From Intention to Reflection: Understanding Self-Directed Learning in the Use of Generative AI in Vietnam

Diep-Ngoc Le, Trinh Thi Nguyen, Huong-Giang Thi Doan, An Dieu Trinh and Mai-Huong Dinh Pham
VNU University of Education, Vietnam National University, Hanoi, Vietnam

lediep@vnu.edu.vn (corresponding author)
chingng103@gmail.com
hyang288@gmail.com
andieutrinh@gmail.com
phamh7027@gmail.com

https://doi.org/10.34190/ejel.24.2.4505

Abstract: This study extends the Theory of Planned Behavior (TPB) to explore how students' behavioral intentions toward using generative artificial intelligence (GenAI) are associated with their reflective engagement and self-directed learning (SDL) in higher education. As GenAI tools such as ChatGPT increasingly mediate learning, understanding how learners' intentions are linked to autonomous and reflective learning behaviors becomes essential. Data were collected from 149 first-year university students (predominantly female) in Vietnam who had prior experience with GenAI for academic purposes. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study examined relationships among attitudes, subjective norms, perceived behavioral control, behavioral intention, actual use, reflection, and two dimensions of SDL, including intentional learning and self-management. The results reveal that attitudes and perceived behavioral control significantly predict students' intentions and actual use of GenAI, whereas subjective norms have no significant effect. Behavioral engagement is positively associated with reflection and both dimensions of SDL, while reflection is positively related to intentional learning and self-management, confirming its mediating role within the proposed model linking motivation-related constructs with autonomous learning outcomes. These findings highlight reflection as a metacognitive mechanism that links students' behavioral engagement with GenAI and their SDL-related outcomes. Theoretically, the study advances TPB by positioning reflection and SDL as outcome constructs within the proposed model, rather than fixed learner traits. Practically, it suggests that educators and institutions working with first-year university students or similar learner populations should integrate reflective activities and AI literacy into curricula to promote critical, ethical, and autonomous engagement with GenAI. Designing learning environments that position AI as a reflective partner, rather than merely a content generator, supports learners' self-regulation and reflective engagement. Overall, this research contributes to understanding how intentional and reflective interaction with GenAI is associated with deeper and more autonomous learning of students among first-year university students in a GenAI-supported learning context.

Keywords: Artificial intelligence, Generative AI, Theory of planned behavior, Self-directed learning, Reflective thinking, Higher education, PLS-SEM

1. Introduction

The rapid development of artificial intelligence (AI) has reshaped the higher education landscape, introducing new modes of teaching, learning, and assessment that transcend traditional classroom boundaries (S. Wang et al., 2024; Zawacki-Richter et al., 2019). Among these technologies, generative AI (GenAI) applications such as ChatGPT have emerged as transformative tools capable of generating adaptive and contextually relevant content, including text, images, and code (Abdallah et al., 2025; Li et al., 2025). These innovations enable personalized, interactive learning experiences that foster engagement and creativity, yet they also raise concerns about academic integrity and cognitive dependence (Banh & Strobel, 2023; Darwin et al., 2024). Consequently, understanding how university students regulate and reflect upon their learning when using GenAI has become an issue in higher education.

To explain students' behavioral patterns toward using GenAI, the Theory of Planned Behavior (TPB) has provided a valuable theoretical foundation (Ajzen, 1991; Ajzen, 2002). It posits that attitudes (ATT), subjective norms (SN), and perceived behavioral control (PBC) shape behavioral intention (INT) and subsequent action (BHE). TPB has been widely validated in technology acceptance studies, including mobile learning and online education (Aldammagh, Abdeljawad, & Obaid, 2021; Cheng, 2019; Teo, 2012). Recent research further confirms its relevance to understanding GenAI use, where learners' attitudes and trust strongly influence their intention to engage with these technologies (Bonsu & Baffour-Koduah, 2023; C. Wang et al., 2024; Wu & Dong, 2025). GenAI

Cite this article: Le, D. et al. 2026. "From Intention to Reflection: Understanding Self-Directed Learning in the Use of Generative AI in Vietnam", *Electronic Journal of e-Learning*, 24(2), pp 17-31, https://doi.org/10.34190/ejel.24.2.4505

technologies offer highly personalized and adaptive learning experiences (Li et al., 2025), which suggests a growing need to understand how intention translates into self-regulated learning behaviors in GenAI-supported environments. Learners are now required not only to form positive intentions toward using GenAI but also to regulate and direct their learning within these personalized environments (Ouaazki et al., 2024).

In this regard, self-directed learning (SDL) has gained increasing attention as a learning approach aligned with the adaptive and individualized nature of GenAI-supported education. When combined with digital technologies, SDL enables students to plan and manage their learning more effectively (Sumuer, 2018; Timothy et al., 2010). Empirical evidence further shows that SDL with technology (SDLT) enhances students' readiness and predicts both their intention and actual use of AI-based chatbots in higher education (Esiyok, Sahin, & Kucukergin, 2024). Grounded in Knowles' (1975) concept that learners need to develop proactive and reflective skills with objects in the learning process. Recent studies have explored students' initial reflections during GenAI use (Šedlbauer et al., 2024) and examined how GenAI tools can scaffold reflective thinking (RT) (Wei et al., 2025); these studies have primarily viewed SDL as a pre-existing learner trait rather than a developmental outcome. This present study aims to investigate how students interact with GenAI tools by focusing on intention, actual behaviour use, reflective thinking engagement, and SDL experiences. Within this process, reflection serves as a metacognitive mechanism that allows learners to monitor, evaluate, and adapt their Learning with GenAI.

Complementing this perspective, reflection allows individuals to analyze experiences, connect ideas, and make informed judgments (Lee, 2005; Rodgers, 2002). The immediacy and personalization of feedback offered by GenAI provide unique opportunities for fostering reflective engagement in learning (Ficko et al., 2025; Saritepeci & Yildiz Durak, 2024). Despite growing recognition of this potential, empirical evidence on how RT interacts with SDL in GenAI-based learning remains limited. To address these gaps, the present study integrates TPB, SDL, and RT into a unified framework to examine how university students adopt and learn with GenAI tools. Specifically, it investigates how behavioral intentions toward GenAI are transformed into actual learning behaviors and reflective processes that, in turn, enhance SDL outcomes. By empirically validating this extended model using PLS-SEM, the study aims to deepen theoretical understanding and offer practical insights into promoting reflective and SDL in using GenAI.

2. Literature Review

2.1 Theory of Planned Behavior with using Generative AI

The Theory of Planned Behavior (TPB) was proposed by Ajzen (1991), a theoretical model designed to explain and predict human behavior. TPB assumes that human social behavior is largely under volitional control and can be predicted from an individual's intentions. These intentions are driven by three principal factors: attitude (ATT), subjective norms (SN), and perceived behavioral control (PBC). Ajzen (1991) further divided PBC into controllability and self-efficacy, with facilitating conditions often employed to represent the concept of PBC. Within TPB, behavioral intention (INT) is considered the most influential predictor of actual behavior.

The TPB has been widely applied in studies on technology acceptance (Cheng, 2019; Teo, 2012; C. Wang et al., 2024), including research on electronic recruitment (Parikh, Patel, & Jaiswal, 2021), mobile banking (Aldammagh, Abdeljawad, & Obaid, 2021), and mobile learning (Gómez-Ramirez, Valencia-Arias, & Duque, 2019). A study by Teo (2012) on pre-service teachers' intentions to use technology revealed that their attitude toward computer use had the greatest influence on intention; SN and facilitating conditions (representing PBC) also affected behavioral intention. Consistent with this, Venkatesh, Thong, & Xu (2012) empirically confirmed that intention (INT) is a strong predictor of actual technology usage behavior (BHE). Notably, TPB offers a more comprehensive account of intention and behavior in online collaborative learning, highlighting the combined effects of social and control factors (Cheng, 2019).

