khaldi, Bouzidi, and Nader et al., 2023), primarily emphasizing its role in enhancing learner engagement, motivation, and short-term LOs (Hebbar, Manohar and Hungund, 2024; Behl et al., 2022; Burlacu, Coman and Bularca, 2023; Halachev, 2024; Jayawardena et al., 2021; Patiño-Toro et al., 2022; Tan, Sunar and Goh, 2021; Walaszczyk, 2023; Yu, Yu and Li, 2024; Zamahsari et al., 2023). However, they revealed significant gaps in the personalization of gamified content, the long-term impact on KR, and support for neurodivergent learners.

Table 1: Research Focus and Gaps Identified from Prior Reviews

Study	Focus/Contribution	Identified Gaps
Rohan, Pal and Funilkul, 2020; Tan, Sunar and Goh, 2021; Saputra, Hidayanto and Prabowo, 2021; Jayawardena et al., 2021; Patiño-Toro et al., 2022; Karsen, Masrek and Safawi, 2022; Saleem, Noori and Ozdamli, 2022; Walaszczyk, 2023; Burlacu, Coman and Bularca, 2023; Major and Mira da Silva, 2023; Jarnac de Freitas and Mira da Silva, 2023; Yu, Yu and Li, 2024	Gamified MOOC, cognitive effects, and the role of game elements for motivation, engagement, and LOs.	Lack of personalized adaptive design frameworks and limited understanding of how specific game elements align with individual cognitive profiles. Lack of empirical validation. Minimal evidence of longitudinal knowledge retention
Behl et al., 2022	Gamification effect on cognitive and social development in young learners	No longitudinal studies on cognitive growth. Lack of longitudinal validation of KR and measurable learning results. Limited implementation of responsive gamification strategies
Bennani, Maalel and Ben Ghezala, 2022a	Adaptive gamification for personalized engagement.	Scalability and implementation challenges. Lack of evaluation of KR and academic performance impacts. Limited inclusion of cognitive diversity in adaptive design.
Alalgawi and Sadkhan, 2022; Khaldi, Bouzidi and Nader, 2023	Gamification in higher education, PBL (points, badges, and leaderboards), cognitive engagement	Limited use in non-technical subjects. Lack of adaptive feedback loops and personalized gamified interventions. Lack rigorous validation of AI-driven personalization models
Sabri, Fakhri and Moumen, 2022; Zamahsari et al., 2023	Intrinsic motivation and long-term impact on KR and engagement, language learning	Need for adaptive strategies and ethical challenges like privacy. Limited experimental evaluation of intelligent adaptive models
Hussein et al., 2023; Honorato et al., 2023	Gamification for skill development in special education and focus on sensory needs.	Lack of empirical validation. Limiting insights into sustained LOs and KR.

Study	Focus/Contribution	Identified Gaps
Suresh Babu and Dhakshina Moorthy, 2024; Hebbar, Manohar and Hungund, 2024; Halachev, 2024	Gamification's effects on engagement and retention, perceived quality of learning	Limited verification of long-term learning gains and outcome consistency. Need of adaptive strategies. Scarcity of evidence-based evaluation of AI-powered adaptive platforms

Only a few studies discussed the potential of personalized and adaptive gamification (Bennani, Maalel, and Ben Ghezala, 2022a; Sabri, Fakhri and Moumen, 2022; Alalgawi and Sadkhan, 2022) and explored the integration of machine learning or generative technologies for personalized content delivery, dynamic feedback, or cognitive modeling, and advanced technologies such as AI for customization (Suresh Babu and Dhakshina Moorthy, 2024; Halachev, 2024). Only two reviews (Hussein et al., 2023; Honorato et al., 2023) were focusing on special needs children, but the impact of gamification on neurodivergent learners was not explored. These limitations indicate a need for future research focused on adaptive, inclusive, and AI-powered gamification frameworks that go beyond static designs to support diverse learning needs.

2.1.2 Other empirical and conceptual studies

The recent empirical studies explored diverse applications of gamification in e-Learning, with a strong focus on enhancing student engagement, motivation, and LOs across MOOCs, LMS platforms, and subject-specific domains (El-Sabagh, 2021; Pitthan, 2024; Xiao, 2024; Rahayu et al., 2022). Several studies highlighted positive effects of gamified elements such as adaptive feedback, visual rewards, and social interactions on learner participation and short-term performance (Ng et al., 2021; Poondej and Lerdpornkulrat, 2020; Handayani, Raharjo, and Putra, 2021). Studies in STEM and MOOC domains (Rincón-Flores, Mena and Montoya, 2020; De-Marcos et al., 2020) showed improved engagement, motivation and completion rates but rarely addressed LOs and KR or reinforcement personalization. A few studies recognized the importance of LOs and KR; longitudinal evidence on sustained cognitive gains and inclusive design remains scarce. Few works addressed the intersection of gamification with cognitive diversity or special education contexts (Zairon et al., 2023; Alshammari, 2020), indicating the need for adaptive systems that support varied learner profiles.

The conceptual studies mainly propose frameworks, models, and adaptation strategies for gamified e-Learning without large-scale validation. Framework-based and model-driven designs (Zubkov, 2023; Kamunya et al., 2020; Xiao, 2024) revealed engagement benefits but lacked user-centered customization. Several studies focused on attention-based and affective adaptations in MOOCs to foster learner motivation (Hocine, 2021; Cheng, 2023; and Rohan et al., 2021), yet they lacked depth in personalization and evaluation across diverse learner profiles. Adaptive gamification aligned with learning styles or learner profiles (El-Sabagh, 2021; Chugh, Vyas and Shukla, 2022; Hassan, 2021; Moussa, Maher and Khalifa, 2020; Maher, Moussa and Khalifa, 2020) addressed performance gains among school and university learners, yet often failed to account for neurodivergent cognition or dynamic learning needs. Dynamic adaptation techniques (Shabadurai, Chua and Lim, 2024; Pratama et al., 2024) underscored performance improvements but revealed integration gaps in feedback loops. Works emphasizing collaboration and analytics (Zairon et al., 2023; Maher, Moussa and Khalifa, 2020; Yamani, 2021) remained limited in blending gamification with real-time data insights. Personalization via motivational and personality traits (Abbasi et al., 2021; Shrestha et al., 2023; Leung et al., 2023) focused on retention gains but lacked cognitive diversity validation. Gamified platforms in computing domains (Malone, Wang and Monrose, 2021; Bernik, 2021) demonstrated effectiveness within specific disciplines, raising concerns about transferability. Various other research studies examined gamification's role in addressing technostress and sustainability (Fajri et al., 2021; Rahayu et al., 2022; Park and Kim, 2021), perceived usefulness (Aguilos and Fuchs, 2022; Handayani, Raharjo, and Putra, 2021), and emotional engagement (Taskın and Kılıç Çakmak, 2023; Puig et al., 2023), though these often lacked real-time adaptive emotional feedback. The comparative analysis of empirical and conceptual studies on gamified e-Learning with the primary focus on the impact of learning and research gaps is given in Table 2.

Table 2: Comparative Study of Related Literature in Gamified e-Learning with Gaps identified

Study(s)	Primary Focus	Target Group	Outcome	Gap Identified
Hocine, 2021; Cheng, 2023; Rohan et al., 2021	Attention-based and affective gamified adaptation	MOOC learners	Engagement, Motivation	Limited evaluation in diverse populations and personalization depth.
Bachiri, Mouncif and Bouikhalene, 2023; Sayed et al., 2023; Ng et al., 2021; Bennani et al., 2022b	AI-enhanced gamification and learner profiling	General learners	Engagement, Learning Outcomes	Lack of longitudinal impact studies and real-world deployment.
El-Sabagh, 2021; Chugh, Vyas and Shukla, 2022; Hassan et al., 2021; Moussa, Maher and Khalifa, 2020	Adaptive gamification based on learning styles	School & university students	Engagement, Learning Outcome	Gaps in supporting neurodivergent learning profiles and dynamic adaptation. Lack of longitudinal validation of retention and measurable learning results
Zubkov, 2023; Kamunya et al., 2020; Xiao and Hew, 2024	Gamification frameworks and models	Higher education students	Engagement, Motivation	Limited verification of long-term learning gains and outcome consistency. Lack of user-centered customization and behavioral validation.
Rincón-Flores, Mena and Montoya, 2020; De-Marcos et al., 2020	Gamification for STEM/MOOC completion	MOOC learners	Motivation, Completion Rate	Inadequate focus on KR and LOs. Absence of real-time adaptive personalization and context-aware gamification
Shabadurai, Chua and Lim, 2024; Pratama et al., 2024	Dynamic and static adaptation models	Online trainees or learners	Engagement, Learning Performance	Need for better integration of feedback loops and real-time adaptation.
Zairon et al., 2023; Maher, Moussa and Khalifa, 2020; Yamani, 2021	Collaborative interaction and analytics visualization	e-Learning users	Engagement, Collaboration	Underexplored integration of analytics with gamification elements.
Abbasi et al., 2021; Shrestha et al., 2023; Leung et al., 2023	Personalized gamification	Higher education learners	Motivation, Retention	Limited empirical testing across cognitive diversity. Limited experimental evaluation of intelligent adaptive models
Malone, Wang and Monrose, 2021; Bernik, 2021	Gamified platforms for CS/cybersecurity/higher education	Computer science students	Engagement, Learning Outcomes	Lack of generalizability beyond computing domains.
Fajri et al., 2021; Rahayu et al., 2022; Park and Kim, 2021	Gamification's role in technostress or sustainability	General learners	Motivation, Cognitive Outcomes	Limited attention to emotional regulation and stress factors.
Aguilos and Fuchs, 2022; Handayani, Raharjo, and Putra, 2021	Perceived usefulness of gamification in e-Learning	Undergraduate & LMS users	Engagement, Usefulness	Missing alignment between perceived value and long-term outcomes. Insufficient support for on-the-fly adaptation and tailored engagement models.
Taskın and Kılıç Çakmak, 2023; Puig et al., 2023	Effects of gamification on behavioral and cognitive engagement of students	Online learners	Emotional Engagement, LOs, and completion rate	Few studies address real-time emotion feedback mechanisms. Limited experimental validation for AI-supported gamification systems.
Abdirahma et al., 2023; Palaniappan and Noor, 2022; Schull and Brocksieper, 2021	Self-directed learning and gamification	Online learners	Behavioral & Cognitive Engagement	Customization and autonomy support are still under-theorized. Limited real-world assessment of AI-driven adaptive learning approaches.

Study(s)	Primary Focus	Target Group	Outcome	Gap Identified
Barua and Bharali, 2023; Kashive and Mohite, 2023; Poondej and Lerdpornkulrat, 2020	Gamification effects in regional e-Learning contexts	Computer science & vocational learners	Performance, Motivation	Underexplored assessment of enduring cognitive and educational outcomes. Lack of customization frameworks.
Alshammari, 2020; Acosta-Medina, Torres-Barreto, and Cárdenas-Parga, 2021	Gamification effect in language/elementary domains	Language learners & school students	Engagement, Learning Outcomes	Limited verification of long-term learning gains. Scarce focus on age-appropriate gamification strategies.

The integration of artificial intelligence (AI) and machine learning (ML) has emerged as a promising avenue for enhancing adaptive gamification through learner profiling, personalized content delivery, and dynamic feedback loops (Bennani et al., 2022b; Sayed et al., 2023; Bachiri, Mouncif and Bouikhalene, 2023; Daghestani, 2020), but the empirical evaluation of such systems remains limited. Finally, research on self-directed learning (Abdirahma et al., 2023; Palaniappan and Noor, 2022; Schull and Brocksieper, 2021), regional applications (Barua and Bharali, 2023; Kashive and Mohite, 2023; Poondej and Lerdpornkulrat, 2020), and age-domain-specific use (Alshammari, 2020; Dikcius, 2021; Acosta-Medina, Torres-Barreto, and Cárdenas-Parga, 2021) highlights improvements in engagement but has revealed persistent gaps in gamification customization and age-appropriate design frameworks and fails to systematically address the needs of neurodivergent learners. Hence, this review intends to address these gaps by formulating RQs that focus on gamification for neurodivergent learners in an e-Learning context.

