Empowering student learning with generative AI: A self-determination perspective on adoption in tertiary education

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The rapid integration of generative artificial intelligence (GenAI) in education presents both transformative opportunities and challenges for educators. This study investigated the key determinants influencing students' self-determined motivation to adopt GenAI applications in their learning activities. Using a self-reported questionnaire survey, data from 375 university students in Vietnam were analysed through covariance-based structural equation modelling. Our results indicate that the reliability of GenAI and the personalised learning experience it provides foster students' intention to adopt GenAI, whereas pedagogical drawbacks and concerns over data security and privacy hinder its adoption. Furthermore, our findings reveal that digital competence positively moderates the impact of reliability on students' intention to adopt GenAI. The study highlights the perceived benefits of GenAI in promoting self-determined and personalised learning, alongside its limitations in addressing pedagogical needs and ensuring personal data security thereby enhancingstudent's learning effectiveness within a GenAI-enabled digital learning environment.

Implications for practice or policy:

- University educators can enhance student autonomy and competence by integrating generative AI tools into personalised learning activities.
- Institutional leaders should develop clear guidelines and training to address data privacy and ethical use of AI in teaching.
- Curriculum designers may need to embed digital competence development to support effective and equitable AI adoption among students.

Keywords: self-determination, generative AI, reliability, personalised learning, pedagogical drawbacks, data security and privacy, Vietnam

Introduction

The rapid advancement of generative artificial intelligence (GenAI) has significantly influenced the digital transformation of education (Chu et al., 2022; Knight et al., 2023; Lodge et al., 2023). GenAI, exemplified by chatbots such as ChatGPT, Gemini and Microsoft Copilot, is widely accessible and increasingly integrated into higher education (Dai et al., 2023; Lee et al., 2024; Tan et al., 2024). Research has suggested that GenAI can support personalised and flexible learning by tailoring content to students' capabilities and needs, thereby enhancing learning satisfaction and engagement (Chan & Hu, 2023; Grájeda et al., 2024; Thompson et al., 2023; Yeh, 2024).

However, the integration of GenAI into education is not without challenges. Studies have expressed concerns that overreliance on GenAI may diminish the creativity and critical thinking skills of students (Chan, 2023; Zhang et al., 2024). Besides, students' concerns about data privacy and security also highlight the risks of personal information disclosure when integrating GenAI into personalised learning systems (Chan, 2023; Grájeda et al., 2024). Moreover, educators must develop a deeper understanding of how students perceive both the benefits and limitations of GenAI as this is necessary to effectively leverage its pedagogical potential while critically addressing its inherent risks and constraints (Chan & Zhou, 2023).

Against this backdrop, this study addressed the following research question: "What are the students'perceived determinants of GenAI adoption in their self-determined learning in higher education?". Accordingly, this study examined how students' perceptions of key GenAI features shape their self-determined motivation to adopt GenAI in higher education. In response, this study aimed to investigate the determinants that influence students' self-determined motivation to adopt GenAI in their learning activities. Although research has examined students' adoption of GenAI using technology acceptance models and related frameworks, much of this work has emphasised instrumental evaluations such as usefulness, ease of use and behavioural intention, often within specific learning tasks such as academic or language writing (Almusharraf et al., 2025; Tsai, 2025). While informative, these approaches provide less direct insight into how GenAI shapes students' learning motivation and sense of agency in higher education. In contrast, self-determination theory (SDT), by Ryan and Deci (2017), offers a learning-centred perspective by explaining adoption in terms of whether a technology supports or undermines students' psychological needs for autonomy, competence and relatedness. Recent studies have called for deeper examination of GenAI's implications for learning processes, assessment and student engagement beyond task-level performance outcomes (Weng et al., 2024; Xu et al., 2025). However, empirical research applying SDT to identify which features of GenAI are perceived as need-supportive or need-thwarting for self-determined learning remains limited (Annamalai et al., 2025; Gao et al., 2024; Monisha Thangam et al., 2024).

Importantly, this study extends prior adoption models rather than merely reframing established acceptance constructs. Instead of treating reliability, personalisation and privacy concerns as cognitive evaluations of system performance, we reconceptualised them as motivational conditions that shape students' psychological need fulfilment during learning. By integrating both enabling factors (output reliability, personalised learning experience) and constraining (pedagogical drawbacks, data security and privacy risks) factors within a unified need-support framework, the study advances GenAI adoption research from performance-based prediction towards an explanation grounded in learning motivation. In addition, by incorporating digital competence as a contextual moderator, the model proposed in this study explains when perceived reliability becomes more decisive for adoption, thereby extending static acceptance models towards a more conditional and learner-centred framework.