In the context of AI, GenAI, and ChatGPT, the TPB and its integrated models have remained appropriate theoretical frameworks for examining technology acceptance and use (Bonsu & Baffour-Koduah, 2023; Phuong Dung et al., 2023). GenAI tools such as ChatGPT, with their ability to generate novel and realistic content such as text and images (Banh & Strobel, 2023), have transformed the way learners interact with information and engage in learning processes (Bozkurt, 2023; B. Li et al., 2024). The core constructs of TPB have continued to be investigated: learners' attitudes and trust in ChatGPT as a learning tool have played a crucial role in shaping their self-directed language learning activities (Bearman & Ajjawi, 2023). The SN has primarily exerted its influence through the formation of a positive attitude toward GenAI, which subsequently affects usage intention. In the context of GenAI use, ATT has served as the key determinant of behavioral intention, while SN and PBC played indirect or supporting roles (C. Wang et al., 2024). The study by Wu and Dong (2025) has demonstrated that SN is a key factor exerting a direct and significant influence on the intention to use GenAI. In summary, the TPB has remained a powerful theoretical model for understanding technology acceptance intentions and behaviors, including the rapidly evolving GenAI tools. Although the TPB has been extensively validated, applying it to GenAI use calls for a deeper inquiry into how learners' behavioral intentions give rise to autonomous learning behaviors promoting SDL, thereby reducing potential overreliance on AI tools.

H_1: ATT will have a positive influence on INT.

H_2: SN will have a positive influence on INT.

H_3: PBC will have a positive influence on INT.

H_4: INT will have a positive influence on BHE.

2.2 Self-Directed Learning with Technologies

The concept and role of self-directed learning (SDL) were articulated by the renowned American adult education scholar Malcolm Knowles, who defined it as follows: The SDL refers to a process in which individuals take the initiative to identify their learning needs, set goals, select strategies, and evaluate outcomes, with or without assistance from others (Knowles, 1975, p. 18). For each learner, SDL has occurred through a process involving personalized guidance within the broader teaching and learning process (Hiemstra, 1988). SDL has also been viewed as an approach in which learners assume personal responsibility for self-monitoring cognition and self-managing the learning context to achieve meaningful outcomes (Garrison, 1997). In the modern context, SDL has enabled learners to develop greater control over knowledge construction, engage in responsible self-reflection regarding their learning and learning strategies, and enhance their performance through self-evaluation of self-learning activities (Gibbons, 2002).

In higher education, SDL has become increasingly important in equipping students with the essential skills and competencies required to succeed in the digital era and to engage in lifelong learning (Boyer et al., 2013). Recent work on AI-enhanced information and communication technologies in lifelong learning suggests that AI can be embedded in person-oriented learning environments that support continuous learning and professional retraining through adaptive and personalized opportunities (Papadakis et al., 2024). In addition, qualitative evidence on SDL supported by the use of ChatGPT suggests that learners may incorporate GenAI into planning, monitoring, and evaluating their learning, while the broader socio-technical landscape of GenAI continues to shape the learning context in which SDL unfolds (B. Li et al., 2024). Practicing SDL has served as a vital instrument for personal development in the twenty-first century, enabling students to enhance the quality of their learning and prepare effectively for future careers (Boyer et al., 2013; Dehnad et al., 2014). The advancement of information and communication technology (ICT) has created a favorable environment for students to strengthen their engagement in SDL. The use of technological tools has enabled students to access a vast array of diverse information resources, locate and evaluate information, monitor the process of planning and implementation, and subsequently self-assess their learning progress (Lee et al., 2014). Students' online learning outcomes are indirectly influenced by their online learning readiness, which is mediated by individual competencies such as SDL skills, metacognitive ability, and collaborative skills (Ho, Kuo, & Lin, 2009).

Research on developing SDL measurement scales for university students has attracted growing attention. Hendry and Ginns (2009) have examined SDL as a key construct influencing learners' ability to plan, manage, and evaluate their own learning. In the context of a private university in Singapore, Khiat (2017) identified various indicators of SDL, such as goal setting, time management, preparation, and readiness for learning, and found that they had both direct and indirect effects on students' academic performance. Additionally, Timothy et al. (2010) developed the SDL with Technology Scale (SDLTS) and identified two key components: self-management (SDL_M), which reflects learners' ability to plan and regulate their learning processes, and intentional learning (SDL_I), which represents learners' goal-oriented pursuit of knowledge, encompassing the identification of both academic and non-academic learning goals and the application of acquired skills and knowledge to new contexts. Subsequently, employing a modified version of the SDLTS, Sumuer (2018) has shown that computer self-efficacy had a significant and indirect impact on university students' engagement in SDLT.

The emergence of AI, GenAI tools like ChatGPT, has significantly transformed the landscape of SDL among learners (B. Li et al., 2024; Ouaazki et al., 2024). GenAI has been regarded as a tool capable of revolutionizing the SDL process by providing unprecedented opportunities for personalized education and adaptive learning (Wu et al., 2024). ChatGPT has held great potential to support SDL by offering instant feedback and engaging in interactive communication tailored to learners' individual characteristics and ongoing learning processes (B. Li et al., 2024). ChatGPT has served as a virtual tutor (Lin, 2024), an AI proxy teacher (Chiu et al., 2024), or a personalized learning assistant (Wu et al., 2024) that helps students enhance their learning experience. Personalized learning has been supported by ChatGPT can foster SDL behaviors among students and lead to improved learning outcomes (Li et al., 2025). In this regard, learners' behavioral engagement with GenAI represents a key driver that facilitates both intentional learning and self-management dimensions of SDL

H_5: BHE will have a positive influence on SDL_I.

H_6: BHE will have a positive influence on SDL_M.

2.3 Reflections on Generative AI

The fast-paced evolution of AI has brought about a revolution in the field of education (Abdallah et al., 2025; Chen, Chen, & Lin, 2020; S. Wang et al., 2024; Zawacki-Richter et al., 2019). Particularly with the emergence of GenAI and applications such as ChatGPT, which are capable of generating new and realistic content, including text, images, and programming code, based on users' basic prompts (Banh & Strobel, 2023; Bordas et al., 2024). GenAI has offered numerous significant benefits for higher education by providing personalization and adaptivity in learning (Adiguzel, Kaya, & Cansu, 2023; Atlas, 2023; Li et al., 2025), enabling the customization of curricula and learning materials according to individual students' needs (B. Li et al., 2024), thereby enhancing the overall learning experience and educational quality (Chen, Chen, & Lin, 2020). GenAI tools have assisted instructors in designing differentiated lesson plans, creating personalized assignments, and analyzing or assessing students' competencies (Monzon & Hays, 2025). For students, GenAI has facilitated interactive learning, instant feedback (Chang et al., 2024), knowledge exploration, problem-solving (Ouaazki et al., 2024), and academic writing (Wang, Li, & Bonk, 2024). Moreover, GenAI has contributed to developing learning habits, fostering interest and motivation (Li et al., 2025; Monzon & Hays, 2025), particularly in the domain of SDL (Bosch & Kruger, 2024; Esiyok, Sahin, & Kucukergin, 2024; Belle Li et al., 2024).

However, the integration of GenAI into higher education has also presented numerous challenges and risks (Banh & Strobel, 2023). One of the major concerns has been the potential increase in students' dependence and complacency (Ouaazki et al., 2024). Students have been overusing GenAI to complete assignments quickly, leading to superficial learning and a decline in critical thinking ability (Darwin et al., 2024; van den Berg & du Plessis, 2023). The accuracy and reliability of AI-generated content have also been worrisome, as GenAI has produced information that appears plausible but is actually incorrect or fabricated (Banh & Strobel, 2023) or delivers biased responses, necessitating significant effort for verification (B. Li et al., 2024). Other ethical concerns include risks related to privacy, copyright infringement, and the lack of transparency in GenAI's data collection and processing mechanisms (Banh & Strobel, 2023). Given these challenges, fostering RT becomes essential for ensuring that learners engage with GenAI critically and responsibly. At the same time, recent pedagogical scholarship argues that higher education should prepare students to engage with AI systems whose internal decision-making processes are not fully transparent or traceable, emphasizing the development of evaluative judgement through orientation to quality standards and meaningful interactions with AI systems (Bearman & Ajjawi, 2023). In this framing, AI tools can be positioned less as shortcut mechanisms and more as learning partners that support lifelong learning orientations when their use is pedagogically guided, ethically grounded, and aligned with SDL processes (Papadakis et al., 2024; B. Li et al., 2024).