2.2 Gaps Identified

Despite the proliferation of gamification research across diverse educational domains, several persistent gaps remain:

- Limited Personalization and Inclusivity: Most e-Learning systems optimize for neurotypical users, fail to accommodate neurodivergent learners, and do not dynamically adapt to individual learning styles and cognitive profiles.
- Lack of Longitudinal Evidence: While engagement and motivation are commonly evaluated, there is a lack of longitudinal studies assessing the sustained impact of gamification on learning outcomes and knowledge retention in special education and inclusive contexts.
- Shallow Customization: The depth of customization and integration of real-time feedback in adaptive gamification systems remains insufficiently developed.
- Insufficient Integration of Intelligent Technologies: AI-driven personalization and analytics are rarely deployed in real-world educational settings; the integration of such technologies into gamified e-Learning environments remains limited.

These gaps indicate the importance of more adaptive, inclusive, and empirically validated gamification models that use intelligent technologies to support diverse learners across evolving e-Learning systems.

3. Research Methodology

The review focused on identifying and analyzing scholarly literature published between 2020 and 2024 related to gamification in e-Learning, with a particular emphasis on its relevance and effectiveness for neurodivergent learners. This publication period was selected because the scope of online learning got much attention during the COVID-19 pandemic.

3.1 Search Strategy and Study Selection

The search was done in the Scopus, Web of Science, and Google Scholar databases, and most of the articles were retrieved from the following publishers: IEEE, Springer, ACM, Semantic Scholar, SAGE, and ScienceDirect. Thus, the quality of the review was maintained by selecting high-quality articles from these sources. The search strings used were (gamification OR gamified AND e-Learning OR MOOC OR LMS OR Moodle AND neurodivergent OR neurodivergence OR special needs OR intellectual disability OR cognitive disability OR cognitive impairment OR autism spectrum disorder OR ASD). The initial search retrieved 375 documents from Scopus, 102 from Web of Science, and 1,350 from Google Scholar, totaling 1,827 documents. The document selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocols (Page et al., 2021), as shown in Figure 1.

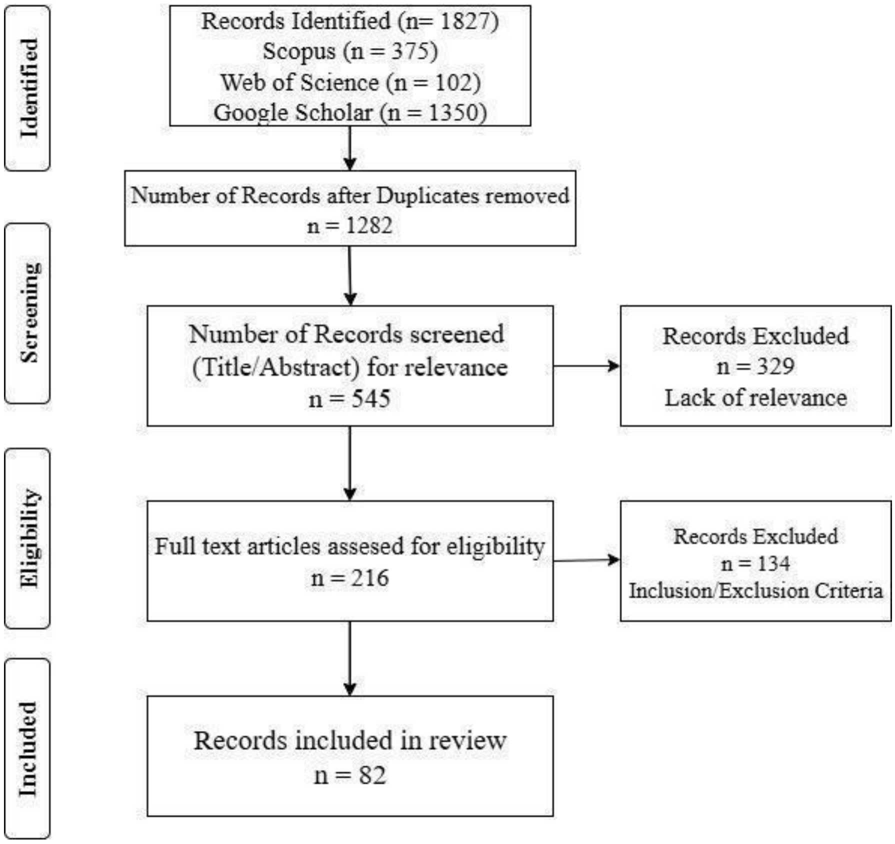

Figure 1: PRISMA Flow Diagram outlining the Document Selection Process

A manual screening was performed to select the relevant studies for this SLR. After removing 1,282 duplicate entries, 545 unique records remained and were screened based on title and abstract. Of these, 329 records were excluded for lack of relevance. A full-text assessment was conducted on 216 articles, from which 134 were excluded based on predefined inclusion and exclusion eligibility criteria. Due to scope limitations, several papers were excluded from the analysis. For instance, some studies focused solely on gamification concepts without any application to e-Learning environments, while others examined e-Learning platforms without incorporating any gamified elements. We finally selected 82 studies on gamification in e-Learning for qualitative analysis, aiming to address the RQs.

3.2 Inclusion and Exclusion Criteria

The SLR was relevantly screened using specific inclusion and exclusion criteria, ensuring that the selected studies aligned with research objectives and provided sufficient data for analysis. Table 3 summarizes the inclusion and exclusion criteria outlined. We included peer-reviewed journal and conference papers published between 2020 and 2024 in English that focused on the application of gamification within e-Learning platforms, specifically targeting neurodivergent learners. As there is a lack of studies on this population, we also included studies on neurotypical learners with a focus on inclusion, personalization, or adaptability. We excluded studies that dealt solely with general game-based learning or serious games, as these typically involve fully immersive gameplay rather than the integration of game elements into existing educational systems.

Table 3: Inclusion-Exclusion Criteria

Criteria	Inclusion	Exclusion
Literature Type	Journal, Conference proceedings	Book chapters, Thesis
Language	English	Non-English
Timeline	Between 2020 and 2024	Before 2020
Context	Education	Other than education context
Learning Approach	Gamification in e-Learning, online learning	Game-based, serious game-based learning, other than e-Learning

3.3 Data Extraction and Analysis

A structured data extraction process was employed to ensure consistency and relevance to the research objectives. A predefined spreadsheet template was used to systematically record key information from the studies included in this review. The extracted data fields included study title, year, author and domain; participant type (with a focus on neurodivergent learners, such as those with ASD, ADHD, or dyslexia or neurotypical learners with a focus on inclusion, personalization, or adaptability); type of intervention (e.g., gamification strategies and adaptive mechanisms); reported outcomes (such as engagement, KR, and LOs); technologies used (including AI, ML, reinforcement learning (RL), augmented reality/virtual reality (AR/VR), and GenAI); and theoretical frameworks applied. While the initial extraction was conducted by the lead author, all entries were independently verified by a second reviewer to ensure accuracy and reduce bias. Any discrepancies were resolved through collaborative discussion among authors and consensus after revisiting the original articles.

4. Findings by Research Question

This section addresses the proposed research questions by synthesizing findings from the selected literature to determine the current state of research on gamification in e-Learning environments, with special focus on neurodivergent students.

RQ 1 : How do different e-Learning systems and pedagogical models impact engagement, knowledge retention, and learning outcomes among neurodivergent learners?

Neurodivergent students need e-Learning with customizable interfaces and easy navigation to avoid overload and improve engagement (attention, interest, interaction, and participation) (El-Sabagh, 2021). Assistive technology integration helps KR remember information and show learning effectiveness (Bernik, 2021). Different accessibility options are needed for various learning styles. Alternative assessment methods are required to measure learning outcomes (LOs) (knowledge, skills, and competencies) (Kamiliya, Syahchari, and Omar, 2024). The rest of the section summarizes the current e-Learning systems and pedagogical models and how they perform in the objective.

Pedagogical models in e-Learning are frameworks derived from learning theories that guide instructional and learning practices, aiming to enhance educational outcomes (Yamani, 2021). Synchronous e-Learning focuses on real-time interaction and immediate feedback, while asynchronous e-Learning offers flexibility but lacks live engagement. Blended learning combines face-to-face and online instruction, and the flipped classroom reverses traditional learning by having students prepare at home and engage in activities during class. Adaptive learning personalizes content and pace using technology, and collaborative learning encourages group problem-solving. Self-paced learning allows learners to progress at their speed, while gamified learning uses game elements like points and badges to boost engagement and comprehension. Differentiated instruction tailors lessons to individual student needs, ensuring equitable and effective learning experiences.

Pedagogical models are integrated into e-Learning systems to enhance learning experiences. Learning Management Systems (LMS) like Moodle provide the foundation for institutional e-Learning, enabling synchronous and asynchronous learning, progress tracking, and customizable assessments for LOs (Handayani, Raharjo, and Putra, 2021). Virtual Learning Environments (VLEs) create online collaborative spaces with tools like forums, video conferencing, and file sharing to boost student engagement (Acosta-Medina, Torres-Barreto, and Cárdenas-Parga, 2021). Massive Open Online Courses (MOOCs) offer global access to diverse education through multimedia content and self-paced modules (Abdirahma et al., 2023; Schull and Brocksieper, 2021). Mobile Learning (M-learning) delivers educational content via smartphones and tablets, and the focus is on accessibility and flexibility. Digital learning platforms have advanced, but their effectiveness in addressing the unique needs and engagement challenges of neurodivergent learners remains largely unexplored.

The proposal of the Universal Design for Learning (UDL) framework for inclusive education tries to address this gap. UDL principles—multiple means of engagement, representation, and action/expression—directly tackle the shortcomings of existing systems and promote diverse content and customized assessment. Integrating UDL into platforms like MOOCs, LMS, and VLEs can transform them into inclusive spaces, guaranteeing equitable learning for everyone, including neurodivergent students.

The literature reports success in the use of synchronous and asynchronous learning techniques (Antonopoulou et al., 2022) in e-Learning during the Covid-19 pandemic in elementary school children with learning and behavioral problems. Gamified MOOCs have been suggested as a solution to address low engagement and high dropout in MOOCs (Rinc´on Flores et al., 2020; de Marcos et al., 2020) as they report improved engagement (Ortega-Arranz et al., 2022; Wen, Hu, and Fang, 2024), KR (Oliveira et al., 2021), and LOs (Boboc et al., 2023; Palaniappan and Noor, 2022). Adaptive gamification within MOOCs personalizes the learning experience and dynamically adjusts the content to match the learner's progress. This approach holds promise for neurodivergent learners, who often require customized pacing and multimodal content delivery. More research is required to explore the potential of MOOCs in addressing the unique needs of neurodivergent learners.

Gamified LMS has also been reported to improve learning engagement (Bouchrika et al., 2021; Toimah, Maulana, and Fajar, 2021), motivation (Rahayu et al., 2022; Vapiwala and Pandita, 2022; Kuˇcak, Biuk, and Mršić, 2022), and LOs for general learners (Poondej and Lerdpornkulrat, 2020; Alshammari, 2020; Raju et al., 2021). Gamified LMSs promote active learning, self-pacing, and collaboration (Aguilos and Fuchs, 2022; Barua and Bharali, 2023; Gupta, 2024), but these systems may be challenging for neurodivergent learners with difficulties in social interaction. Personalized gamification in LMSs could significantly benefit neurodivergent learners, as it can address their unique sensory and cognitive needs by adapting specific gamification strategies (Kashive and Mohite, 2023).