Drawing on SDT (Ryan & Deci, 2017), which posits individuals' motivation and engagement in activities are driven by the fulfilment of three core psychological needs (competence, autonomy and relatedness), this study proposed five key determinants (e.g. output reliability, personalised learning experience, pedagogical drawbacks, data security and privacy and digital competence) for addressing the research objective. Vietnam was selected as the research context not merely for practical reasons but also because it represents a substantively meaningful and under-explored setting for examining students' adoption of GenAI in higher education (Duong & Vu, 2025). The integration of GenAI technologies in its education sector remains in its early stages (Cong-Lem et al., 2024), which makes it an ideal setting to explore students' motivations and concerns regarding this emerging technology. Furthermore, Vietnamese higher education is shaped by an examination-oriented pedagogical tradition influenced by Confucian-heritage culture (Ho, 2020, p. 135), where summative assessment and performance outcomes often dominate instructional practices (Han, 2022; Xiao et al., 2022). This coexistence of established assessment norms with emerging personalised and AI-supported learning approaches provides a distinctive non-Western context for investigating how students evaluate the benefits and limitations of GenAI for self-determined learning. Studying Vietnam therefore offers insights that complement research largely conducted in Western settings and contributes to a more geographically diverse understanding of GenAI adoption in tertiary education.

This study contributes to the literature in three ways. First, it specifies how particular GenAI features operate as need-supportive or need-thwarting conditions within students' learning experiences, thereby extending SDT-informed adoption research. Second, it integrates enabling and constraining determinants within a single explanatory framework, helping reconcile mixed findings in prior GenAI studies. Third, it offers context-sensitive insights for higher education systems undergoing rapid digitalisation, where motivational quality and ethical governance are closely intertwined.

The paper is organised as follows. The next section reviews the relevant literature and outlines the hypotheses. The following section details the sampling methods, questionnaire design and validity and reliability tests. The subsequent section presents the analysis and findings of the results. The final section concludes our study with the implications of our findings, limitations and directions for future research.

Theoretical background and hypotheses development

Self-determined learning with GenAI adoption

SDT posits that individuals' motivation and engagement in learning activities are driven by the fulfilment of three core psychological needs: *competence*, *autonomy* and *relatedness* (Kapasi & Grekova, 2018; Morselli, 2018). Ryan and Deci (2000) distinguished between two types of motivation in SDT: intrinsic and extrinsic. Intrinsic motivation arises when individuals engage in an activity because they find it inherently interesting or enjoyable, whereas extrinsic motivation refers to participation driven by external goals or contingencies, such as rewards, approval, performance requirements or the avoidance of sanctions (Ryan & Deci, 2000). When these needs are met, individuals experience intrinsic motivation, leading to a greater willingness to adopt and integrate new applications into their learning practices (Kapasi & Grekova, 2018).

In educational contexts, competence reflects students' perceptions of their ability to perform effectively, autonomy refers to experiencing volition and control over learning and relatedness concerns feeling connected within the learning environment (Ryan & Deci, 2017, 2000). Applied to GenAI, these needs provide a framework for understanding how students interpret technological features as either supportive or constraining of their learning experience. For instance, autonomy may be enhanced when students can tailor AI-generated responses to their individual learning goals, pacing and preferences (Li et al., 2024; Xia et al., 2022). Competence may be strengthened when GenAI offers structured explanations, feedback or problem-solving assistance that helps students feel capable of completing academic tasks (Annamalai et al., 2025; Monisha Thangam et al., 2024). Relatedness, although less directly associated with AI systems, may be indirectly supported when GenAI is embedded within collaborative or socially interactive learning designs (Arpaci & Kusci, 2025; Gao et al., 2024). Therefore, the adoption intention of GenAI necessitates satisfying students' psychological needs for autonomy, competence and relatedness, in the forms of fostering a sense of control, confidence and connection within the GenAI-driven learning process, ultimately enhancing their self-determined motivation and willingness to adopt GenAI in learning activities.