In this context, the RT has emerged as a crucial construct for mediating how learners engage with GenAI responsibly and meaningfully (Šedlbauer et al., 2024; Wei et al., 2025). Reflection is a process of constructing meaning and enables learners to move from one experience to another with a deeper understanding of how these experiences and ideas are interconnected (Rodgers, 2002). RT enables learners in higher education to critically examine their learning and professional actions, fostering continuous improvement and greater insight (Lee, 2005). A four-level instrument construct has been applied to measure students' RT, including: habitual action, understanding, reflection, and critical reflection (Kember et al., 2000). In addition, the frequency of RT occurring and the objects that learners reflect on have also been utilized to evaluate students' RT (Hong & Choi, 2015).

Further, Rodgers (2002) has stated that the manifestations of reflection will appear through interaction and dialogue with others. Hence, the personalized nature of the interaction and the near-immediate feedback provided by GenAI provided opportunities that are suitable for performing RT by the learner during SDL (Ficko et al., 2025; Wu et al., 2024). Recent research has emphasized the potential of GenAI to trigger reflection (Lee, 2005; Wei et al., 2025), but the mechanisms through which such reflection contributes to SDL need to be explored. This gap highlights the need for empirical research to examine how RT mediates or enhances SDL when learners interact with GenAI tools.

H_7: BHE will have a positive influence on RT.

H_8: RT will have a positive influence on SDL_I.

H_9: RT will have a positive influence on SDL_M.

The study proposes nine hypotheses to examine the structural relationships among the constructs. Specifically, ATT, SN, and PBC are hypothesized to influence INT (H_1-H_3). The INT is expected to affect BHE and SDL (H_4), while BHE is assumed to impact RT, SDL_I, and SDL_M (H_5-H_7). Finally, RT is hypothesized to influence SDL_I and SDL_M (H_8-H_9). Overall, the proposed model extends TPB by incorporating RT as a cognitive mechanism through which SDL_I and SDL_M. The proposed research model is presented in Figure 1.

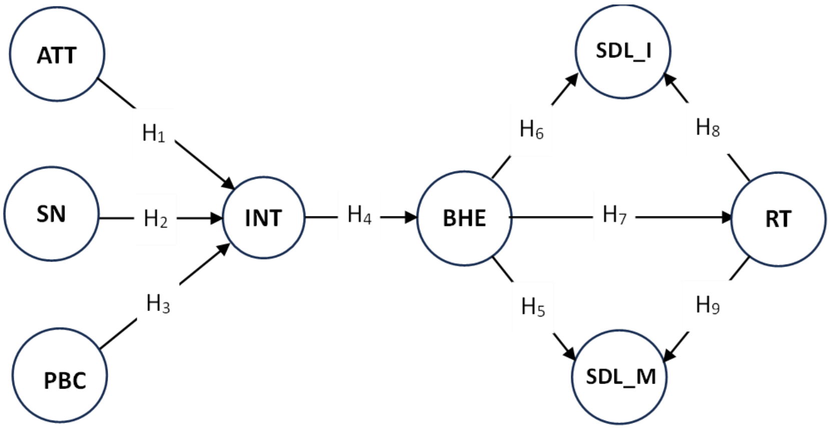

Figure 1: Proposed Research Model

3. Research Methodology

A total of 149 students participated in the survey. In terms of gender, females accounted for the majority with 91.3% (136 students), while males represented 8.7% (13 students). All participants were first-year students, and the survey link was distributed through first-year class groups, allowing students from different classes to voluntarily participate based on their prior experience using GenAI in their learning processes (Table 1). While this sampling approach was appropriate for the study context, the resulting gender imbalance constitutes a methodological limitation that should be taken into account when interpreting the findings.

Table 1: Demographic Distribution of Participants

Measure	Item	N	Percentage
Gender	Male	13	8.7%
	Female	136	91.3%
Which GenAI application have you used the most for your learning?	ChatGPT	106	71.1%
	Gemini	27	18.1%
	Microsoft Copilot	8	5.4%
	DeepSeek	8	5.4%

The study adopted a quantitative research approach, employing a cross-sectional survey design to investigate the relationships among the TPB, SDL, and RT in the context of using GenAI for learning. Data were gathered through a 24-item questionnaire, which incorporated measurement scales adapted from prior studies and refined to align with the context of Vietnamese university students. The instrument consisted of statements rated on a five-point Likert scale (ranging from “strongly disagree” to “strongly agree”) and items modified from existing validated scales. The questionnaire was translated into Vietnamese, and language accuracy was ensured through expert consultation and revision (see Table 2).

Table 2: Descriptive Statistics

Construct	Items	M	SD	Sources
Attitude	ATT1. I think using GenAI (like ChatGPT) is useful for my learning.	3.899	0.939	(Ajzen, 1991; Teo, 2012; Teo & van Schaik, 2012)
	ATT2. I think using GenAI will help me study more effectively.	3.906	0.763	
	ATT3. I think using GenAI for learning is a positive thing and should be encouraged.	3.772	0.844	
Subjective Norm	SN1. My friends think that I should use GenAI to support my learning.	3.839	0.751	
	SN2. I feel influenced by people around me in my decision to use GenAI.	3.711	0.780	
	SN3. My lecturers or university support my use of GenAI in learning.	3.691	0.759	
Perceived Behavioral Control	PBC1. I have enough skills to use GenAI tools for my studies.	3.872	0.735	
	PBC2. I know how to control my use of GenAI to match my learning goals.	3.906	0.679	
	PBC3. Even without guidance, I feel confident using GenAI tools effectively.	3.705	0.799	
Intention	INT1. I plan to use (or continue using) GenAI tools to support my learning in the future.	4.000	0.769	
	INT2. I want to explore different ways to use GenAI to improve my learning.	4.128	0.744	
	INT3. I am willing to try different GenAI tools to make my learning more effective.	4.081	0.790	
Behavior	BHE1. I often use GenAI tools to complete my study tasks.	3.899	0.801	(Venkatesh, Thong, & Xu, 2012).
	BHE2. I have shared GenAI responses or content with my classmates for discussion and learning.	3.899	0.792	
	BHE3. I regularly use GenAI tools for my study and research activities.	4.000	0.695	
Reflective Thinking	RT1. I think using GenAI helps me learn better, but it cannot replace personal effort.	4.007	0.798	(Kember et al., 2000; Šedlbauer et al., 2024)
	RT2. I feel responsible for using AI tools ethically in my learning.	4.081	0.755	
	RT3. I think I need to learn more about how to check and evaluate the content created by GenAI.	4.060	0.813	
Intentional Learning	SDL_I1. I look for more information using GenAI to help me understand my lessons better.	3.953	0.679	(Timothy et al., 2010)
	SDL_I2. I use GenAI tools to find and organize information that supports my learning goals.	3.913	0.759	
	SDL_I3. I use GenAI to become better at a skill I am interested in.	3.805	0.792	
	SDL_I4. I use GenAI to get ideas from websites and other people to learn more about a topic.	3.899	0.801	
Self-Management	SDL_M1. I use GenAI to ask questions about my lessons when I don't understand something, so I can learn by myself.	4.054	0.703	
	SDL_M2. I use GenAI to express and develop my own thoughts and ideas for school tasks or assignments.	3.893	0.725	