The literature proposes a theoretical model called the Personalized Adaptive Gamified e-Learning model (PAGE) that combines adaptive learning with gamification, using student data and advanced technologies such as AI and ML to create a personalized and engaging learning experience (Moussa, Maher, and Khalifa, 2020). The PAGE model dynamically adjusts game mechanics, content difficulty, and learner feedback based on individual progress and preferences (Abbasi et al., 2021). This model has shown significant potential to increase engagement, KR, and LO among diverse learners' populations (Leung et al., 2023; Pradana et al., 2023). The adaptive capabilities proposed in PAGE make it particularly promising for neurodivergent learners, as it allows the delivery of customized content and challenges that align with unique learning styles and needs (Daghestani et al., 2020).

The impact of different platforms and the PAGE model on engagement, KR, and LOs, as reported in the literature, is detailed in Figure 2, revealing that KR is the least explored aspect among them. Research on MOOC-based systems mainly focuses on learner engagement (Rohan, Pal and Funilkul, 2020; Saputra et al., 2021; and Cheng, 2023). Some studies (Patino-Toro et al. 2022 and Karsen et al. 2022) investigated engagement and KR in MOOCs. Other studies (Bachiri, Mouncif and Bouikhalene, 2023) stand out for addressing all three impacts—engagement, KR, and LOs—across MOOC, LMS, and PAGE systems. LMS-focused studies (Poondej and Lerdpornkulrat, 2020; Raju et al., 2021; and Handayani, Raharjo, and Putra, 2021) concentrated mainly on enhancing engagement through gamified dashboards and performance tracking tools but often omitted metrics for KR or adaptive support. Yuliana et al. (2023) integrated both MOOC and LMS platforms, measuring all three learning impacts. PAGE-based studies, representing personalized adaptive gamification (Hocine et al., 2021; Moussa and Khalifa; and Pitthan et al., 2024), were largely focused on adaptive engagement and LO improvement, although only a few (Ng et al., 2021, and Bennani et al., 2022) discussed KR. Thus, stronger research on KR may be necessary to properly benefit neurodivergent learners, who frequently need repeated reinforcement, even while engagement and LOs are highly focused. The findings emphasize the need for adaptive gamification and personalized learning strategies (PAGE) to better support neurodivergent learners in e-Learning environments.

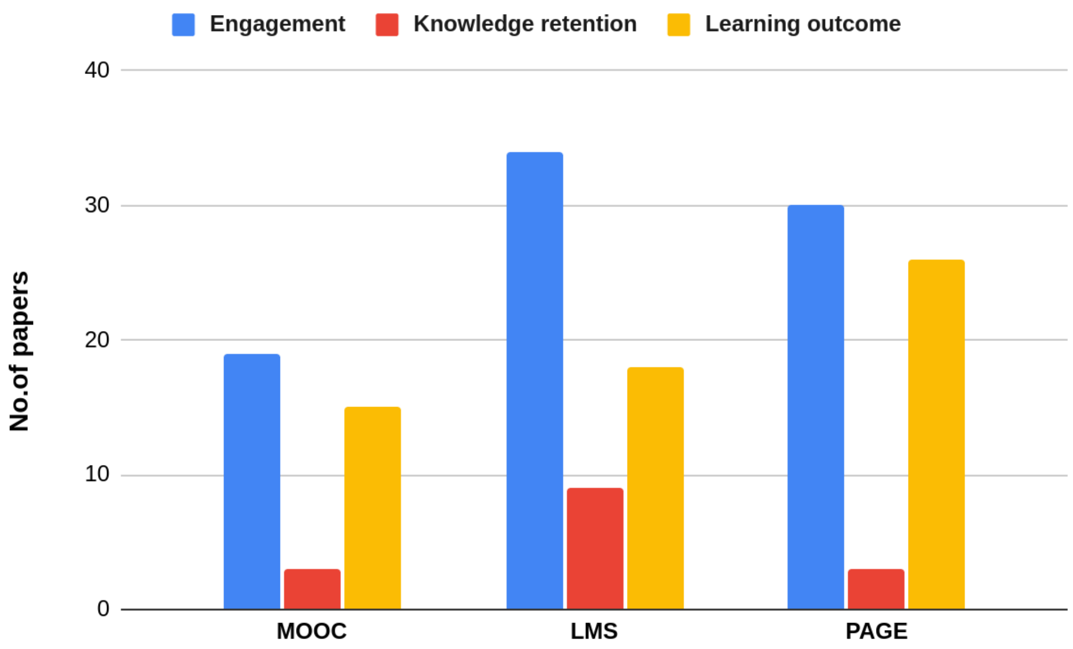

Figure 2: Comparative Analysis of Studies on MOOC, LMS, and PAGE Platforms, Focusing on the Learning Impacts of Engagement, Knowledge Retention, and Learning Outcomes

There are many commercial e-Learning products that incorporate the ideas that have been recommended in literature, like Khan's Academy, Coursera, Udemy, Quizlet, and Kahoot, to name a few. Khan's Academy focuses on self-paced learning and provides the user with adaptive content that is provided as per the progress of the student based on its algorithms. It provides multimodal content and offers support for many accessibility tools. These adaptations improve the engagement of learners. Coursera and Udemy are examples of MOOCs with limited gamification and a lot of multimodal content to engage learners of diverse learning styles (Kurteva et al., 2023). Adaptive personalization of learning paths, which might be helpful to neurodivergent individuals who struggle with planning and execution are missing. The ability to revisit content, frequent quizzes, and assignments help in KR and attainment of LOs. The KR is implemented better in Quizlet and Quizz, which allows users to create flashcards and quizzes to allow spaced repetition of concepts. Kahoot gamifies the learning process, reinforces learning, and improves KR (Sari, Ftriani and Saputra, 2020). Neurodivergent learners usually need differentiated and scaffolded learning through an appropriate multisensory approach. Currently, to the best of the author's knowledge, there is no study evaluating the same.

To provide equitable education to all, it is essential to adopt a more comprehensive strategy to ensure that the e-Learning systems and pedagogical models are effective for neurodivergent learners. The study indicates that learners' sensory, cognitive, and social challenges can be better addressed by incorporating adaptive learning technologies, multimodal content delivery, and inclusive design principles.

RQ 2: How can gamification approaches be customized to address the diverse learning styles of neurodivergent students?

Gamification in e-Learning can improve learner engagement, KR, and LO by integrating game elements and narrative-driven tasks into educational contexts . While its benefits are well documented across general learners' populations, its application to neurodivergent learners requires thoughtful customization. Neurodivergent learners exhibit diverse cognitive, sensory and social-emotional profiles that require customized approaches to meet their unique learning needs. E-Learning platforms can accommodate diverse learning styles by incorporating gamified elements, enhancing motivation, satisfaction, and outcomes, especially for neurodivergent students, by integrating adaptive and inclusive design principles.

There are several learning style models that categorize and describe how people prefer to learn and process information. The literature identifies three primary learning style models: VARK, Kolb's, and Felder-Silverman (FSLSM). VARK categorizes learners by sensory preference (visual, auditory, read/write, or kinesthetic) for practical application in instructional settings. Kolb's experiential learning theory proposes a four-stage cycle (concrete experience, reflective observation, abstract conceptualization, and active experimentation) and is applied in adult and higher education. FSLSM is applied more in STEM disciplines and explores learning preferences across four dimensions: sensing/intuitive, visual/verbal, active/reflective, and sequential/global. Sensing learners prefer concrete, practical information, and intuitive learners favor abstract, theoretical information. Visual learners prefer pictures, diagrams, and other visual aids, and verbal learners prefer written and spoken explanations. Active learners prefer hands-on activities and group work, and reflective learners prefer to think things through and work independently. Global learners favor broad learning, while sequential learners favor linear learning. Instead of simply categorizing students into a few different types of learning, the FSLSM offers a thorough analysis of different learning styles, distinguishing between preferences in four dimensions (Hassan et al., 2021; Shrestha et al., 2023). To improve engagement and efficacy, e-Learning materials can be designed and delivered with an understanding of various learning styles (Smiderle et al., 2020). Auditory learners might benefit from spoken instructions and sound-based feedback, while visual learners engage better with graphics and diagrams. Kinesthetic learners thrive in hands-on interactive simulations, highlighting the critical role of multimodal content delivery. Gamified e-Learning platforms can use artificial intelligence-based techniques to detect learners' learning styles automatically and customize the delivery of content. Gamification approaches can be customized as given in Table 4 to address the diverse learning styles of neurodivergent students by using the following.

- Adaptive and multimodal gamification
- Incorporating feedback and rewards
- Using AI and analytics for personalization

Adaptive gamification dynamically adjusts challenges and game mechanics based on learners' real-time performance (Zairon et al., 2023). This ensures that the content aligns with individual abilities and pace preferences, preventing cognitive overload or disengagement. Adaptive platforms used personalized learning paths to address individual cognitive strengths and weaknesses (Alsubhi, Ashaari and Wook, 2021).

Table 4: Gamification Customization Approaches to Address the Diverse Learning Styles

Category	Key Features	Method	Study
Adaptive and Multimodal Gamification	Real-time challenge adjustments	Reinforcement Learning	Sezgin and Yüzer, 2022; Shrestha et al., 2023
	Multisensory content (visual, auditory, tactile)	Multimodal Integration Frameworks	Yuliana and Palumian, 2023; Xiao and Hew, 2024
	Dynamic pacing	Adaptive Algorithms	Alsubhi, Sahari and Wook, 2020; Moussa, Maher, Moussa and Khalifa, 2020; Hassan et al., 2021; Hocine, 2021; Malone, Wang and Monrose, 2021; Villegas and Aguero, 2023; Puig et al., 2023; Shabadurai, Chua and Lim, 2024; Pratama et al., 2024
Personalized Feedback and Rewards	Performance based feedback	Gamified Feedback Loops	Maher, Moussa and Khalifa, 2020; Kamunya et al., 2020; Zubkov, 2023; Zairon et al., 2023
	Reward system integration	Reinforcement Learning, Incentive Algorithms	Dikcius et al., 2021; Sayed et al., 2023
AI and Analytics	Personalization, Predictive analytics	AI recommendation engines, ML models	Ng et al., 2021; Cheah, 2021; Bennani et al., 2022b; Sayed et al., 2023
	Behavioral tracking	Data-driven insights	Bennani et al., 2022b; Taskın and Kılıç Çakmak, 2023; Xiao and Hew, 2024

Multimodal designs integrate visual aids, auditory feedback, and tactile simulations to engage learners in all sensory modalities and allow them to interact effectively with content. Gamification platforms incorporate personalized feedback and reward mechanisms to maintain motivation. Studies integrate feedback loops and performance-based adjustments to improve motivation and sustain learning. Dynamic adjustments to rewards, such as badges for achievement-oriented learners or avatars for creative individuals (Pakinee and Puritat, 2021), help in ensuring that neurodivergent students remain engaged. AI-powered systems (Ng et al., 2021) analyze learners' interactions to personalize the game's elements dynamically. Reinforcement learning techniques optimize difficulty levels and reward structures, ensuring alignment with individual learning styles. Learning analytics platforms provide insight into user behavior, enabling the continuous refinement of gamification strategies.

The reviewed studies bring out the potential of gamification to improve engagement and LOs when customized to diverse learning styles, although the explicit focus on neurodivergent learners remains limited.

RQ 3: What impact does the integration of advanced intelligent technologies have on enhancing student performance in personalized e-Learning platforms?