Research on GenAI in higher education presents a mixed and sometimes contradictory picture. On the one hand, studies have highlighted GenAI's potential to enhance learning efficiency, support personalised learning, and improve academic performance across tasks such as academic and language writing (Almusharraf et al., 2025; Tsai, 2025; Yeh, 2024). On the other hand, persistent concerns have been raised regarding pedagogical quality, overreliance on AI support, academic integrity, and the protection of student data (Chan & Hu, 2023; Kshetri, 2024; Zhang et al., 2024). While some studies have portrayed GenAI as empowering student learning through increased flexibility and personalised support, others have cautioned that its uncritical adoption may undermine key educational processes and learner agency (Weng et al., 2024; Xu et al., 2025). These divergent perspectives suggest that GenAI adoption cannot be understood solely in terms of functional usefulness. Rather, students evaluate GenAI in relation to whether it supports or frustrates their psychological needs within specific learning contexts.

Unlike technology acceptance models that emphasise cognitive evaluations of system performance (Davis, 1989), SDT explains GenAI adoption in terms of students' motivational experiences during learning (Ryan & Deci, 2017). In this study, perceived output reliability and personalised learning experiences are conceptualised as need-supportive conditions that strengthen students' competence and autonomy, whereas pedagogical drawbacks and data security concerns represent potential threats to these psychological needs and to students' sense of relatedness. This reconceptualisation shifts the explanatory focus from performance beliefs to motivational mechanisms, thereby extending GenAI adoption research towards a learning-centred theoretical framework. Framing GenAI adoption through the lens of need support and need frustration redirects attention from students' intention to use the technology towards the quality of their learning engagement with GenAI, a dimension that has received growing attention in recent educational technology research (Ryan & Deci, 2017; Weng et al., 2024; Xu et al., 2025).

Taken together, the literature reveals a central theoretical tension: GenAI simultaneously promises enhanced autonomy and competence while raising concerns about dependency, integrity and data control. Rather than treating these perspectives as mutually exclusive, the present study theorised that students' adoption decisions depend on how specific AI attributes are interpreted as need supportive or need thwarting. The following subsections therefore translate these tensions into directional hypotheses grounded in SDT (Ryan & Deci, 2017).

Output reliability

Output reliability of GenAI applications plays a crucial role in fulfilling students' diverse learning needs for competence and autonomy. GenAI has emerged as a valuable tool that supports students in overcoming learning challenges while enhancing soft skills such as self-reflection, problem-solving and decision-making (Chan & Hu, 2023; Chen et al., 2024). The acceptance of technology is strongly influenced by perceived usefulness and ease of use (Zheng et al., 2024), while perceived enjoyment encourages students to continue online learning (Chiu, 2021a). For instance, Generation Z and Millennials increasingly rely on technology for independent learning, using it as a primary tool for problem-solving and information retrieval (Chan & Lee, 2023). GenAI offers significant pedagogical benefits including assistance in research, skill development, personalised learning support and language translation and writing skills for students who are non-native English speakers or from countries where English is a second language (Yeh, 2024). Particularly during periods of disruption, such as pandemics or natural disasters, GenAI may serve as a supplementary virtual learning support that helps sustain learning continuity, assuming that technological infrastructure and system access remain stable (Major et al., 2021). However, excessive reliance on such technologies without adequate safeguards may introduce additional risks if system functionality is compromised. Moreover, students are more likely to adopt emerging digital technologies when they perceive them as trustworthy (Boubker, 2024). Confidence in GenAI's reliability in providing dependable learning support can foster students' sense of competence (Grájeda et al., 2024), while trust in its fairness and transparency enhances their autonomy as they feel in control of their personalised learning process (Boguslawski et al., 2024). Hence, students who view GenAI applications as trustworthy, accurate and reliable are more likely to feel confident using them as learning aids (Bilquise et al., 2024).

However, studies have also shown that students expect guaranteed ease of use of GenAI applications as their frequent interaction with various advent technologies allows them to directly compare their learning experiences with other best-in-class products (Terblanche et al., 2022). Moreover, GenAI-generated academic writing outputs often contain inaccurate references and lack in-depth analytical insights (Boguslawski et al., 2024; Zhang et al., 2024). As it is challenging for students to evaluate the accuracy and validity of the responses generated in GenAI, careful evaluation remains essential to ensure the reliability of the GenAI outputs (Grájeda et al., 2024; Kshetri, 2024). These contrasting findings indicate that output reliability functions as a decisive boundary condition: when GenAI is perceived as accurate and trustworthy, it reinforces competence and autonomy; when perceived as unreliable, it undermines confidence and motivation. Using Ryan and Deci's (2017) SDT perspective, we therefore posited that reliability operates as a need-supportive condition that strengthens adoption intention. Accordingly, we hypothesised:

Hypothesis 1. Improved output reliability of GenAI fosters the adoption intention of GenAI.