The participants of the survey were undergraduate students from a university in Vietnam who had prior experience with or interest in utilizing GenAI tools for learning purposes. Data were collected online via Google Forms during May 2025. After screening and data cleaning, a total of 149 valid responses were retained for analysis. The sample size was deemed adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis based on the criteria suggested by Hair et al. (2019). Firstly, given the study parameters (significance level $\alpha = 0.05$, statistical power = 0.90, and effect size $f^2 = 0.15$), and according to the research model (Figure 1), the maximum number of independent variables influencing a single dependent variable was three. The actual sample size was 149, and this configuration aligns with the sample size of 88 when estimation was obtained using G*Power (Kock & Hadaya, 2018). Secondly, the obtained sample met the minimum thresholds recommended by Hair et al. (2010) and Hair et al. (2019). The PLS-SEM procedure followed two main stages: assessment of the measurement model and evaluation of the structural model. Firstly, for the measurement model, item reliability was verified with factor loadings expected to exceed 0.70. Construct reliability was assessed using Cronbach's alpha and composite reliability (CR), both with a recommended minimum threshold of 0.70 (Hair et al., 2019). Convergent validity was established when the average variance extracted (AVE) was greater than 0.50. Discriminant validity was confirmed through the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT), both expected to be below 0.85 (Fornell & Larcker, 1981; Henseler, Ringle, & Sarstedt, 2015). For the structural model, explanatory power was evaluated based on the R^2 values (0.25 = weak, 0.50 = moderate, 0.75 = substantial) (Hair et al., 2019), effect sizes f^2 (0.02 = small, 0.15 = medium, 0.35 = large), and predictive relevance Q^2 (> 0). Finally, bootstrapping with 5,000 resamples was performed to test the significance of the path coefficients ($t > 1.96$, $p < 0.05$) (Hair et al., 2019).

4. Results

4.1 Measurement Model

The factor loadings in this study ranged from 0.706 to 0.925 (see Table 3), most of which met the recommended threshold suggested by Hair et al. (2019). SN3 demonstrated a loading of 0.672, which is slightly below the recommended threshold of 0.70. It was retained because the overall reliability (CR = 0.858) and convergent validity (AVE = 0.671) of the SN construct remained acceptable. To ensure convergent validity, both the composite reliability (CR) and average variance extracted (AVE) values must be at least 0.50 (Hair et al., 2019). In this model, the CR values ranged from 0.848 to 0.914, and the AVE values ranged from 0.651 to 0.841 (see Table 3), confirming that the measurement model achieved satisfactory levels of reliability and convergent validity. Furthermore, the Cronbach's Alpha and rho_A values for all constructs exceeded 0.70, indicating satisfactory internal consistency reliability.

The overall model fit was assessed using SRMR and NFI. The SRMR value of the saturated model was 0.079, confirming good model fit, while the NFI value of 0.700 was within the acceptable range for PLS-SEM (Hair et al., 2019). Collinearity was assessed through the variance inflation factor (VIF), and all indicators showed acceptable VIF values between 1.215 and 2.295, well below the conservative cut-off value of 3.3 (Hair et al., 2021; Kock, 2017), indicating no multicollinearity issue.

Next, the study examined discriminant validity using both the Fornell–Larcker and Heterotrait-Monotrait ratio (HTMT) criteria. The square roots of the AVE values (displayed on the diagonal of Table 4) were greater than all corresponding inter-construct correlations, confirming discriminant validity following (Fornell & Larcker, 1981). Furthermore, as recommended by Franke and Sarstedt (2019), most HTMT values were below the 0.90 threshold, except for the ATT-SN pair (HTMT = 0.972), which slightly exceeded the cut-off. However, given that the constructs remain theoretically distinct and other validity criteria (Fornell-Larcker and cross-loadings) were satisfied, the measurement model still demonstrates acceptable standards for validity and reliability (Hair et al., 2019).

Table 3: Reliability and Convergent Validity Indices of the Measurement Scale

Components	Outer loading	VIF	Cronbach's Alpha	rho_A	CR	AVE
ATT1	0.752	1.388	0.781	0.805	0.873	0.697
ATT2	0.898	2.047				
ATT3	0.849	1.885				
BHE1	0.821	1.725	0.818	0.831	0.892	0.734
BHE2	0.838	1.800				
BHE3	0.908	2.275				
INT1	0.822	1.701	0.803	0.806	0.884	0.719
INT2	0.893	2.145				
INT3	0.826	1.659				
PBC1	0.706	1.215	0.727	0.735	0.848	0.651
PBC2	0.842	1.778				
PBC3	0.864	1.862				
RT1	0.866	2.013	0.849	0.850	0.909	0.768
RT2	0.892	2.295				

Components	Outer loading	VIF	Cronbach's Alpha	rho_A	CR	AVE
RT3	0.871	1.973				
SDL_I1	0.776	1.532	0.834	0.836	0.889	0.668
SDL_I2	0.841	1.956				
SDL_I4	0.824	1.910				
SDL_I3	0.827	2.017				
SDL_M1	0.925	1.876	0.812	0.816	0.914	0.841
SDL_M2	0.910	1.876				
SN1	0.910	1.749	0.770	0.883	0.858	0.671
SN2	0.856	1.688				
SN3	0.672	1.421				

*Note.*VIF = Variance Inflation Factor; rho_A = construct reliability; CR = composite reliability; AVE = average variance extracted; ATT = Attitude; SN = Subjective Norm; PBC = Perceived Behavioral Control; INT = Intention; BHE = Behavior; SDL_I = Intentional Learning; SDL_M = Self-Management; RT = Reflective Thinking.

4.2 Structural Model

The hypotheses of the model were tested using the bootstrapping method (Hair et al., 2021; Hair et al., 2019). The results indicated that ATT had a strong and significant positive effect on INT ($\beta = 0.557$; $t = 5.063$; $p < 0.001$), while PBC also significantly influences INT ($\beta = 0.339$; $t = 3.945$; $p < 0.001$). However, the effect of SN on INT was not significant ($\beta = -0.035$; $t = 0.288$; $p = 0.778$). Moreover, INT showed a strong association with BHE ($\beta = 0.782$; $t = 12.009$; $p < .001$) (see Table 4).

In addition, BHE significantly affected SDL_I ($\beta = 0.413$; $t = 5.683$; $p < 0.001$), SDL_M ($\beta = 0.289$; $t = 2.728$; $p < 0.005$), and RT ($\beta = 0.550$; $t = 5.344$; $p < 0.001$). Similarly, RT positively influences both SDL_I ($\beta = 0.473$; $t = 5.303$; $p < 0.001$) and SDL_M ($\beta = 0.556$; $t = 5.945$; $p < 0.001$). These findings confirmed that most of the direct hypotheses in the research model are statistically supported (see Fig. 2).

Regarding the indirect effects, the results showed that ATT and PBC had significant indirect influences on SDL_I and SDL_M through INT to BHE and BHE to RT pathways. The indirect effect of ATT on SDL_I and SDL_M through INT to BHE to RT was approximately $\beta = 0.113$ and 0.133. Similarly, PBC indirectly influences SDL_I and SDL_M ($\beta = 0.069$ and $\beta = 0.081$). However, SN was not statistically supported to impact learners' SDL indirectly. In short, these indirect effects were positive and meaningful, demonstrating that RT serves as the key mediating mechanism construct within the proposed model linking individuals' intentions and behavioral outcomes (see Table 5).

Table 4: Fornell-Larcker and HTMT Indices for the Discriminant Validity

Fornell-Larcker Criterion	ATT	BHE	INT	PBC	RT	SDL_I	SDL_M	SN
ATT	0.835							
BHE	0.687	0.857						
INT	0.677	0.782	0.848					
PBC	0.438	0.552	0.565	0.807				
RT	0.510	0.550	0.651	0.396	0.877			
SDL_I	0.606	0.673	0.678	0.418	0.700	0.817		
SDL_M	0.576	0.594	0.580	0.510	0.714	0.803	0.917	
SN	0.789	0.650	0.572	0.495	0.384	0.540	0.464	0.819
Heterotrait-Monotrait Ratio								
ATT								
BHE	0.853							
INT	0.848	0.959						
PBC	0.592	0.719	0.740					

Fornell-Larcker Criterion	ATT	BHE	INT	PBC	RT	SDL_I	SDL_M	SN
RT	0.614	0.654	0.787	0.509				
SDL_I	0.738	0.808	0.822	0.656	0.825			
SDL_M	0.708	0.727	0.716	0.550	0.858	0.970		
SN	0.972	0.797	0.652	0.680	0.420	0.606	0.550	

Note. ATT = Attitude; SN = Subjective Norm; PBC = Perceived Behavioral Control; INT = Intention; BHE = Behavior; SDL_I = Intentional Learning; SDL_M = Self-Management; RT = Reflective Thinking.