Personalization through AI techniques promises to enhance e-Learning by addressing individual needs. ML models, capable of predictive analytics, can identify areas where students are likely to struggle and recommend targeted interventions. These capabilities result in better KR, higher test scores, and increased motivation. They can also provide real-time modifications to the learning path based on the learner's performance. This adaptive functionality is crucial for neurodivergent learners, who may require individualized pacing and multimodal content delivery. RL optimizes performance through dynamic adaptation in gamified platforms. RL addresses motivational needs by personalizing gamification elements and adjusting learning objectives to help students stay committed to their educational goals. RL-based gamification has been reported to reduce dropout rates and increase task completion by providing customized support and appropriate challenges. Immersive technologies (AR/VR/MR) boost KR and engagement (Yakubov, Nazarov and Rodionov, 2024). Further studies are required to look at how it impacts neurodivergent learners in terms of cognitive overload and sensory sensitivities. Generative AI is reported to promote improved engagement and performance by reducing barriers and providing consistent, personalized guidance to a wide range of learners (Son et al., 2024; Arslan et al., 2024; Pesovski et al., 2024). It acts as a virtual tutor in real time to offer consistent support and scaffolding to address specific cognitive or sensory needs. Although there are limited studies with neurodivergent students, it has the potential to improve inclusivity and accessibility. Inherent challenges in technology, such as biases and hallucinations, and their impact on the generated content need to be further studied. The effect of these advanced technologies on personalized e-Learning is shown in Table 5.

Table 5: Impact of Advanced Technologies on Student Performance in Personalized e-Learning Platforms

Technology	Key Studies	Features	Impact on Student Performance
Machine Learning (ML) / Deep Learning (DL)	Rohan et al., 2021; Hocine, 2021; Bennani et al., 2022b; Bachiri, Mouncif and Bouikhalene, 2023; Sayed et al., 2023; Cheah, 2021; Yakubov, Nazarov and Rodionov, 2024; Shabadurai, Chua and Lim, 2024; Bucchiarone et al., 2024	Personalization, predictive analytics, adaptive gamification, intelligent tutoring systems, LS classification, learner profiling	Improved engagement, perception, boosted retention, cognitive flexibility, and customized learning pathways
Reinforcement Learning (RL)	Chugh, Vyas and Shukla, 2022; Sayed et al., 2023	Gamification optimization, difficulty scaffolding, dynamic adaptation	Higher engagement, reduced dropout rates and performance improvement.
Immersive Technologies (AR/VR/MR)	Yakubov, Nazarov and Rodionov, 2024	Immersive and experiential learning	Improved practical skills, and cognitive retention
Generative AI	Ng et al., 2021	Content creation, adaptive narratives	Enhanced customization of learning materials, higher engagement and improved KR.

Intelligent systems collect and process vast amounts of learner data to optimize personalization, raising issues about consent and security, especially for vulnerable populations (Fajri et al., 2021). Therefore, focused studies are needed to understand how advanced technologies can achieve transparency and data privacy in learning tools.

5. Discussion of Findings

This section synthesizes the findings of the review in relation to the proposed Research Questions (RQs), with a focus on the applicability of gamified, intelligent e-Learning systems in supporting neurodivergent learners. Each subsection interprets results through the lens of inclusivity and pedagogical adaptability.

RQ 1 : How do different e-Learning systems and pedagogical models impact engagement, knowledge retention, and learning outcomes among neurodivergent learners?

The review indicates that while mainstream platforms such as LMSs, MOOCs, VLEs, and mobile learning apps have evolved in terms of accessibility and interactivity, they often fall short in addressing the heterogeneous cognitive and sensory needs of neurodivergent learners. Most systems implicitly assume neurotypical learning trajectories and fail to implement scaffolds aligned with UDL or the PAGE model. Platforms should integrate multisensory engagement strategies (text, audio, visual, and haptic) and dynamic pacing, which are critical for learners with conditions such as ADHD, ASD, and dyslexia. Pedagogical models based on the user's learning style are a promising direction for improving students' learning experience that can result in better engagement, KR, and LOs.

RQ 2: How can gamification approaches be customized to address the diverse learning styles of neurodivergent students?

The findings reveal the potential of adaptive gamification as a personalization engine for neurodivergent users. Specifically, gamification strategies that adjust in real-time by modulating difficulty levels, pacing, feedback frequency, and content sequencing enhance learner engagement, mitigate overload, and improve LOs.

Key techniques identified include:

- Multimodal feedback loops (e.g., combining audio prompts with visual animations)
- Sensory-aware User Interface/User Experience (UI/UX) design, minimizing cognitive noise while maintaining engagement
- Reward systems personalized through avatars, badges, and creative affordances
- Dynamic challenge scaling based on learner performance or biometric or behavioral cues

AI-driven personalization (e.g., using RL or real-time learning analytics) enables instructional alignment with individual preferences and needs. This includes optimizing flow states, preventing disengagement, and reinforcing motivation through targeted micro-interventions. These findings suggest a gap in current practice, where static gamification schemes often dominate despite growing evidence favoring adaptive models.

RQ 3: What impact does the integration of advanced intelligent technologies have on enhancing student performance in personalized e-Learning platforms?

Advanced intelligent technologies, including ML, RL, generative AI, and immersive XR, exhibit significant utility in developing responsive, learner-centered settings. These technologies facilitate the creation of environments that can compensate for attention or processing challenges. Unlike traditional systems, these platforms facilitate:

- Predictive modeling for early detection of disengagement or learning bottlenecks
- Real-time content adaptation, aligning tasks with learner state
- Emotion-aware interaction, using affective computing to adjust delivery tone or pacing
- Immersive experiences, which compensate for attention deficits through rich sensory input

This aligns with theoretical models of adaptive learning and learner-centered design, reinforcing the value of real-time responsiveness and contextual intelligence in education. However, few empirical studies rigorously validate their use in neurodivergent populations, highlighting an urgent need for domain-specific implementations and longitudinal validation.

6. Implications of the Findings and Conclusion

The findings of this SLR point out the transformative potential of integrating adaptive gamification and intelligent technologies in e-Learning environments to support neurodivergent learners. These insights yield important practical and research implications, as well as a clear direction for future investigations.

6.1 Practical Implications

To build inclusive and personalized e-Learning ecosystems, current platforms must be restructured to address the sensory, cognitive, and behavioral diversity of neurodivergent students. Based on the reviewed literature, the following design recommendations are essential:

- Design for cognitive accessibility: Implement adaptive gamification techniques that include task decomposition, minimalist UI/UX, and personalized difficulty scaling to reduce cognitive overload.
- Adopt multimodal content delivery: Support learning via text, visuals, audio, and haptics to accommodate varying sensory processing preferences.
- Integrate inclusive design frameworks: Apply Universal Design for Learning (UDL) and Personalization for Adaptive Gamified Education (PAGE) principles to ensure accessibility and flexibility.
- Employ AI-driven personalization: Use machine learning models for dynamic adaptation of content pacing, sequencing, and feedback mechanisms.
- Use of emotion-aware technologies: Utilize affective computing to detect user frustration or disengagement in real time and trigger adaptive support.
- Enable learner-driven customization: Incorporate customizable avatars, scaffolded learning structures, and gamified reward systems tailored to learner profiles.

These strategies aim to enhance learner engagement, reduce anxiety, and improve retention and learning outcomes across neurodiverse populations.

6.2 Research Implications

Despite the expanding body of work on adaptive and gamified e-Learning, there remains a critical gap in rigorous empirical studies specifically targeting neurodivergent populations and their unique learning requirements. To advance the field, several key research directions are recommended:

- Focused empirical studies: Address the lack of dedicated investigations on the effect of adaptive gamification on engagement, KR, and LOs among neurodivergent students.
- Profiling for personalization: Develop real-time neurodiversity-aware profiling models using cognitive assessments, behavioral analytics, and learning analytics.
- Framework refinement and validation: Adapt and empirically test theoretical models, such as UDL, PAGE and reinforcement learning within neurodivergent learning contexts.
- Sustained engagement modeling: Explore the role of affective computing, adaptive feedback loops, and motivational design in maintaining long-term engagement.
- Mixed-methods evaluation: Employ integrative approaches that combine quantitative learning analytics with qualitative user feedback to assess usability, effectiveness, and learner satisfaction.
- Ethical considerations in personalization: Examine transparency, algorithmic fairness, bias mitigation, and data privacy in the deployment of AI-driven personalization.

These areas present critical opportunities for expanding evidence-based practices in inclusive e-Learning design.

6.3 Future Research Directions

Building upon the identified gaps and emerging technologies, this review outlines the following strategic research priorities:

- Framework Development: Construct a theoretically grounded and empirically validated framework for inclusive adaptive e-Learning that integrates UDL principles and assistive technologies.
- Longitudinal Impact Studies: Conduct long-term studies to evaluate the sustained effects of adaptive and gamified learning environments on academic and behavioral outcomes among neurodivergent learners.
- Sensory and Cognitive Adaptation: Investigate how digital platforms can mitigate sensory overload and cognitive strain through customizable interfaces and assistive supports.
- Generative AI for Personalization: Evaluate the use of generative AI in creating personalized learning trajectories, with a focus on fairness, transparency, and content bias.
- Immersive Learning Environments: Explore the impact of augmented and virtual reality in providing experiential learning tailored to the sensory and cognitive profiles of neurodivergent users.
- Digital Inclusion Strategies: Examine scalable approaches to reduce the digital divide, ensuring equitable access to adaptive learning technologies in both rural and urban settings.

6.4 Conclusion

This systematic literature review highlights the untapped potential of adaptive gamification, AI-driven personalization, and inclusive design in transforming e-Learning for neurodivergent learners. This paper emphasizes the importance of creating personalized adaptive systems tailored to diverse cognitive profiles that focus on measurable outcomes such as engagement, knowledge retention, and learning performance. However, a notable limitation is the lack of longitudinal studies that assess the sustained impact of these technologies on neurodivergent learners. Despite the limited empirical evidence, the review maps out areas that merit further investigation and provides a foundation for future research. Focused research into personalized adaptive systems, sensory-friendly interfaces, ethically responsible gamification strategies, and effective knowledge retention learning approaches will help bring more neurodivergent individuals into the mainstream and create a more inclusive and equitable society through accessible education.

AI Statement: Large language models were used for sentence restructuring and grammar correction.

Ethics Statement: Ethics approval is not required in this study.

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Comparing Student Attitudes of Cheating Behaviors in the Physical and Online Environments with an Emphasis on AI Usage

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Abstract: This study was conducted to compare students' beliefs about the seriousness of cheating behaviors in the physical and online environment and to analyze how these beliefs relate to self-reported cheating behaviors. Given the recent advances of artificial intelligence (AI) and its growing presence in the college classroom, specific emphasis is placed on cheating behaviors related to this technology. Using a quantitative descriptive approach, a survey was distributed to 328 undergraduate students at a small suburban college in the United States. Using a 5-point Likert scale, students were asked to rank the perceived seriousness of 25 cheating behaviors related to the physical and online classroom environments and to report how frequently they engaged in each of the behaviors. Fifteen of the cheating behaviors were comparable across both environments and an additional 5 behaviors specific to each environment were included. The study aimed to address the following research questions: (RQ1) Is there a difference between the perceived seriousness of academic cheating behaviors in the physical classroom compared to the online classroom? (RQ2) Do students with online experience rank cheating behaviors in the online environment as more serious than those students without online experience? (RQ3) Do students self-report higher levels of cheating online than in the physical classroom? (RQ4) Do students who perceive certain cheating behaviors as more serious forms of cheating, self-report less cheating of those behaviors? (RQ5) Is AI perceived as a more acceptable academic cheating behavior compared to other cheating behaviors? (RQ6) Are students self-reporting the use of AI as frequently as other cheating behaviors in the online and physical classrooms? For RQ1 a Wilcoxon signed rank test revealed that environment does matter with 6 out of 15 cheating behaviors being perceived to be more serious in the online environment and 1 behavior perceived to be more serious in the physical environment. For RQ2, a Mann-Whitney U test revealed that experience does matter with 14 out of 20 behaviors ranked as more unacceptable for students that had online experience. The Wilcoxon signed rank test showed that students were more likely to self-report cheating for 6 of the 15 behaviors in the physical environment so for RQ3 there is not evidence that students cheat more often online. Spearman's rank correlation was used to address RQ4 revealing that overall, students who rank behaviors as more extreme, self-report those behaviors less often. For RQ5 it was found that using AI for homework assignments was considered generally more acceptable than most other cheating behaviors and for RQ6, students were found to be reporting the usage of AI as frequently or more frequently compared to most other cheating behaviors.