Personalised learning experience

The advancement of GenAI in education enables learner-centred, data-driven and personalised learning experiences that align with individual knowledge demands (Boubker, 2024). In conventional pedagogical settings, students value personalised learning materials and closer instructor interactions (Li et al., 2024). Nevertheless, teachers often face challenges in providing timely feedback and personalised support for student group inquiries, which can hinder the effectiveness of formative assessment (Zhang & Zhang, 2024). Hence, the personalised learning experience provided by GenAI, such as tailored feedback, personalised guidance and adaptable learning pathways, helps students develop competence in their coursework, thus ensuring they engage at an optimal learning level (Monisha Thangam et al., 2024; Yeh, 2024). For instance, GenAI applications can provide instant and accurate responses to students' questions while integrating interdisciplinary knowledge that enriches their understanding across various subjects (Li et al., 2024; Tan et al., 2024). Moreover, students who feel that GenAI enables them to learn at their own pace and receive instant feedback experience greater autonomy in their learning process (Lee et al., 2024). The personalised learning experiences facilitated by GenAI applications sustain students' self-determined motivation by granting them greater control over their learning journey and fulfilling their individual needs (Annamalai et al., 2025; Li et al., 2024).

Furthermore, students adopting GenAI for their studies have increasingly high expectations of its functionality in providing personalised learning. For instance, beyond grammar checking and idea generation, students consistently seek advanced new features in GenAI to enhance their academic writing (Chan & Hu, 2023). They also expect GenAI functionality to go beyond literature searches and summaries by generating hypotheses from data analysis and refining their work, which is not typically offered by common educational technologies (Park & Doo, 2024). However, concerns have been raised about whether the learning materials and content provided by GenAI are truly suitable for personalised learning. For example, GenAI applications developed by native English speakers often present challenges for some students due to their language proficiency limitations, making it difficult for them to formulate effective prompts to obtain better responses (Yeh, 2024). These mixed findings suggest that personalisation is not inherently empowering; its motivational effect depends on whether students experience it as genuinely adaptive and competence-enhancing. From an SDT perspective (Ryan & Deci, 2017), this study proposed that when personalised learning experiences are perceived as strengthening autonomy and competence, they should promote adoption. Therefore, we hypothesised:

Hypothesis 2. Improved personalised learning experiences foster the adoption intention of GenAI.

Pedagogical drawbacks

Another variable of interest to us in addressing the challenges of GenAI is pedagogical drawbacks. Pedagogical drawbacks could negatively impact self-determined motivation by affecting students' relatedness and competence (Ahmad et al., 2023; Kshetri, 2024). Students seek to feel connected in immersive learning environments. If GenAI is perceived as an isolating tool that diminishes engagement and social interactions, students are more likely to feel less motivated to adopt it in their learning activities (Zhang et al., 2024). Besides, if students believe that GenAI applications hinder their development of essential soft skills such as teamwork, critical thinking and problem-solving, their intrinsic motivation may decrease (Chan & Hu, 2023). There is increasing concern that excessive use of GenAI may impede students' intellectual development and the cultivation of key skills, such as creativity, interpersonal skills and leadership abilities (Chiu et al., 2023). Moreover, overreliance on GenAI applications could also undermine students' academic competence, weakening their personal development and growth in learning capabilities (Saihi et al., 2024). Specifically, students may perceive over-dependence on GenAI for information retrieval, rather than actively searching for and critically evaluating sources themselves, which may limit cognitive growth (Ahmad et al., 2023; Larson et al., 2024). Furthermore, there are concerns about academic integrity, cheating, plagiarism and transparency in using GenAI (Chan & Hu, 2023; Zhang et al., 2024). As most plagiarism detection tools are unable to recognise AI-generated content, it can be challenging to determine whether a piece of writing is an author's genuine work (Zhang et al., 2024). GenAI may undermine the credibility of assessment practices, particularly written assignments, causing student anxiety over potential plagiarism accusations and grade penalties. These concerns illustrate how GenAI may shift from being need supportive to need thwarting when students perceive threats to skill development, academic integrity or social connection. From an SDT perspective (Ryan & Deci, 2017), this study argued that such perceptions undermine competence and relatedness, thereby reducing self-determined motivation to adopt the technology. Accordingly, we hypothesised:

Hypothesis 3. Pedagogical drawbacks of GenAI hinder the adoption intention of GenAI.