Table 5: Path Coefficients of the Structural Model

Relationship	β	SD	t-value	f^2	Result
ATT → INT	0.557	0.110	5.063**	0.257	Supported
BHE → RT	0.550	0.103	5.344**	0.433	Supported
BHE → SDL_I	0.413	0.073	5.683**	0.305	Supported
BHE → SDL_M	0.289	0.106	2.728**	0.135	Supported
INT → BHE	0.782	0.065	12.009**	1.578	Supported
PBC → INT	0.339	0.086	3.945**	0.190	Supported
RT → SDL_I	0.473	0.089	5.303**	0.400	Supported
RT → SDL_M	0.556	0.093	5.945**	0.500	Supported
SN → INT	- 0.035	0.123	*0.288*	0.001	Unsupported
Specific Indirect Effects					
ATT → INT → BHE → RT → SDL_I	0.113	0.045	2.540*		Supported
PBC → INT → BHE → RT → SDL_I	0.069	0.031	2.209*		Supported
SN → INT → BHE → RT → SDL_I	- 0.007	0.027	*0.270*		Unsupported
ATT → INT → BHE → RT → SDL_M	0.133	0.053	2.534*		Supported
PBC → INT → BHE → RT → SDL_M	0.081	0.036	2.252*		Supported
SN → INT → BHE → RT → SDL_M	- 0.008	0.031	*0.275*		Unsupported

Note: SD = Standard Deviation; ATT = Attitude; SN = Subjective Norm; PBC = Perceived Behavioral Control; INT = Intention; BHE = Behavior; SDL_I = Intentional Learning; SDL_M = Self-Management; RT = Reflective Thinking.

Significance levels: * p < 0,05; ** p < 0,01

4.3 Explanatory Power and Effect Sizes

The analysis results demonstrate that the extended model provides a solid explanation for behavioral and learning outcomes among university students. Specifically, the R^2 value of INT reached 0.539, indicating a moderate level of explanatory power, while BHE (R^2 = 0.609) also showed a high level of explanatory power. In contrast, RT (R^2 = 0.297) demonstrates a lower but still meaningful level of explanatory power. The SDL_I (R^2 = 0.604) and SDL_M (R^2 = 0.563) achieved moderate explanatory power (see Table 6). These findings confirm that the proposed model accounts for a considerable proportion of the variance in the key endogenous constructs.

Regarding the effect sizes (f^2), the path from INT to BHE showed the strongest effect (f^2 = 1.578), representing a very large contribution to the explained variance. The effects of ATT on INT (f^2 = 0.257) and PBC on INT (f^2 = 0.190) were also substantial, while the SN on INT showed a negligible impact (f^2 = 0.001). Moreover, RT demonstrated a meaningful role within the model, exhibiting a strong effect on SDL_I (f^2 = 0.400) and an effect on SDL_M (f^2 = 0.500). Overall, these results highlight the central role of BHE and RT as a mediating construct that bridges intention and actual behavior, supporting the view that individuals' ability to regulate and direct their own learning is pivotal in translating motivational factors into effective behavioral outcomes. The combination of high R^2, significant effect sizes, and positive predictive relevance (Q^2 values ranging from 0.219 to 0.450) confirms that the structural model achieves both explanatory and predictive adequacy in this study context (see Table 6).

Table 6: Coefficient of Determination and Predictive Relevance of the Structural Model

Variable	R^2 Adjusted	Q^2
INT	0.539	0.376
BHE	0.609	0.436
RT	0.297	0.219
SDL_I	0.604	0.379
SDL_M	0.563	0.450

Note: INT = Intention; BHE = Behavior; SDL_I = Intentional Learning; SDL_M = Self-Management; RT = Reflective Thinking.

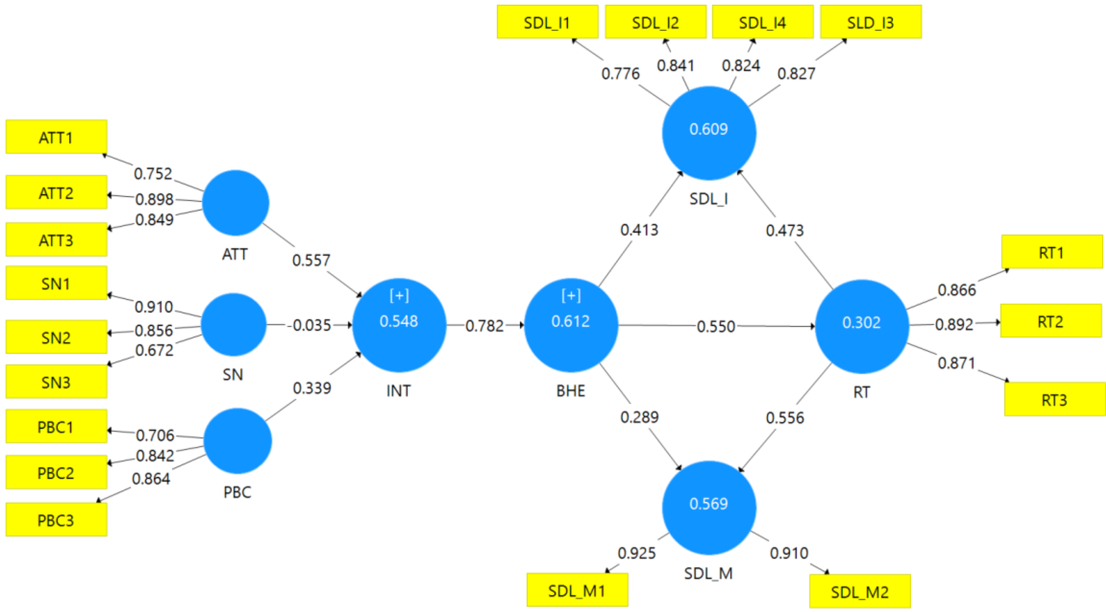

Figure 2: Empirical Model

5. Discussion

The findings of the present study suggest a sequential pattern of associations within the proposed model, whereby behavioral intention is linked to actual use, which is associated with reflective engagement and, in turn, with SDL dimensions. This pathway extends the TPB (Ajzen, 1991; Ajzen, 2002) by explaining how motivational factors are associated with autonomous learning behaviors through reflection within the proposed model. The non-significant effect of SN supports prior research (Cheng, 2019; Watson & Rockinson-Szapkiw, 2021; Yao et al., 2022). It suggests that social influence plays a limited role in AI-supported learning environments similar to the present study context, where self-direction and independence are more central (B. Li et al., 2024; Li et al., 2025). In GenAI settings, characterized by personalized and immediate feedback (Abdallah et al., 2025), learners' choices are shaped more by intrinsic motivation and self-regulation than by external expectations. From a gender perspective, prior studies have reported that differences in technology-supported learning extend beyond technology acceptance to self-regulatory processes central to SDL and reflective learning practices (Møgelvang et al., 2024; Sobieraj & Krämer, 2020). Female students, in particular, have been associated with greater emphasis on self-regulation underpinning autonomous and SDL, reflective engagement, and autonomous learning management in digital learning contexts (Møgelvang et al., 2024; Sobieraj & Krämer, 2020). Given that the present sample consists predominantly of female first-year students, peer influence may be particularly salient during the early stages of the university transition. However, within the scope of the proposed cross-sectional model, SDL-related behaviors are more closely associated with reflective engagement and self-regulatory mechanisms, while the influence of social norms may operate in more indirect or temporally diffuse ways that are less salient at a single point of measurement. This gender-skewed sample composition may therefore help explain why SN did not emerge as a significant predictor in the proposed model, despite their established role in technology acceptance research (Goswami & Dutta, 2016). In addition, it is possible that the non-significant effect of SN reflects differences in the sources of normative influence captured by the measurement, as perceptions of peer expectations and institutional or instructor expectations may exert opposing influences, potentially canceling each other within the SN construct. In addition to substantive explanations related to gender composition and learning context, the role of statistical power should also be considered when interpreting the non-significant paths involving SN. Although the sample size met the minimum requirements for PLS-SEM analysis (Hair et al., 2019), it may have limited the detection of smaller or unstable effects of SN that have been shown to vary across contexts in technology acceptance research (Venkatesh et al., 2003). Accordingly, the absence of statistically significant effects for SN should be interpreted with caution, as it may reflect limited power rather than the complete absence of social influence.