Keywords: Artificial Intelligence in education, Online learning, Classroom, Academic cheating, Academic dishonesty

1. Introduction

The methods for delivering course content to undergraduate students has been evolving over the last couple of decades integrating more online learning into and in place of the traditional face-to-face learning environment. In 2005, 3.2 million higher education students in the United States were taking at least one online course (Allen and Seaman 2006). By 2016 this number had risen to 6.4 million (Seaman, Allen and Seaman, 2018) and by 2021, it had grown to 9.4 million which represents 61 percent of all undergraduate students in the U.S. (U.S. Department of Education, 2022).

The trend in online enrollment was starting to take shape in the early 2000's but was accelerated during the worldwide pandemic. The popularity of e-learning grew as schools, colleges, and universities started introducing online and blended learning methods while in-person education was unavailable. Similarly, during the pandemic, students had limited options for continuing in their traditional face-to-face courses and thus many had to adjust to the online learning environment with little or no prior experience with this method of instruction. As such, many online services that were available to students before the pandemic such as private tutoring and online companies offering homework assistance for a fee received a boost. As more students began navigating the online learning environment looking for resources to help them succeed, the existence of these resources became more widely accessible. Although post-Covid most higher education institutions transitioned back to face-to-face teaching, many colleges and universities perceived the adoption of e-learning as an opportunity for growth and began offering more online learning options than they did before or began new online programs to meet demand.

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While the benefits of online learning for college students are abundant (flexibility, convenience, cost-savings), there are many potential disadvantages as well. To be successful in the online environment, college students must be self-motivated, independent learners with good time management skills, traits not always highly developed by students during their high school years. In addition, a lack of student feedback and lower rates of interactions and engagement among the instructor and the student can lead to gaps in skill development especially in the area of communication which is essential for students when they enter the workforce (Sevnarayan, 2022; Noorbehbahani, Mohammadi and Aminazadeh, 2022.) Social isolation is also a concerning factor among students who choose online learning as it can lead to mental health issues stemming from stress and anxiety (Gibbons, Mize and Rogers, 2002; Lee and Aslam, 2023).

Finally, a major concern of online learning present both pre and post-Covid is the issue of academic dishonesty. Academic dishonesty is often used as a general term to refer to any fraudulent actions by a student to use unauthorized means in any academic work (Theart and Smit, 2012). Academic cheating on the other hand, is often used to describe specific behaviors and has been defined as 'any action taken before, during, or after the administration of a test or assignment, that is intended to gain an unfair advantage or produce inaccurate results,' (Cizek, 2012, p.16).

Extensive research has been conducted on academic cheating in both the face-to-face and online environments (Adzima, 2020). More recently, research has begun to explore how advances in Generative artificial intelligence (GenAI) impact academic integrity within the online environment suggesting rising levels of cheating using automated plagiarism and chatbots to complete assignments (Nguyen and Goto, 2024; Sholikhah *et al.,* 2023; Naidu and Sevnarayan, 2023) as well as a loss of academic integrity in online assessments (Susnjak, 2022; Humble et al., 2024).

Although there are many scholarly articles and studies focusing on academic dishonesty in the face-to-face and online environments, and an increasing number of articles beginning to examine the impact of integrating GenAI tools such as ChatGPT (Generative Pre-trained Transformer) in the classroom, there remains a gap in understanding what students consider to be acceptable behavior when it comes to using technology in different environments. This paper seeks to address this gap by (1) analyzing how students feel about the acceptability or severity of various cheating behaviors by comparing attitudes in the online versus traditional face-to-face environments and (2) examining self-reported cheating behaviors in these two environments. A subsequent and parallel goal in this paper is to analyze whether the newer types of cheating behaviors (those that make use of AI) are considered more acceptable and thus occur as, or more frequently compared to other more traditional cheating behaviors.

2. Literature Review

Academic dishonesty is not a new phenomenon. Concerns over academic misconduct can be found as early as the 1960's when the first large-scale survey from Columbia University in the United States revealed that issues such as cheating on exams and tests and plagiarizing on papers and assignments was perceived to be a problem by academic deans and student body presidents (Bowers, 1964). The study also revealed that three-fourths of the 5,000 respondents in the study had engaged in one or more acts of academic dishonesty (Mcabe and Trevino, 2001). From the 1960s to the 1990s much of the literature on academic dishonesty focused on individual factors such as gender, age, grade point average, and work ethic and a few studies included contextual factors such as honor codes, faculty responses to cheating and social learning (McCabe and Trevino, 2001).

With advances in technology and Internet usage becoming more commonplace in the early 2000's, there were many claims and expectations that the level of academic dishonesty was going to rise (McCabe 2001). Ali, Sultan and Aboelmaged (2021) performed a bibliometric analysis revealing that between 2000-2020 there was substantial growth in research pertaining to academic misconduct. Their findings found a cluster of keywords revealing four major themes being addressed during this timeframe related to the issues addressed in this paper. The first theme revealed that plagiarism was the most common keyword with many articles focusing on plagiarism policies and perceptions. For instance, research showed that many students found plagiarism policies difficult to understand (Gullifer and Tyson, 2014; Leonard *et al.,* 2015; Palmer, Pegrum and Oakley, 2019) with new undergraduate students having more difficulty than postgraduate students (Newton, 2016). A more recent review of the literature found that the most common reasons for committing plagiarism are easy access to electronic resources, being unaware of the instructions, a busy schedule, an abundance of homework and laziness (Kampa *et al.,* 2025). Finally, a new term has emerged in this area of research that combines AI and plagiarism known as "AI-giarism." This new terminology encompasses unethical practices using AI technologies to generate content without appropriate citation (Chan 2025). A study by Chan (2025) finds that students are not as well informed about what constitutes the misuse of AI tools in academic writing (AI-giarism) compared to more traditional forms of plagiarism.

The second theme discussed by Ali, Sultan and Aboelmaged (2021) and found to be prevalent in the research from 2000-2020, is referred to as contract cheating which occurs when students submit work that has been completed by someone else. Within this theme, various topics are discussed such as the key facilitators of contracting like higher access to the Internet, social media or other website resources (Trushell, Byrne, and Simpson, 2012; Rowland *et al.,* 2018). Additional research in this area focused on the environment with findings that online students are more apt to engage in this type of academic misconduct than residential students (Lancaster and Clark, 2014).

The third important theme in the review dealt with academic misconduct in online education. These studies compare misconduct between online and face-to-face students and suggest strategies to mitigate cheating. Although there are many studies that reveal both faculty (Guyette, King and Piotrowski, 2008; Rogers, 2006; Kennedy *et al.,* 2000; Patnaude, 2008) and students (Dillé, 2011; Kennedy *et al.*, 2000; King, Guyette and Piotrowski, 2009; Miller and Young-Jones, 2012; Watson and Sottile, 2010) perceive online testing to offer more cheating opportunities than in face-to-face, proctored learning environments, research that compares actual cheating behaviors between the online and traditional classrooms offers mixed results.

For example, Gullifer and Tyson (2014), Peled (2019), Hart and Morgan (2010), Kidwell and Kent (2008), Stuber-McEwan, Wisely and Hoggatt (2009), Miller and Young-Jones (2012) report less incidents of online cheating, while others find more incidents of cheating in the online classroom (Lanier, 2006; Goff, Johnston, and Bouboulis, 2020; Arnold, 2016; Fendler, Beard and Godbey, 2021). There are also studies that find the levels of cheating to be comparable between online and traditional face-to-face courses (Grijalwa, Nowell and Kerkvliet*,* 2006; Watson and Scottie, 2010). The strategies suggested to reduce cheating in online education include formulating strong regulations and confirming students' identity, the use of web proctoring technology, and advanced software to detect and prevent instances of academic dishonesty (McGee, 2013; Hylton, Levy, and Dringus, 2016; Tsai, 2016).

The fourth theme emerging as an important topic during this timeframe is academic collusion. This theme received relatively less attention compared to the first three themes but remains a critical issue within the academic dishonesty literature. Academic collusion most commonly occurs when students work together on an assignment or exam without permission from their instructor. Research has found increasing incidents of academic collusion (Kim and LaBianca 2018; Newton 2016). According to Barrett and Cox (2005) and Taylor, Glaister, and Sutton (2007) reasons for this trend could be attributed to confusion amongst students when distinguishing between legitimate collaboration and collusion.

Another important topic or theme related to academic dishonesty (not directly specified in the themes mentioned above) are the contextual factors such as student perceptions of cheating, peer behavior, perceived opportunities, classroom environment, and faculty actions that play a significant role in developing student attitudes and beliefs about academic dishonesty. Research has shown that "peers' cheating behavior, peers' disapproval of cheating, a student's perception of the culture of academic integrity on campus, and the perceived severity of penalties of cheating" are related to students' reported academic misconduct (McCabe, Butterfield, and Trevino, 2012, p. 113).

Similarly, according to Chala (2021), differences in socio cultural settings, demographic composition and educational policies and programs influence students' beliefs or attitudes about the severity of various cheating behaviors and these beliefs affect both the frequency and likelihood of the behavior. For example, if students believe that looking at an exam that someone kept from a previous semester is trivial cheating, then it is likely that this behavior will occur more often. More generally, studies have shown that students who have a favorable attitude toward academic misconduct display higher levels of cheating behaviors (Elias and Farag, 2010; Lee *et al.,* 2017; Yu *et al.,* 2018; Renata *et al*., 2024). Dyer, Pettyjohn and Saladin, (2020) hypothesized that there would not be a difference in student attitudes regarding the acceptability of cheating behaviors in unproctored versus proctored settings but found that students considered cheating as being more acceptable on an unproctored test than on a proctored test. Overall, these findings suggest that investigating student beliefs about the severity of cheating behaviors in both the physical and online environments is of particular importance as technological advancements, specifically in AI, continue to offer new ways and opportunities for students to engage in academic dishonesty.

3. Methodology

3.1 Research Problem

Despite the increasing number of scholarly articles and studies examining online cheating behaviors and the use of AI in the college classroom, there is still a lack of research that examines student beliefs about the seriousness or acceptability of those behaviors in different environments. Furthermore, given the rapid advancement of technologies, studies that examine self-reported cheating behaviors involving AI are still in their infancy.

3.2 Research Objective

This study compares students' beliefs about the seriousness of cheating behaviors in the physical and online environment and analyzes how these beliefs relate to self-reported cheating behaviors. Specific emphasis is placed on cheating behaviors related to AI.

3.3 Research Questions

To address the research objectives, this study examines the following six research questions:

RQ1: Is there a difference between the perceived seriousness of academic cheating behaviors in the physical classroom compared to the online classroom?

RQ2: Do students with online experience rank cheating behaviors in the online environment as more serious than those students without online experience?

RQ3: Do students self-report higher levels of cheating online than in the physical classroom?

RQ4: Do students who perceive certain cheating behaviors as more serious forms of cheating, self-report less cheating of those behaviors?

RQ5: Is AI perceived as a more acceptable academic cheating behavior compared to other cheating behaviors?

RQ6: Are students self-reporting the use of AI as frequently as other cheating behaviors in the online and physical classrooms?

3.4 Materials and Methods

This research employed quantitative research design, utilizing an online survey as the primary data collection instrument. The author developed and distributed the survey using Qualtrics. The survey was administered at a small suburban four-year college to undergraduate students in the United States taking business courses during the 2024-25 academic year. Participants used a hyperlink that was supplied by their instructor or made available to them at a student lab. Participants were made aware that the surveys would remain anonymous, and that any identifying information would not be used to match student answers for any purpose. Students were offered extra credit for completing the survey as determined by their individual instructors.