Data security and privacy

A significant challenge of GenAI is its potential cybersecurity risks (Ferrara, 2024). Data security and privacy risks affect students' autonomy and sense of relatedness in adopting GenAI (Annamalai et al., 2025). If students perceive their personal information to be at risk, they may feel a loss of autonomy in their learning environment, thus leading to resistance towards using GenAI (Arpaci & Kusci, 2025). A lack of trust in GenAI data security and privacy policies can also diminish students' sense of relatedness, making them feel disconnected from a pedagogical environment that fails to prioritise their data protection (Chan, 2023). In contrast, strong data privacy protections can foster a sense of safety and belonging by assuring students that their information is handled responsibly (Chiu, 2021b). Moreover, privacy breaches or unethical data practices can lead to feelings of isolation and vulnerability, hence negatively affecting their learning outcomes (Park & Doo, 2024). Conversely, strong and transparent data protection policies can strengthen students' self-determined motivation to use GenAI by fostering trust in the technology (Chan & Hu, 2023). These findings highlight a critical theoretical tension between technological affordance and perceived loss of control. When students fear data misuse, autonomy and trust are compromised, transforming GenAI into a need-thwarting condition. From an SDT perspective (Ryan & Deci, 2017), this study therefore argued that the perceived privacy risks should weaken students' motivation to adopt GenAI. Given these concerns, we hypothesised:

Hypothesis 4. Data security and privacy risks of GenAI hinder the adoption intention of GenAI.

Moderating role of digital competence

Students' digital competence in using GenAI applications correlates with their competence and autonomy in learning (Annamalai et al., 2025; Grájeda et al., 2024). It equips them to adapt to technology-centric learning environments (Chan & Hu, 2023; Gao et al., 2024). For students from countries where English is a second language, digital proficiency plays a crucial role in overcoming language barriers when crafting effective prompts in GenAI applications, leveraging the applications for language support and critically evaluating responses for accuracy and relevance (Chan & Hu, 2023). However, there is a dearth of research on the moderating role of digital competence in GenAI adoption. This gap is theoretically significant because digital competence may determine whether students interpret AI attributes as supportive or threatening. More digitally capable students may feel greater control over evaluating outputs and managing risks, thereby altering the motivational impact of reliability, personalisation and perceived threats.

Our study argues that higher digital competence strengthens students' capacity to interact effectively with GenAI, evaluate outputs and manage usage-related uncertainties. As a result, students with higher digital competence are more likely to translate positive AI attributes into stronger adoption intention. Specifically, digitally competent students may be better positioned to obtain reliable outputs through effective prompting and verification practices and experience greater personalisation by configuring and iterating interactions to suit their learning needs. Furthermore, this study proposes that the negative impacts of data security and privacy risks on GenAI adoption weaken when students' digital competence increases. For example, students who are more digitally savvy about data security and privacy measures, such as avoiding sensitive prompts and improving their understanding of data risk management, may perceive lower data security and privacy risks during their GenAI adoption (Grájeda et al., 2024). Accordingly, we theorised digital competence as a contextual condition that shapes how need-supportive and need-thwarting attributes influence adoption. We therefore hypothesised:

Hypothesis 5. Students' digital competence in GenAI positively moderates the relationship between the adoption intention of GenAI and its output reliability.

Hypothesis 6. Students' digital competence in GenAI positively moderates the relationship between the adoption intention of GenAI and personalised learning experiences.

Hypothesis 7. Students' digital competence in GenAI negatively moderates the relationship between the adoption intention of GenAI and its data security and privacy risks.