This research reconceptualizes SDL as an outcome construct within the proposed model, rather than solely as a fixed learner trait. In doing so, it addresses a theoretical gap in the current literature. Previous research often regarded SDL as an antecedent of technology adoption (Esiyok, Sahin, & Kucukergin, 2024; Sumuer, 2018; Timothy et al., 2010), treated SDL as an antecedent of technology adoption, whereas the current findings show that engagement with GenAI, when accompanied by reflective engagement, is associated with higher levels of SDL-related behaviors within the model. This perspective aligns with the view that learners can be strengthened through guided reflection and purposeful engagement (Lee et al., 2014), and supports recent empirical evidence that reflection is the link between AI interaction and meaningful learning (Šedlbauer et al., 2024). Whereas Wei et al. (2025) conceptualized RT as an outcome of GenAI-assisted learning, this study identifies RT as the underlying mechanism through which behavioral engagement is associated with SDL dimensions. It should be acknowledged that the observed associations do not establish the direction of influence between GenAI use and reflective engagement. It is possible that reflective learners engage with GenAI in more reflective ways, just as structured interaction with GenAI may afford opportunities for reflection. Longitudinal or experimental designs are required to disentangle these two-way relationships.

For practical and pedagogical implications, the results show the need to position GenAI as a reflective partner rather than a simple information provider. Within the scope of the observed associations, GenAI-based learning tasks may be designed to emphasize personal goal-setting and self-monitoring features that support learners' intrinsic motivation. The link between RT and SDL found in this study shows that integrating structured reflection activities can directly reinforce learners' autonomy in learning. Educators should design AI-integrated tasks that require learners to analyze, critique, and justify AI-generated outputs, as such reflective activities promote deeper engagement and self-regulation (Ficko et al., 2025; Saritepeci & Yildiz Durak, 2024). Curriculum designers and teacher educators should also integrate reflective learning tasks, such as AI–human comparison or justification writing, to reinforce the link between GenAI use and SDL (Li et al., 2025; Ouaazki et al., 2024). Furthermore, professional development for instructors should focus on cultivating students' reflective and autonomous skills when using GenAI responsibly, mitigating the risks of overreliance and superficial learning noted by Banh & Strobel (2023).

At the institutional and policy level, the study's findings support integrating AI literacy and reflective learning competencies into higher education frameworks (S. Wang et al., 2024; Zawacki-Richter et al., 2019). Universities should develop assessment systems that evaluate not only students' technical proficiency with GenAI but also their reflective and self-directed capacities. Institutional policies should emphasize transparency and ethical use of AI tools, encouraging students to engage critically and autonomously with technology while maintaining academic integrity (Abdallah et al., 2025). Additionally, institutional AI policies can promote structured reflection cycles within learning management systems or GenAI platforms, ensuring that learners engage in monitoring, feedback, and self-evaluation. These initiatives align with the global movement to foster autonomous, lifelong learners who can navigate AI-driven educational ecosystems responsibly.

Although the PLS-SEM results provide robust evidence for the proposed model, several limitations should be acknowledged. The cross-sectional design restricts causal inference; future longitudinal or experimental research could better capture the developmental nature of SDL across different stages of GenAI use. The sample was drawn from first-year students across multiple classes within a single university. Although participants represented diverse classes within the institution, the use of a single-institution sample limits the generalizability of the findings to other higher education contexts. Cross-cultural or multi-institutional replication would help examine whether the intention, reflection, and SDL mechanism hold across different learning environments. In addition, the sample exhibited a pronounced gender imbalance, with female students accounting for over 90% of the participants. Prior research in technology acceptance and AI adoption consistently identifies gender as a moderating factor shaping individuals' responses to social influence, trust in AI systems, perceived competence, and affective reactions such as anxiety (Goswami & Dutta, 2016; Møgelvang et al., 2024; Russo et al., 2025).

However, existing studies also emphasize that the direction and strength of these gender-related effects are not uniform, but vary considerably across technologies, levels of technological complexity, learning tasks, and usage contexts (Goswami & Dutta, 2016; Sobieraj & Krämer, 2020). Given the skewed gender composition of the present sample, meaningful gender-based comparisons or moderation analyses could not be conducted. Moreover, the limited gender variability may have attenuated the observable contribution of SN through restricted variance and cohort-specific contextual influences, such as shared peer environments and institutional norms. Consequently, the non-significant effect of SN should be interpreted with caution and should not be generalized to broader higher education populations without further validation using more gender-balanced samples, particularly in light of documented gender-related disparities in AI adoption within higher education contexts (Kalim et al., 2025). Cross-cultural validation could test whether the same intention, reflection, and SDL mechanism holds in diverse learning cultures. Future research could also employ learning analytics or reflective journals to trace how intention and reflection develop over time, providing deeper insights into learners' cognitive regulation. In addition, examining affective factors such as trust in AI, learning satisfaction, or perceived cognitive load (Bonsu & Baffour-Koduah, 2023; Wu & Dong, 2025) could enhance understanding of how emotional and cognitive dimensions jointly shape reflective learning with AI.

6. Conclusion

This study advances the understanding of how first-year university students' intentions to use GenAI are associated with reflective engagement and SDL. By extending the TPB with RT and SDL, the research demonstrates that behavioral engagement acts as a critical mechanism linking motivation to autonomous learning. The ATT and PBC were found to be key predictors of intention, whereas SN showed no significant influence, highlighting the intrinsic and self-regulatory nature of learning based on GenAI. Reflection emerged as a pivotal process associated with meaningful SDL-related experiences in GenAI-supported learning contexts.

The findings contribute theoretically by conceptualizing SDL as a developmental outcome rather than a fixed learner attribute, emphasizing the role of reflection in fostering metacognitive awareness and learner autonomy. Practically, the study recommends lecturers integrating structured reflective activities, such as critique and justification, into instructional design to promote responsible and autonomous GenAI use. Educators and policymakers should embed AI literacy, ethical awareness, and reflective practice into curricula and institutional frameworks to support lifelong learning and academic integrity in using AI.

Despite its strong empirical support, this study acknowledges limitations related to its cross-sectional design and single-university sample. Future research should employ longitudinal and cross-cultural approaches to explore how intention, reflection, and SDL develop over time. Expanding the model to include affective factors such as trust, motivation, and cognitive load would further enrich the understanding of how emotional and cognitive dimensions interact in GenAI-supported learning. Overall, this study underscores that, within a predominantly female student sample, when guided by reflective and self-directed approaches, GenAI can serve as a supportive learning partner in fostering behaviors associated with SDL, thereby laying the foundations of autonomous, ethical, and lifelong learning in university education.

Acknowledgements

The encouragement, collaboration, and support of the VNU University of Education, Vietnam National University, Hanoi, are gratefully acknowledged. This research was supported under grant no. QS.NH.25.27.

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

Ethics Statement: Ethical approval was not required for this study, as all participants provided informed consent by proceeding after reading a statement on the study's purpose, anonymity, and the voluntary nature of participation.

Competing Interest Statement: The authors declare that they have no competing interests.

References

Abdallah, N., Katmah, R., Khalaf, K., & Jelinek, H. F. (2025). Systematic review of ChatGPT in higher education: Navigating impact on learning, wellbeing, and collaboration. *Social Sciences & Humanities Open*, *12*, 101866. https://doi.org/10.1016/j.ssaho.2025.101866

Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology*, *15*(3), ep429. https://doi.org/10.30935/cedtech/13152

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology*, *32*, 665–683.