Data were collected from 328 students, however, response rates varied somewhat by question. Sixty-three percent of the participants were freshman, 22 percent were sophomores, 8 percent were juniors and 7 percent were seniors. Approximately 63 percent of participants had declared (or intended to declare) a traditional business major (finance, marketing, economics, etc.), with the remaining participants majoring in (or planning to major in) fields from other schools within the college such as engineering, humanities, and science. Variation in the age of the students was limited, with 90.5 percent being between the ages of 18-21, 8.0 percent being between 22-25 and 1.5 percent being over 25. Female respondents made up approximately 31 percent of the survey population, and approximately 44 percent of participants had taken both online and traditional face-to-face courses.

The survey was designed to build upon existing research and address gaps in the literature related to new forms of academic cheating such as the use of AI. Questions for this survey were adopted from other studies investigating the perceived seriousness of cheating behaviors and the perceptions of cheating online versus the traditional classroom (Oneill and Pfeifer, 2012; Witherspoon et al., 2012; Chala, 2021; Miller and Young-Jones, 2012). The author piloted the questions pertaining to AI. The first section of the survey introduced Likert scale questions regarding student beliefs about the acceptability of the described cheating behaviors (rated in five scale, i.e. 1=Not at all ….. 5 = Extremely). Participants were asked to rank the severity of 25 behaviors from the perspective of both the physical and online learning environments. Fifteen of the behaviors were common among both environments. The second set of questions dealt with how frequently the students had engaged in those same set of cheating behaviors in both the face-to-face classroom and the online classroom also formatted as Likert scale (with 1 = Never ….. 5 = Always). Only participants who had taken online courses answered the online cheating behavior frequency questions.

3.5 Results

The purpose of the first two research questions, (R1 and R2) is to assess the perceived seriousness of academic cheating behaviors among undergraduates and look for differences in the rankings between the face-to-face and online classroom environments as well as possible differences between student beliefs for those with and without online experience.

Students ranked the severity of behaviors 1-15 (B1-B15) for both environments. Students ranked behaviors 16-20 for only the physical environment and behaviors 21-25 for only the online classroom. The behaviors from the survey are listed in the first column of Table 1 (and all subsequent tables). A Wilcoxon signed rank test was conducted to compare the reported level of seriousness for cheating between the physical classroom and the online classroom for the first 15 behaviors listed. Table 1 gives the z-value in column three which determines if the null of “no difference between the paired observations” can be rejected. Seven of the listed behaviors (B1, B6, B8, B10, B11, B12, B14) were significantly different at the five percent level (denoted with ** in the tables) when comparing the median of the differences between the two environments. Behavior 1 was perceived to be more serious in the physical environment and the remaining six behaviors were perceived to be more serious in the online environment. The absolute value of effect size (Pearson’s r) is listed in the third column for the seven statistically significant behaviors. According to Cohen (1988) an $r < 0.10$ has little effect, an r between 0.1 and 0.3 has a small effect, an r greater than 0.3 but less than 0.5 has a medium effect, and an r greater than 0.5 has a large effect. B6 (falsifying reasons for missing an exam) and B11 (working on a take home exam with others without permission) both had a medium effect, while the other behaviors B1, B8, B10, B12, and B14 were found to have a small effect (column four).

To analyze whether students with and without online experience have different beliefs about the severity of cheating behaviors in the online environment, a Mann-Whitney U test was conducted to determine if there is a difference in the median rankings for behaviors B1-B15 and B21-B25. As reported in the fourth column of Table 1, 14 of the 20 behaviors (B1, B2, B4, B5, B6, B7, B9, B10, B11, B12, B13, B23, B24, B25) were found to be significantly different. More specifically, all 14 behaviors were ranked as more unacceptable for those students who had online experience, although in all cases, the effect size was determined to be small (columns six and seven).

Table 1: Differences in Cheating Behaviors in the Physical and Online Classrooms and Between Students with and without Online Experience

Behaviors Physical and Online Classrooms	Obs	Wilcoxon signed rank z-value	Effect size (r)	Obs	Mann-Whitney z-value	Effect size (r)
B1: Copying a classmate’s answers while taking an exam	328	1.93**	0.11	321	-3.79**	0.21
B2: Permitting others to use my exam answers	325	0.41		319	-2.25**	0.13
B3: Using an old exam to study while knowing it hasn’t been made available to others	327	0.01		320	-1.58	
B4: Letting someone else complete an assignment for you and taking credit	323	-1.34		316	-2.46**	0.14
B5: Not participating in a group assignment and taking credit	323	-0.81		317	-2.77**	0.16
B6: Falsifying reasons for missing an exam	327	-6.55**	0.36	320	-2.78**	0.16
B7: Letting someone else write a paper for you	322	-0.55		318	-2.39**	0.13
B8: Buying a paper or assignment from an online source	325	-2.57**	0.14	320	-1.81	
B9: Paraphrasing/copying a few sentences from an electronic source without referencing	323	-1.03		318	-2.02**	0.11
B10: Working on an assignment with others when asked to work individually	325	-2.69**	0.15	319	-3.61**	0.20

Behaviors Physical and Online Classrooms	Obs	Wilcoxon signed rank z-value	Effect size (r)	Obs	Mann-Whitney z-value	Effect size (r)
B11: Working on a take home exam with others when asked to work individually	320	-7.57**	0.42	314	-2.37**	0.13
B12: Using any advantage to improve your grade that is not available to everyone	320	-4.52**	0.25	316	-2.34**	0.13
B13: Breaking a rule that was explicitly mentioned in the syllabus	324	-1.04		319	-2.12**	0.12
B14: Using artificial intelligence software to complete a homework assignment	288	-2.50**	0.15	283	-1.25	
B15: Using artificial intelligence to write a paper	290	-1.05		284	-0.45	
B16: Writing notes on your hand or other area of the body						
B17: Using a cell phone to look up an answer while taking an exam						
B18: Asking a friend who has taken the exam previously about the questions						
B19: Using your notes to look up an answer when the teacher isn't looking						
B20: Texting exam answers to friends during an exam						
B21: Looking up answers to an online homework assignment from another Internet source				316	-1.75	
B22: Looking up answers to an online exam from another Internet source				319	-1.55	
B23: Buying exam answers from an online site or person				318	-2.85**	0.16
B24: Letting a friend or other person take an exam for you				319	-3.35**	0.19
B25: Using screen sharing software such as Zoom, Google Meet, collaborate with others while taking an online exam				317	-2.78**	0.16

Notes: Obs = Observations, Pearson correlation coefficient is labeled as “r”

For discussion purposes, Table 2 presents the students’ attitudes toward the level of cheating as percentages for each of the 15 comparable behavior categories and Table 3 presents the percentages for the separate behaviors relevant to only one type of learning environment. Analyzing the percentages provides a summary for each learning environment and helps to better evaluate how students rank the severity of different behaviors based on their online experience.

Table 2 reveals that B1, “copying a classmate’s answers while taking an exam” and B7, “letting someone else write a paper for you” were the two highest ranked cheating behaviors from both the physical and online perspectives. B1 ranged from 52 to 71 percent of students choosing the extremely serious category, and B7 ranged from 56 to 67 percent of students choosing the extremely serious category. When examining the “not at all” serious choice category, B10, “working on an assignment when asked to work individually” and B5, “not participating in a group assignment and taking credit,” were the behaviors found to be most trivial in the physical environment. B12, “using any advantage to improve your grade that is not available to others” and B3, “using an old exam to study,” were considered the least serious cheating behaviors in the online environments. For B12, between 15 -26 percent of students found this behavior to be “not at all” serious and for B3, the range was 11 to 17 percent.

In Table 3, the two behaviors perceived to be the most severe for the physical classroom are B17, “using a cell phone to look up answers while taking an exam” and B20 “texting answers to a friend during exam,” with 76 percent and 68 percent of students rating those behaviors as extreme forms of cheating. For the online only behaviors, B24, "letting a friend take an exam for you" was ranked the most severe at 67 percent, followed by B23, "buying exam answers from an online site or person," at about 58 percent for students with and without online experience. When comparing those students with online experience to those students who have not taken an online course, it is worth noting that all five behaviors (B21-B25) received a higher percentage of "extremely serious" rankings from those with online experience and all five behaviors received a higher percentage of "not at all" serious from the students without online experience. Specifically, 16 percent of students without online experience claimed that looking up homework answers on the Internet is not at all serious and 10 percent claimed that looking up exam answers is not at all serious. For students with online experience, these numbers were about eight and three percent respectively.

To examine the third research question (R3) "do students self-report higher levels of cheating behaviors online than in the physical classroom?" data for the 15 similar behaviors between online cheating and physical face-to-face cheating were examined for those students who had experience in the online classroom. Table 4 (column three) displays the results of the Wilcoxon signed rank test which shows that there was a significant difference in the medians for six of the behaviors (B1, B3, B6, B8, B10, and B12) implying that students were statistically more likely to self-report cheating behaviors in the physical classroom for these six items. B6 (falsifying reasons for missing an exam) showed a medium effect size when calculating the rank correlation, (z-value/ square root of observations) while the other behaviors revealed a small effect as displayed in column four of Table 4.

Table 2: Ranked Cheating Behaviors as Percentages

Behaviors Physical and Online Classrooms	Physical Extreme	Online All Extreme	Online Experience Extreme	Online No Experience Extreme	Physical Very	Online All Very	Online Experience Very	Online No Experience Very
B1: Copying a classmate's answers while taking an exam	64.94	60.06	70.92	51.67	19.51	22.87	19.15	26.67
B2: Permitting others to use my exam answers	57.80	54.60	60.00	50.84	20.49	26.69	28.57	25.70
B3: Using an old exam to study while knowing it hasn't been made available	21.95	23.55	24.29	23.33	17.68	18.04	20.71	16.11
B4: Letting someone else complete an assignment for you and taking credit	52.44	54.18	62.04	49.72	21.95	20.43	18.98	21.23
B5: Not participating in a group assignment and taking credit	35.17	38.89	43.48	35.75	27.52	22.22	4.32	19.55
B6: Falsifying reasons for missing an exam	19.57	30.89	37.14	26.67	21.41	22.02	23.57	21.11
B7: Letting someone else write a paper for you	58.46	60.31	66.91	55.87	21.23	20.31	20.14	20.67
B8: Buying a paper or assignment from an online source	49.08	55.05	60.71	51.67	22.39	21.41	20.00	23.33
B9: Paraphrasing/copying a few sentences without referencing	27.69	30.77	35.25	28.49	24.00	24.00	25.18	22.91
B10: Working on an assignment with others when asked to work individually	19.02	20.25	28.78	14.44	17.18	22.09	21.58	21.67

Behaviors Physical and Online Classrooms	Physical Extreme	Online All Extreme	Online Experience Extreme	Online No Experience Extreme	Physical Very	Online All Very	Online Experience Very	Online No Experience Very
B11: Working on a take home exam with others when asked to work individually	23.31	38.01	42.22	34.64	24.23	25.86	29.63	23.46
B12: Using any advantage to improve your grade that is not available to everyone	16.05	21.98	29.20	16.20	21.30	20.12	18.98	21.79
B13: Breaking a rule that was explicitly mentioned in the syllabus	41.23	44.48	51.08	41.11	27.69	25.46	24.46	26.67
B14: Using artificial intelligence software to complete a homework assignment	24.83	30.00	32.76	29.34	22.07	16.90	20.69	14.97
B15: Using artificial intelligence to write a paper	40.55	40.89	43.59	40.12	22.34	24.40	22.22	25.15

Table 2: Ranked Cheating Behaviors as Percentages (continued)