Figure 1 illustrates the proposed research model:

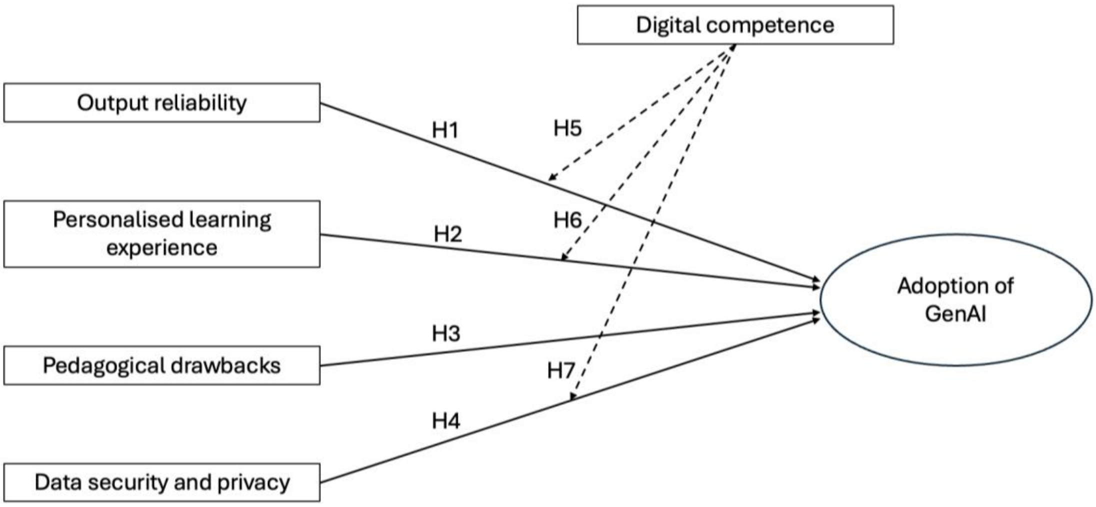

Figure 1. Research model

Research methodology

Sampling and data collection

An online survey questionnaire was administered to collect data from a sample of 900 students across the three biggest universities in Vietnam. The survey questionnaires were administered in the Vietnamese language, and the sample data were collected in 2024. As a result, 387 completed survey questionnaires were collected, representing a response rate of 43%. Finally, 375 answered survey questionnaires were utilised for data analysis after discarding 12 surveys due to incomplete responses. The sample size was determined following Hair et al.'s (2014) recommendation of five to 10 observations per parameter. Therefore, the final data set of 375 responses is deemed sufficient for this study. The collected data sample consisted of undergraduate (97.9%) and postgraduate (2.1%) students, with 60.3% of respondents being female and 39.7% male.

This study adhered to ethical standards for research involving human participants. Participants were informed about the purpose of the study, and their participation was voluntary with the right to withdraw at any time. Informed consent was obtained prior to data collection, and all responses were anonymised and used solely for academic purposes. Ethical approval for this study was granted by the University of Economics Ho Chi Minh City's COB Research Ethics Board (Project No. 2025-04-04-2939).

Measurements

As presented in Table A1 in the Appendix, the survey questions for each construct of this study were derived from literature: Bilquise et al. (2024), Boubker (2024), Chan and Hu (2023), Chan and Zhou (2023), Grájeda et al. (2024) and Guida (2021). In the survey questionnaire, the respondents' responses were measured on a five-point Likert scale with responses ranging from 1 (*strongly disagree*) to 5 (*strongly* *agree*). A total of 25 survey questions were established as observed items for the six constructs (i.e., output reliability, personalised learning experience, pedagogical drawbacks, data security and privacy, digital competence, and adoption of GenAI). The observed items utilised for output reliability included factors that examined students' trust in GenAI applications, focusing on their belief in the faith they have in the information provided. The items evaluated whether students perceive GenAI applications as unbiased and accurate, honest and trustworthy, and capable of providing reliable support for learning.

For personalised learning experience, the observed items assessed how students perceived the personalised guidance and support offered by GenAI applications in their learning journey. They explored such areas as their belief that GenAI could provide personalised guidance for coursework with immediate feedback for assignments and their willingness to pursue a fully online degree with the assistance of a personalised AI tutor. To measure pedagogical drawbacks, the observed items investigated students' concerns about the potential negative impacts of GenAI applications on their learning. They explored whether they felt using GenAI applications undermined the value of university education, limited their opportunities to interact with others and socialise, hindered the development of generic or transferable skills such as teamwork, problem-solving, and leadership, or led to overreliance on GenAI applications for learning tasks.