Aldammagh, Z., Abdeljawad, R., & Obaid, T. (2021). Predicting mobile banking adoption: An integration of TAM and TBP with trust and perceived risk. *Financial Internet Quarterly*, *17*(3), 35-46. https://doi.org/10.2478/fiqf-2021-0017

Atlas, S. (2023). *ChatGPT for Higher Education and Professional Development: A Guide to Conversational*. https://digitalcommons.uri.edu/cba_facpubs/548

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets*, *33*(1), 63. https://doi.org/10.1007/s12525-023-00680-1

Bearman, M., & Ajjawi, R. (2023). Learning to work with the black box: Pedagogy for a world with artificial intelligence. *British Journal of Educational Technology*, *54*(5), 1160-1173. https://doi.org/10.1111/bjet.13337

Bonsu, E. M., & Baffour-Koduah, D. (2023). From the Consumers' Side: Determining Students' Perception and Intention to Use ChatGPT in Ghanaian Higher Education. *Journal of Education, Society & Multiculturalism*, *4*(1), 1-29. https://doi.org/10.2478/jesm-2023-0001

Bordas, A., Le Masson, P., Thomas, M., & Weil, B. (2024). What is generative in generative artificial intelligence? A design-based perspective. *Research in Engineering Design*, *35*(4), 427-443. https://doi.org/10.1007/s00163-024-00441-x

Bosch, C., & Kruger, D. (2024). AI chatbots as Open Educational Resources: Enhancing student agency and Self-Directed Learning. *Italian Journal of Educational Technology*, *32*(1), 53-68.

Boyer, S. L., Edmondson, D. R., Artis, A. B., & Fleming, D. (2013). Self-Directed Learning: A Tool for Lifelong Learning. *Journal of Marketing Education*, *36*(1), 20-32. https://doi.org/10.1177/0273475313494010

Bozkurt, A. (2023). Generative artificial intelligence (AI) powered conversational educational agents: The inevitable paradigm shift. *Asian Journal of Distance Education*, *18*(1). http://www.asianjde.com/ojs/index.php/AsianJDE/article/view/718

Chang, C.-Y., Yang, C.-L., Jen, H.-J., Ogata, H., & Hwang, G.-H. (2024). Facilitating nursing and health education by incorporating ChatGPT into learning designs. *Educational Technology & Society*, *27*(1), 215-230. https://doi.org/10.30191/ETS.202401_27(1).TP02

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. *IEEE Access*, *8*, 75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cheng, E. W. L. (2019). Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM). *Educational Technology Research and Development*, *67*(1), 21-37. https://doi.org/10.1007/s11423-018-9598-6

Chiu, T. K. F., Moorhouse, B. L., Chai, C. S., & Ismailov, M. (2024). Teacher support and student motivation to learn with Artificial Intelligence (AI) based chatbot. *Interactive Learning Environments*, *32*(7), 3240-3256. https://doi.org/10.1080/10494820.2023.2172044

Darwin, Rusdin, D., Mukminatien, N., Suryati, N., Laksmi, E. D., & Marzuki. (2024). Critical thinking in the AI era: An exploration of EFL students' perceptions, benefits, and limitations. *Cogent Education*, *11*(1), 2290342. https://doi.org/10.1080/2331186X.2023.2290342

Dehnad, A., Afsharian, F., Hosseini, F., Arabshahi, S. K. S., & Bigdeli, S. (2014). Pursuing a Definition of Self-directed Learning in Literature from 2000–2012. *Procedia - Social and Behavioral Sciences*, *116*, 5184-5187. https://doi.org/10.1016/j.sbspro.2014.01.1097

Esiyok, E., Sahin, G., & Kucukergin, K. G. (2024). Acceptance of Educational Use of AI Chatbots in the Context of Self-Directed Learning with Technology and ICT Self-Efficacy of Undergraduate Students. *International Journal of Human–Computer Interaction*, *41*(1), 641-650. https://doi.org/10.1080/10447318.2024.2303557

Ficko, A., Sarkki, S., Gultekin, Y. S., Egli, A., & Hiedanpää, J. (2025). Reflective thinking meets artificial intelligence: Synthesizing sustainability transition knowledge in left-behind mountain regions. *Geography and Sustainability*, *6*(1), 100257. https://doi.org/10.1016/j.geosus.2024.100257

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. *Internet Research*, *29*(3), 430-447. https://doi.org/10.1108/IntR-12-2017-0515

Garrison, D. R. (1997). Self-directed learning: Toward a comprehensive model. *Adult Education Quarterly*, *48*(1), 18-33. https://doi.org/10.1177/074171369704800103

Gibbons, M. (2002). *The self-directed learning handbook: Challenging adolescent students to excel*. John Wiley & Sons, Amercan.

Gómez-Ramirez, I., Valencia-Arias, A., & Duque, L. (2019). Approach to M-learning Acceptance Among University Students: An Integrated Model of TPB and TAM. *International Review of Research in Open and Distributed Learning*, *20*(3). https://doi.org/10.19173/irrodl.v20i4.4061

Goswami, A., & Dutta, S. (2016). Gender Differences in Technology Usage—A Literature Review. *Open Journal of Business and Management*, *4*, 51-59. https://doi.org/10.4236/ojbm.2016.41006

Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate data analysis: A global perspective*. Pearson Education, Upper Saddle River, NJ.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Third Edition. SAGE Publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hendry, G. D., & Ginns, P. (2009). Readiness for self-directed learning: Validation of a new scale with medical students. *Medical Teacher*, *31*(10), 918–920. https://doi.org/10.3109/01421590802520899

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hiemstra, R. (1988). Self-directed learning: Individualizing instruction. In H. B. L. Associates (Ed.), *Self-directed learning: Application & theory* (pp. 99-124). Athens, GA: Adult Education Department, University of Georgia.

Ho, L.-A., Kuo, T. H., & Lin, B. (2009). Influence of online learning skills in cyberspace. *Internet Research*, *20*(1), 55-71. https://doi.org/10.1108/10662241011020833

Hong, Y.-C., & Choi, I. (2015). Assessing reflective thinking in solving design problems: The development of a questionnaire. *British Journal of Educational Technology*, *46*(4), 848-863. https://doi.org/10.1111/bjet.12181

Kalim, U., Kanwar, A., Sha, J., & Huang, R. (2025). Barriers to AI adoption for women in higher education: a systematic review of the Asian context. *Smart Learning Environments*, *12*(1), 38. https://doi.org/10.1186/s40561-025-00390-5

Kember, D., P., L. D. Y., Alice, J., Yuen, L. A., Jan, M., Kit, S., and Yeung, E. (2000). Development of a Questionnaire to Measure the Level of Reflective Thinking. *Assessment & Evaluation in Higher Education*, *25*(4), 381-395. https://doi.org/10.1080/713611442

Khiat, H. (2017). Academic performance and the practice of self-directed learning: The adult student perspective. *Journal of Further and Higher Education*, *41*(1), 44-59. https://doi.org/10.1080/0309877X.2015.1062849

Knowles, M. (1975). *Self-directed learning: A guide for learners and teachers*. New York: Association Press.