Behaviors Physical and Online Classrooms	Physical Somewhat	Online All Somewhat	Online Experience Somewhat	Online No Experience Somewhat	Physical Slightly	Online All Slightly	Online Experience Slightly	Online No Experience Slightly
B1: Copying a classmate's answers while taking an exam	5.18	9.15	8.51	10.00	2.13	3.05	0.71	4.44
B2: Permitting others to use my exam answers	9.79	8.59	5.71	10.61	3.67	5.52	4.29	6.70
B3: Using an old exam to study while knowing it hasn't been made available	29.57	26.30	29.29	24.44	13.41	14.98	14.29	15.56
B4: Letting someone else complete an assignment for you and taking credit	12.20	16.41	13.87	18.44	4.57	4.33	4.38	3.91
B5: Not participating in a group assignment and taking credit	18.35	21.30	6.47	20.67	8.87	11.42	0.00	16.20
B6: Falsifying reasons for missing an exam	27.52	25.99	25.00	26.67	15.90	11.62	9.29	13.33
B7: Letting someone else write a paper for you	9.23	10.46	8.63	11.73	2.15	3.38	2.16	4.47
B8: Buying a paper or assignment from an online source	12.88	13.76	13.57	12.78	6.13	4.28	3.57	5.00
B9: Paraphrasing/copying a few sentences without referencing	26.15	22.46	22.30	22.91	12.00	15.08	14.39	15.08
B10: Working on an assignment with others when asked to work individually	31.29	30.06	31.65	30.00	21.17	17.79	12.23	21.67
B11: Working on a take home exam with others when asked to work individually	25.15	19.00	17.78	20.67	15.34	9.03	5.19	11.17

Behaviors Physical and Online Classrooms	Physical Somewhat	Online All Somewhat	Online Experience Somewhat	Online No Experience Somewhat	Physical Slightly	Online All Slightly	Online Experience Slightly	Online No Experience Slightly
B12: Using any advantage to improve your grade that is not available to everyone	23.15	25.39	24.09	26.82	13.27	13.31	12.41	13.97
B13: Breaking a rule that was explicitly mentioned in the syllabus	17.85	17.18	17.27	16.11	6.46	7.98	5.04	10.00
B14: Using artificial intelligence software to complete a homework assignment	21.72	26.90	24.14	28.74	16.90	13.45	12.07	12.57
B15: Using artificial intelligence to write a paper	19.59	19.24	18.80	20.36	7.90	6.87	10.26	4.19

Table 2: Ranked Cheating Behaviors as Percentages (Continued)

Behaviors Physical and Online Classrooms	Physical Not at all	Online All Not at all	Online Experience	Online No Experience
B1: Copying a classmate's answers while taking an exam	8.23	4.88	0.71	7.22
B2: Permitting others to use my exam answers	8.26	4.60	1.43	6.15
B3: Using an old exam to study while knowing it hasn't been made available	17.38	17.13	11.43	20.56
B4: Letting someone else complete an assignment for you and taking credit	8.84	4.64	0.73	6.70
B5: Not participating in a group assignment and taking credit	10.09	6.17	0.72	7.82
B6: Falsifying reasons for missing an exam	15.60	9.48	5.00	12.22
B7: Letting someone else write a paper for you	8.92	5.54	2.16	7.26
B8: Buying a paper or assignment from an online source	9.51	5.50	2.14	7.22
B9: Paraphrasing/copying a few sentences without referencing	10.15	7.69	2.88	10.61
B10: Working on an assignment with others when asked to work individually	11.35	9.82	5.76	12.22
B11: Working on a take home exam with others when asked to work individually	11.96	8.10	5.19	10.06
B12: Using any advantage to improve your grade that is not available to everyone	26.23	19.20	15.33	21.23
B13: Breaking a rule that was explicitly mentioned in the syllabus	6.77	4.91	2.16	6.11
B14: Using artificial intelligence software to complete a homework assignment	14.48	12.76	10.34	14.37
B15: Using artificial intelligence to write a paper	9.62	8.59	5.13	10.18

Table 3: Cheating Behaviors Ranked by Environment

Behaviors Physical Classroom Only	Physical Obs	Extreme	Very	Somewhat	Slightly	Not at all
Writing notes on your hand or other area of the body	328	55.18	23.48	9.45	4.27	7.62
Using a cell phone to look up an answer while taking an exam	325	76.00	11.69	3.69	1.23	7.38
Asking a friend who has taken the exam previously about the questions	327	11.31	13.15	27.83	23.55	24.16
Using your notes to look up an answer when the teacher isn't looking	327	53.52	26.91	9.48	1.83	8.26

Behaviors Physical Classroom Only	Physical Obs	Extreme	Very	Somewhat	Slightly	Not at all
Texting exam answers to friends during an exam	324	67.90	18.21	4.94	0.93	8.02
Not participating in a group assignment and taking credit	327	35.17	27.52	18.35	8.87	10.09
Behaviors Online Classroom Only (all observations)	**Online All Obs**	**Extreme**	**Very**	**Somewhat**	**Slightly**	**Not at all**
Looking up answers to a homework assignment from another Internet source	323	24.46	21.67	25.39	15.79	12.69
Looking up answers to an online exam from another Internet source	326	48.77	26.69	12.88	4.60	7.06
Buying exam answers from an online site or person	325	57.54	21.85	9.54	6.15	4.92
Letting a friend or other person take an exam for you	326	67.18	17.48	6.13	4.29	4.91
Using screen sharing software such as Zoom, Google Meet, or others to collaborate with others while taking an online exam	324	50.31	23.46	14.81	5.25	6.17
Behaviors Online Classroom Only (with online experience)	**Online Experience Obs**	**Extreme**	**Very**	**Somewhat**	**Slightly**	**Not at all**
Looking up answers to a homework assignment from another Internet source	138	27.54	23.19	26.81	14.49	7.97
Looking up answers to an online exam from another Internet source	139	50.36	32.37	12.23	2.16	2.88
Buying exam answers from an online site or person	138	64.49	23.91	6.52	3.62	1.45
Letting a friend or other person take an exam for you	139	76.98	13.67	5.76	1.44	2.16
Using screen sharing software such as Zoom, Google Meet, or others to collaborate with others while taking an online exam	137	57.66	23.36	14.60	1.46	2.92
Behaviors Online Classroom Only (with no online experience)	**No Online Experience Obs**	**Extreme**	**Very**	**Somewhat**	**Slightly**	**Not at all**
Looking up answers to a homework assignment from another Internet source	178	23.03	20.79	24.72	15.73	15.73
Looking up answers to an online exam from another Internet source	180	47.78	22.78	13.89	6.11	9.44
Buying exam answers from an online site or person	180	52.22	21.11	12.22	7.78	6.67
Letting a friend or other person take an exam for you	180	60.00	20.56	6.67	6.67	6.11
Using screen sharing software such as Zoom, Google Meet, or others to collaborate with others while taking an online exam	180	45.00	23.89	15.56	7.78	7.78

Notes: Obs = Observations, column headings are Likert scale anchors

Table 4: Frequency of Cheating Online versus the Physical Classroom and Percentage of Students who have Admitted to Cheating at Least Once

Behaviors Physical and Online Classrooms	Obs	z-value	Rank (r)	Obs Physical	Physical Cheating percent	Obs Online	Online Cheating percent
B1: Copying a classmate's answers while taking an exam	139	2.93**	0.25	320	23.13	139	12.23
B2: Permitting others to use my exam answers	138	0.60		317	19.56	139	17.27
B3: Using an old exam to study while knowing it hasn't been made available	139	3.47**	0.29	319	26.96	139	22.30
B4: Letting someone else complete an assignment for you and taking credit	137	0.55		318	11.95	139	9.35
B5: Not participating in a group assignment and taking credit	139	0.48		319	14.42	139	11.51
B6: Falsifying reasons for missing an exam	139	3.83**	0.32	320	18.75	139	9.35
B7: Letting someone else write a paper for you	139	0.40		320	7.19	139	6.47
B8: Buying a paper or assignment from an online source	139	2.10**	0.18	320	8.13	139	3.60
B9: Paraphrasing/copying a few sentences without referencing	136	0.38		318	39.94	138	42.03
B10: Working on an assignment with others when asked to work individually	139	2.18**	0.18	319	45.45	139	38.85
B11: Working on a take home exam with others when asked to work individually	138	1.05		320	26.25	138	25.36
B12: Using any advantage to improve your grade that is not available to everyone	138	2.57**	0.22	318	30.19	139	31.65
B13: Breaking a rule that was explicitly mentioned in the syllabus	138	0.02		318	24.21	139	30.94
B14: Using artificial intelligence software to complete a homework assignment	115	1.30		281	52.31	116	57.76
B15: Using artificial intelligence to write a paper	102	0.94		250	28.40	139	33.09
B16: Writing notes on your hand or other area of the body				320	17.81		
B17: Using a cell phone to look up an answer while taking an exam				319	14.42		
B18: Asking a friend who has taken the exam previously about the questions				320	56.56		
B19: Using your notes to look up an answer when the teacher isn't looking				320	11.88		
B20: Texting exam answers to friends during an exam				318	7.55		
B21: Looking up answers to an online homework assignment from another Internet source							51.08
B22: Looking up answers to an online exam from another Internet source							32.61
B23: Buying exam answers from an online site or person							4.32
B24: Letting a friend or other person take an exam for you							3.60
B25: Using screen sharing software such as Zoom, Google Meet, collaborate with others while taking an online exam							7.19

Notes: Obs = Observations, r = Spearman's rank correlation (rho)

Columns six and eight in Table 4 also displays the percentage of students who admitted to cheating at least once for each of the 15 similar behaviors and for the behaviors specific to each environment. For eleven of the behaviors, the percentage of students admitting to cheating at least once was greater for the physical classroom. Two of the behaviors had the same percentage of self-reported cheating (B9, B13), and the last two behaviors, B14 and B15 (which deal with the use of AI for homework and writing papers) were greater for the online environment.

For behaviors (B16-B20) that were only asked for the physical classroom, B18 (asking a friend who has taken the exam previously about the questions) was the highest self-reported cheating behavior at 57 percent, with the next highest, B16 (writing notes on your hand) at 18 percent. For behaviors (B21-B25) that were only asked for the online environment, B21 (looking up answers to a homework assignment from an Internet source) and B22 (looking up exam answers from an Internet source) were the two highest self-reported cheating behaviors with 49 percent of students admitting to doing B21 at least once and 31 percent admitting to doing B22 at least once.

To examine the fourth research question, "do students who perceive certain cheating behaviors as more serious forms of cheating, self-report less cheating of those behaviors?" (R4), Spearman's rank correlation (rho) is used for each of the cheating behaviors. Table 5 displays the results for each behavior and the associated p-value. Column three in the table displays the correlation between the acceptability of cheating and actual cheating in the physical classroom and column five displays the correlation between the acceptability of cheating and actual cheating in the online classroom. For the physical classroom, all but one behavior (B4) shows a statistically significant negative correlation between the acceptability of the behavior and the actual behavior. This implies that most students who rank a cheating behavior higher are less likely to self-report engaging in that behavior. The strength of the relationship between most of the beliefs and self-reported behaviors is considered "weak" with coefficients less than 0.30. However, two behaviors, B14 (paraphrasing without citation) and B20 (using AI for homework) have a medium relationship. For the online classroom, all but three behaviors (B1, B3, and B5) show a statistically significant negative correlation between beliefs and self-reported behavior. In this case all but four behaviors are considered weak relationships. The four that have medium effect relationships are B11(letting someone else complete an assignment for you), B12 (paraphrasing without citation), B16 (using screen-sharing to collaborate on exams), and B20 (breaking a rule not mentioned in the syllabus). Overall, given the results of both the physical and online correlation tests, most students who rank behaviors as more extreme, self-report those behaviors less often.