Furthermore, for measuring data security and privacy, the observed items included factors that evaluated students' concerns regarding how their data was handled when using GenAI applications. The items examined whether they trusted that GenAI policies ensure their data will not be used improperly, reflected the data controller's commitment to privacy, and stated that their data would be treated with due confidentiality. To assess the digital literacy of students in applying GenAI, the observed items measured students' self-reported competence in using GenAI applications for learning. They assessed their ability to formulate prompts in GenAI applications, ease of using the applications to solve problems, frequency of using the applications to support learning, and mastery of the applications in their learning. In addition, the observed items for the adoption of GenAI measured students' usage patterns and future intentions regarding GenAI applications. They examinedhow frequently they engaged with GenAI (whether they use it daily, frequently, or often) and their willingness to integrate it into their teaching and learning practices in the future.

Data analysis

To enhance methodological transparency regarding measurement purification, an exploratory factor analysis (EFA) was first used as a diagnostic step to examine whether the adapted items behaved as expected in the Vietnamese higher education context. EFA settings and decision rules were pre-specified (e.g., factor retention based on eigenvalues and interpretability; rotation method aligned with the expectation of correlated factors; item retention based on loading strength and cross-loading diagnostics). Following purification, confirmatory factor analysis (CFA) was then used to validate the measurement model, assessing model fit and establishing convergent and discriminant validity prior to testing structural paths (Kline, 2016).

Covariance-based structural equation modelling (CB-SEM) was employed in this study to assess the hypothesised relationships and test the theoretical framework grounded in SDT. CB-SEM is well suited for theory testing and confirmation, particularly when the research objective involves validating pre-established models with well-defined constructs (Hair et al., 2014). CB-SEM adopts a confirmatory approach, treating latent constructs as common factors and estimating both shared and unique variances of the observed indicators (Kline, 2016).

Given the theoretical nature of this study and its emphasis on confirming the structural relationships between the proposed determinants (e.g., reliability, personalised learning, pedagogical drawbacks, and data privacy) and students' motivation to adopt GenAI in higher education, CB-SEM was deemed an appropriate methodological choice. Additionally, the study's data met the assumptions of multivariate normality, and the sample size (N = 375) was sufficient for robust maximum likelihood estimation, further justifying the use of CB-SEM (Schumacker & Lomax, 2016).

By employing CB-SEM, the study was able to examine both the direct and moderating effects within the proposed structural model, allowing for a rigorous statistical evaluation of the model's overall fit and the significance of individual path coefficients. This method provided a comprehensive understanding of how the theoretical constructs influence students' self-determined adoption of GenAI technologies in a higher education context.

Results analysis

Measurement model assessment

Table 1 presents the results of construct reliability and validity. Measurement items were initially developed based on their theoretical relevance and expected association with the underlying constructs. During the scale purification process, items exhibiting an item-total correlation below the recommended threshold of 0.35 were excluded to enhance internal consistency (Bagozzi & Yi, 2012). Specifically, for perceived reliability, the items "GenAI provides consistent responses across similar learning tasks" and "I can rely on GenAI outputs without frequently verifying information from other sources" were removed. For personalised learning experience, the items "GenAI adapts learning content based on my emotional or motivational state" and "GenAI personalises learning pace effectively for different types of subjects" were excluded. Regarding educational drawbacks, the items "Excessive use of GenAI reduces students' motivation to attend traditional classes" and "GenAI discourages collaboration and peer learning among students" did not meet the reliability criteria and were therefore eliminated. Similarly, for data security and privacy, the items "GenAI platforms may share user data with third parties without explicit consent" and "I am concerned that my academic work may be reused by GenAI systems without permission" were removed. Finally, within adoption of GenAI, the items "I intend to experiment with new GenAI features as soon as they are released" and "I am willing to recommend GenAI tools to peers for academic purposes" were excluded.

The factors identified through EFA showed extracted variances ranging from 70% to 91.9%. Composite reliability (CR) was assessed to evaluate the reliability and internal consistency of the constructs, with all CR values exceeding 0.70 (ranging from 0.79 to 0.88), confirming adequate internal consistency (Hair et al., 2019). CFA was conducted, and the results demonstrated a good overall fit of the measurement model with χ^2/df = 2.48, which is below the threshold of 3.0, indicating that the proposed five-factor model was highly compatible with the data (Kline, 2005). The root-mean-square error of approximation was 0.063, and the comparative fit index was 0.933, supporting the unidimensionality of the constructs (Hair et al., 2014). Furthermore, standardised regression weights, standard errors, and average variance extracted (AVE) were calculated for each construct to assess convergent validity. Most items had standardised regression weights exceeding 0.50 with values at least twice their corresponding standard errors, demonstrating strong convergent validity (Hair et al., 2014). The constructs of the variables have substantial R^2 values exceeding 0.30, indicating a strong explanatory power of the model (Hair et al., 2014).