Kock, N. (2017). Common Method Bias: A Full Collinearity Assessment Method for PLS-SEM. In H. Latan & R. Noonan (Eds.), *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 245-257). Springer International Publishing. https://doi.org/10.1007/978-3-319-64069-3_11

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, *28*(1), 227-261. https://doi.org/10.1111/isj.12131

Lee, H.-J. (2005). Understanding and assessing preservice teachers' reflective thinking. *Teaching and Teacher Education*, *21*(6), 699-715. https://doi.org/10.1016/j.tate.2005.05.007

Lee, K., Tsai, P. S., Chai, C. S., & Koh, J. H. L. (2014). Students' perceptions of self-directed learning and collaborative learning with and without technology. *Journal of Computer Assisted Learning*, *30*(5), 425-437. https://doi.org/10.1111/jcal.12055

Li, B., Bonk, C. J., Wang, C., & Kou, X. (2024). Reconceptualizing Self-Directed Learning in the Era of Generative AI: An Exploratory Analysis of Language Learning. *IEEE Transactions on Learning Technologies*, *17*, 1489-1503. https://doi.org/10.1109/TLT.2024.3386098

Li, B., Wang, C., Bonk, C. J., & Kou, X. (2024). Exploring Inventions in Self-Directed Language Learning with Generative AI: Implementations and Perspectives of YouTube Content Creators. *TechTrends*, *68*(4), 803-819. https://doi.org/10.1007/s11528-024-00960-3

Li, Y., Sadiq, G., Qambar, G., & Zheng, P. (2025). The impact of students' use of ChatGPT on their research skills: The mediating effects of autonomous motivation, engagement, and self-directed learning. *Education and Information Technologies*, *30*(4), 4185-4216. https://doi.org/10.1007/s10639-024-12981-9

Lin, X. (2024). Exploring the Role of ChatGPT as a Facilitator for Motivating Self-Directed Learning Among Adult Learners. *Adult Learning*, *35*(3), 156-166. https://doi.org/10.1177/10451595231184928

Møgelvang, A., Bjelland, C., Grassini, S., & Ludvigsen, K. (2024). Gender Differences in the Use of Generative Artificial Intelligence Chatbots in Higher Education: Characteristics and Consequences. *Education Sciences*, *14*(12), 1363. https://doi.org/10.3390/educsci14121363

Monzon, N., & Hays, F. A. (2025). Leveraging Generative Artificial Intelligence to Improve Motivation and Retrieval in Higher Education Learners. *JMIR Med Educ*, *11*, e59210. https://doi.org/10.2196/59210

Ouaazki, A., Bergram, K., Farah, J. C., Gillet, D., & Holzer, A. (2024). *Generative AI-Enabled Conversational Interaction to Support Self-Directed Learning Experiences in Transversal Computational Thinking* Proceedings of the 6th ACM Conference on Conversational User Interfaces, Luxembourg, Luxembourg. https://doi.org/10.1145/3640794.3665542. Article 13, https://doi.org/10.1145/3640794.3665542

Papadakis, S., Lytvynova, S., Mintii, I., Ivanova, S., Selyshcheva, I., & Semerikov, S. (2024). *Advancing lifelong learning with AI-enhanced ICT: A review of 3L-Person 2024.* CEUR Workshop Proceedings.

Parikh, A., Patel, J. D., & Jaiswal, A. K. (2021). Managing job applications online: integrating website informativeness and compatibility in theory of planned behaviour and technology acceptance model. *DECISION*, *48*(1), 97-113. https://doi.org/10.1007/s40622-020-00266-2

Phuong Dung, P. T., An, H. M., Huy, P. Q., & Dinh Quy, N. L. (2023). Understanding the startup's intention of digital marketing's learners: An application of the theory of planned behavior (TPB) and technology acceptance method (TAM). *Cogent Business & Management*, *10*(2), 2219415. https://doi.org/10.1080/23311975.2023.2219415

Rodgers, C. (2002). Defining Reflection: Another Look at John Dewey and Reflective Thinking. *Teachers College Record*, *104*(4), 842-866. https://doi.org/10.1111/1467-9620.00181

Russo, C., Romano, L., Clemente, D., Iacovone, L., Gladwin, T. E., & Panno, A. (2025). Gender differences in artificial intelligence: the role of artificial intelligence anxiety [Original Research]. *Frontiers in Psychology*, *Volume 16 - 2025*. https://doi.org/10.3389/fpsyg.2025.1559457

Saritepeci, M., & Yildiz Durak, H. (2024). Effectiveness of artificial intelligence integration in design-based learning on design thinking mindset, creative and reflective thinking skills: An experimental study. *Education and Information Technologies*, *29*(18), 25175-25209. https://doi.org/10.1007/s10639-024-12829-2

Šedlbauer, J., Činčera, J., Slavík, M., & Hartlová, A. (2024). Students' reflections on their experience with ChatGPT. *Journal of Computer Assisted Learning*, *40*(4), 1526-1534. https://doi.org/10.1111/jcal.12967

Sobieraj, S., & Krämer, N. C. (2020). Similarities and differences between genders in the usage of computer with different levels of technological complexity. *Computers in Human Behavior*, *104*, 106145. https://doi.org/10.1016/j.chb.2019.09.021

Sumuer, E. (2018). Factors related to college students' self-directed learning with technology. *Australasian Journal of Educational Technology*, *34*(4). https://doi.org/10.14742/ajet.3142

Teo, T. (2012). Examining the intention to use technology among pre-service teachers: an integration of the Technology Acceptance Model and Theory of Planned Behavior. *Interactive Learning Environments*, *20*(1), 3-18. https://doi.org/10.1080/10494821003714632

Teo, T., & van Schaik, P. (2012). Understanding the Intention to Use Technology by Preservice Teachers: An Empirical Test of Competing Theoretical Models. *International Journal of Human–Computer Interaction*, *28*(3), 178-188. https://doi.org/10.1080/10447318.2011.581892

Timothy, T., Seng Chee, T., Chwee Beng, L., Ching Sing, C., Joyce Hwee Ling, K., Wen Li, C., & Horn Mun, C. (2010). The self-directed learning with technology scale (SDLTS) for young students: An initial development and validation. *Computers & Education*, *55*(4), 1764-1771. https://doi.org/10.1016/j.compedu.2010.08.001

van den Berg, G., & du Plessis, E. (2023). ChatGPT and Generative AI: Possibilities for Its Contribution to Lesson Planning, Critical Thinking and Openness in Teacher Education. *Education Sciences*, *13*(10). https://doi.org/10.3390/educsci13100998

Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User Acceptance of Information Technology: Toward A Unified View. *MIS Quarterly*, *27*, 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178.

Wang, C., Li, Z., & Bonk, C. (2024). Understanding self-directed learning in AI-Assisted writing: A mixed methods study of postsecondary learners. *Computers and Education: Artificial Intelligence*, *6*, 100247. https://doi.org/10.1016/j.caeai.2024.100247

Wang, C., Wang, H., Li, Y., Dai, J., Gu, X., & Yu, T. (2024). Factors Influencing University Students' Behavioral Intention to Use Generative Artificial Intelligence: Integrating the Theory of Planned Behavior and AI Literacy. *International Journal of Human–Computer Interaction*, *41*(11), 6649-6671. https://doi.org/10.1080/10447318.2024.2383033

Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems with Applications*, *252*, 124167. https://doi.org/10.1016/j.eswa.2024.124167

Watson, J. H., & Rockinson-Szapkiw, A. (2021). Predicting preservice teachers' intention to use technology-enabled learning. *Computers & Education*, *168*, 104207. https://doi.org/10.1016/j.compedu.2021.104207

Wei, X., Wang, L., Koszalka, T. A., Lee, L.-K., & Liu, R. (2025). Enhancing pre-service teachers' reflective thinking skills through generative AI-assisted digital storytelling creation: A three-dimensional framework analysis. *Computers & Education*, *235*, 105356. https://doi.org/10.1016/j.compedu.2025.105356

Wu, D., Zhang, S., Ma, Z., Yue, X.-G., & Dong, R. K. (2024). Unlocking Potential: Key Factors Shaping Undergraduate Self-Directed Learning in AI-Enhanced Educational Environments. *Systems*, *12*(9). https://doi.org/10.3390/systems12090332

Wu, H., & Dong, Z. (2025). What Motivates Second Language Majors to Use Generative AI for Informal Learning? Insights From the Theory of Planned Behavior. *IEEE Access*, *13*, 34877-34886. https://doi.org/10.1109/ACCESS.2025.3544489

Yao, Y., Wang, P., Jiang, Y., Li, Q., & Li, Y. (2022). Innovative online learning strategies for the successful construction of student self-awareness during the COVID-19 pandemic: Merging TAM with TPB. *Journal of Innovation & Knowledge*, *7*(4), 100252. https://doi.org/10.1016/j.jik.2022.100252

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0