To examine the last two research questions "is generative AI perceived as a more serious academic cheating behavior compared to others? (R5) and "are students self-reporting the use of AI as frequently as other cheating behaviors in the online and physical classrooms?" (R6), it is useful to look back at Tables 2 and 4. In Table 2, "using artificial intelligence software to complete a homework assignment" was ranked as extremely serious by 25 percent of students for the physical classroom, 33 percent for the online classroom for students with online experience, and 29 percent for students without online experience. When combining the "extremely" and "very" serious categories the percentage increases to 47 percent for the physical classroom and 53 percent (online experience) and 44 percent (no online experience) for the online classroom. For the second AI question, "Using artificial intelligence to write a paper" the ranking for extremely serious was 41 percent for the physical classroom, 44 percent for the online classroom for students with online experience, and 40 percent for students without online experience. When combining the "extremely" and "very" serious categories the percentages are 63 percent for the physical classroom and 66 percent (online experience) and 65 percent (no online experience) for the online classroom.

To examine the last research question, (R6), Table 4 shows that 28 percent of students in the physical classroom self-reported using AI to write a paper at least once and 52 percent self-reported using AI to complete their homework at least once. For the online classroom, 33 percent self-reported using AI to write a paper and 58 percent self-reported using AI for homework at least once. Using AI to complete a homework assignment was the highest self-reported behavior that students admitted to doing at least once in both learning environments.

Table 5: Comparing Cheating Beliefs to Frequency of Cheating

Behaviors Physical and Online Classrooms	Physical Obs	Rank (r)	Online Obs	Rank (r)
B1: Copying a classmate's answers while taking an exam	321	-0.16**	139	-0.03
B2: Permitting others to use my exam answers	317	-0.12**	138	-0.24**

Behaviors Physical and Online Classrooms	Physical Obs	Rank (r)	Online Obs	Rank (r)
B3: Using an old exam to study while knowing it hasn't been made available	320	-0.22**	138	0.01**
B4: Letting someone else complete an assignment for you and taking credit	319	-0.20**	136	-0.33**
B5: Not participating in a group assignment and taking credit	319	-0.15**	137	-0.21**
B6: Falsifying reasons for missing an exam	320	-0.13**	138	-0.12
B7: Letting someone else write a paper for you	318	-0.20**	138	-0.28**
B8: Buying a paper or assignment from an online source	319	-0.16**	138	-0.10
B9: Paraphrasing/copying a few sentences without referencing	317	-0.36**	137	-0.47**
B10: Working on an assignment with others when asked to work individually	319	-0.26**	138	-0.23**
B11: Working on a take home exam with others when asked to work individually	320	-0.25**	133	-0.25**
B12: Using any advantage to improve your grade that is not available to everyone	316	-0.26**	136	-0.30**
B13: Breaking a rule that was explicitly mentioned in the syllabus	317	-0.27**	138	-0.38**
B14: Using artificial intelligence software to complete a homework assignment	279	-0.33**	114	-0.24**
B15: Using artificial intelligence to write a paper	249	-0.25**	116	-0.24**
B16: Writing notes on your hand or other area of the body	321	-0.22**		
B17: Using a cell phone to look up an answer while taking an exam	317	-0.12**		
B18: Asking a friend who has taken the exam previously about the questions	321	-0.24**		
B19: Using your notes to look up an answer when the teacher isn't looking	320	-0.21**		
B20: Texting exam answers to friends during an exam	315	-0.21**		
B21: Looking up answers to an online homework assignment from another Internet source			137	-0.21**
B22: Looking up answers to an online exam from another Internet source			137	-0.19**
B23: Buying exam answers from an online site or person			137	-0.25**
B24: Letting a friend or other person take an exam for you			138	-0.29**
B25: Using screen sharing software such as Zoom, Google Meet, collaborate with others while taking an online exam			136	-0.34**

Notes: Obs = Observations, r = Spearman's rank correlation (rho)

3.6 Discussion

The current study was designed to examine several research questions comparing student attitudes towards academic cheating behaviors and the frequency of cheating behaviors in the physical and online environments. Understanding how students feel about the severity of cheating behaviors in these two environments and examining the self-reported behaviors provides a framework for faculty and administrators as they continue to try and address the prevalence of academic cheating at their institutions.

For the first research question, the results showed that students perceive six of the behaviors to be more unacceptable in the online environment compared to the physical environment. Two of those behaviors deal with collaboration which is consistent with previous findings showing how the absence of a close relationship and interaction with an instructor can encourage unauthorized group work (Sendag, Duran and Fraser, 2012; McGee, 2013; Hearn Moore, Head, and Griffin, 2017). Students may find these behaviors more unacceptable because they suspect it is harder to get caught in the online setting (King, Guyette, and Piotrowski, 2009; Walsh *et al.,* 2021). The finding that not all cheating behaviors are considered equally unacceptable in both environments is worth additional consideration and further research. The reasons "why" students view cheating behaviors differently depending on the environment is an important question with limited coverage. Only one paper was found to address this issue citing a lack of proctoring, extenuating circumstances (pandemic), and cheating influences (Walsh *et al*., 2021). Additional research in this area is needed to gain perspective on how these beliefs are formed. Answers to these questions could help teachers and administrators develop strategies to ensure that all cheating behaviors are deemed unacceptable regardless of the learning environment.

Table 1 results address (RQ2) revealing that students with online experience tended to rank cheating behaviors as more unacceptable overall. In addition, for three of the five behaviors that were specific to online cheating opportunities (B23, B24, B25), the Mann-Whitney test revealed that students with online experience ranked them as more serious as well. This finding suggests that once students have online experience they may better understand or gain perspective as to why cheating behaviors in the online environment are just as unacceptable and thus will not perpetuate the idea that cheating is an accepted or expected behavior in this environment. Students with online experience may also better understand how online cheating can be detected through proctoring tools and other technologies.

The third research question (RQ3) asked if self-reported cheating behaviors online were more frequent than the physical classroom. When comparing median values, there were six behaviors for which students reported more cheating in the physical classroom and in all but three behaviors the percentage of students who self-reported cheating at least once was higher for the physical classroom (two of the behaviors reported the same number). This finding contrasts with studies such as Lanier (2006), Fendler, Beard and Godbey (2024) and Miller and Young-Jones (2012), who have found higher rates of cheating being reported in the online environment. However, the percentage of students self-reporting cheating at least once in the online environment for behaviors such as "looking up answers to an online homework assignment from another Internet source," and "looking up answers to an online exam from another Internet source," were still quite high at 51 percent and 33 percent respectively. These percentages are significant findings for faculty who are designing online courses since homework measures how well students understand course material, and exams are usually the main determinant for assessing if learning objectives are being met. These results also suggest that more advanced forms of proctoring such as monitoring students through webcams and using LockDown Browser are necessary to ensure that students are fairly assessed and that students are learning the material.

The fourth research question (RQ4) asked if students self-report less cheating for behaviors they deem more serious. The results from this survey provide evidence that this is true. Students who consider certain behaviors to be more unacceptable are less likely to self-report engaging in those behaviors in both the physical and online environments. This finding is consistent with previous studies such Dyer, Pettyjohn and Saladin, (2020) and Mensah, Azila-Gbettor and Appietu, (2016) whose results reveal both small and modest correlations between students' beliefs and their likelihood of engaging in cheating behaviors especially for proctored examinations. These results underscore the importance of studying student beliefs to better understand how to combat various forms of cheating. Determining why certain behaviors get labeled as "trivial" by students, will help faculty and administrators develop strategies that ensure all cheating behaviors are understood to be unacceptable.

Finally, the last two research questions focus on ranking the seriousness of AI as a cheating behavior and the frequency with which students are using it. To answer the research question (RQ5), "is AI perceived as a more acceptable compared to other cheating behaviors," the data from Table 2 can be further examined. Roughly 27 percent of students (when averaging across the two environments) consider using AI to complete a homework assignment to be an extremely serious form of cheating. This percentage is lower than all but three other cheating behaviors when looking at the ranking of "extremely serious" (B6 is 25 percent, B10 is 20 percent, B12 is 19 percent). These results provide evidence that most students (about three-quarters) do not consider this to be an extremely serious form of cheating compared to other behaviors and thus perceive it as more acceptable. Roughly 41 percent of students believe that using AI to write a paper is an extremely serious cheating behavior (again averaging across the two environments). Although this behavior is considered more serious relative to using AI for HW, it is still ranked as less serious than six other cheating behaviors.

The sixth research question, (RQ6) asks if students are self-reporting the use of AI as frequently as other cheating behaviors. Table 4 revealed that about 55 percent of the students surveyed admitted to using AI to complete a homework assignment at least once. This percentage was greater compared to all other cheating behaviors providing evidence that students are self-reporting this behavior more frequently than other cheating behaviors.

Roughly 31 percent of students self-reported using AI to write a paper. This percentage is greater than 11 of the other behaviors again providing evidence that students are self-reporting the use of AI more frequently than many other cheating behaviors. This finding is consistent with other studies finding a growing trend of AI usage in academic work (Jo, 2023; Playfoot, Quigley, and Thomas 2024). The incorporation of AI into educational settings is occurring at an unprecedented pace and research examining student perceptions as well as usage of AI is beginning to grow as well. As students continue to become more experienced with using these technologies, determining how to use large language models to improve learning outcomes while ensuring that student attitudes toward academic integrity remain intact will be an important goal for all institutions of higher learning.

3.7 Limitations

This study is not without limitations. First, the study was conducted at a single higher institution to undergraduate students who were all enrolled in a business course, which limits the generalizability of the findings to other contexts. Second, behavioral data was based on self-reports which often leads to social desirability bias because of the sensitive nature of the topic. This may have led to under-reporting of cheating behaviors. Despite the limitations, this study has added to the literature on academic dishonesty by considering how students rank cheating behaviors in different environments and by introducing the usage of AI as a type of cheating behavior to be analyzed in this way.

4. Conclusion

There are many studies that examine student perceptions of cheating levels in traditional face-to-face versus online cheating as well as self-reported cheating behaviors in these two environments. There are relatively fewer studies that have examined how student beliefs about the seriousness of different cheating behaviors impact the frequency of cheating. As of this writing, the author is not aware of any studies that directly compare student beliefs about specific cheating behaviors related to AI in both the physical and online classroom environments. In this study, students were asked to rank how serious they consider a particular cheating behavior in each of these two environments. Out of fifteen comparable cheating behaviors, results showed that students considered one behavior to be more serious in the in the physical classroom and six cheating behaviors to be more serious in the online classroom. Not surprisingly, this study also found that students with online experience tend to rank cheating behaviors in the online environment as more serious than those students who have not taken an online class.

The present study also supports previous findings that a moderate amount of cheating occurs within the academic setting. However, when looking at the frequency of cheating behaviors, the results of this study did not find evidence of significantly more cheating in the online environment compared to the face-to-face environment. Overall, this study also found that there is a correlation between student beliefs and cheating behavior. That is, when students consider a behavior to be a more unacceptable form of cheating, they are less likely to self-report engaging in that behavior. Finally, when looking at perceptions and frequency of using AI for homework and paper writing assistance, many students consider these to be at least somewhat acceptable behaviors and therefore engage in these behaviors more often than other cheating behaviors

This study was designed to better understand student attitudes about cheating in different environments. As technology continues to offer newer and more efficient ways to obtain information, faculty members and higher education institutions must keep up with how it is being used in both the physical and online environments. Previous literature and the findings of this study would suggest that to influence students to be more honest and ethical in the classroom, faculty and administrators must devise strategies to impact their belief systems. Although students will typically enter college with preliminary ideas about cheating, there is evidence that when faculty members discuss academic integrity in the classroom and enforce violations consistently, positive student attitudes toward cheating among students decreases as does the prevalence of cheating (Carpenter *et al.*, 2006). Providing a strong ethical foundation that becomes rooted within students' personalities throughout their studies is an overarching goal that can start to take shape by including academic integrity discussions into every curriculum, updated frequently to keep up with changing technologies.

AI Statement: The use of AI has not formed any part of this research and/or the drafting of this article.

Ethics Statement: Prior to their participation, all individuals were fully informed about the study's nature, objectives, and how the data would be used. Informed consent was obtained, with participants explicitly assured that their involvement was entirely voluntary and that their responses would be used solely for academic research.

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

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