Table 1
CR and validity

Constructs	Codes	EFA		CFA			CR	AVE
		Factor loadings	Item-total correlation	Standardised factor loading	SE	R^2		
Perceived reliability	OR1	0.862	0.748	0.816	0.027	0.666	0.887	0.662
	OR2	0.880	0.775	0.834	0.025	0.696		
	OR3	0.871	0.763	0.833	0.025	0.695		
	OR4	0.843	0.722	0.770	0.033	0.593		
	PL1	0.786	0.600	0.671	0.033	0.451	0.791	0.488
	PL2	0.753	0.561	0.630	0.056	0.397		

Constructs	Codes	EFA		CFA			CR	AVE
		Factor loadings	Item-total correlation	Standardised factor loading	SE	R^2		
Personalised learning experience	PL3	0.827	0.650	0.783	0.028	0.613		
	PL4	0.766	0.571	0.700	0.039	0.490		
Educational drawbacks	PD1	0.822	0.674	0.756	0.035	0.571	0.856	0.599
	PD2	0.876	0.758	0.838	0.028	0.702		
	PD3	0.866	0.736	0.813	0.034	0.662		
	PD4	0.760	0.596	0.678	0.046	0.460		
Data security and privacy	DS1	0.909	0.788	0.873	0.036	0.762	0.879	0.708
	DS2	0.882	0.738	0.809	0.041	0.654		
	DS3	0.899	0.768	0.841	0.046	0.707		
Digital competence	DC1	0.700	0.582	0.578	0.051	0.334	0.872	0.535
	DC2	0.762	0.656	0.640	0.041	0.410		
	DC3	0.818	0.720	0.739	0.028	0.546		
	DC4	0.747	0.626	0.735	0.032	0.540		
	DC5	0.820	0.712	0.821	0.028	0.674		
	DC6	0.842	0.748	0.841	0.027	0.707		
Adoption of GenAI	AG1	0.731	0.572	0.627	0.030	0.393	0.879	0.650
	AG2	0.882	0.744	0.855	0.024	0.731		
	AG3	0.919	0.837	0.898	0.019	0.806		
	AG4	0.861	0.740	0.817	0.028	0.668		

Common method bias was also assessed statistically. Firstly, a Harman single-factor test was conducted as a baseline diagnostic; the results indicated that a single factor did not account for the majority of variance. Secondly, a common latent factor (or equivalent CFA-based) approach was employed to examine whether adding a method factor materially altered standardised loadings and structural path estimates; changes were not substantial, suggesting that common method bias was unlikely to threaten the substantive conclusions (Podsakoff et al., 2003).

Structural model results analysis

Table 2 presents the results of the direct effect and moderating effect. The results show that the adoption of GenAI is positively influenced by personalised learning experience (0.212, $p < 0.01$) and output reliability of GenAI (0.279, $p < 0.01$). Thus, the results indicate that output reliability and personalised learning experience foster the adoption of GenAI, thus providing evidence that supports H1 and H2. Besides, the results report that the adoption of GenAI is negatively impacted by data security and privacy (-0.232, $p < 0.01$) and pedagogical drawbacks of GenAI (-0.118, $p < 0.01$). Notably, the results reveal that data security and privacy have twice the negative impact on the adoption of GenAI, compared to its pedagogical drawbacks. Hence, the results indicate that the risk of data security and privacy and the pedagogical drawbacks hinder the adoption of GenAI, thus providing evidence that supports H3 and H4. Regarding moderating effects, the results indicate that digital competence positively moderates the relationship between output reliability and GenAI adoption ($\beta = 0.163$, $t = 2.819$, $p = 0.005$). This suggests that the positive effect of perceived output reliability on students' intention to adopt GenAI becomes stronger when students report higher levels of digital competence. Therefore, H5 is supported. No significant evidence was found for the influence of digital competence on the relationships between the adoption of GenAI and the personalised learning experience and data security and privacy of GenAI applications. Thus, H6 and H7 are rejected.

Table 2
Direct and moderating effect testing results

Regression	Correlations	Mean	*t* statistic	*p* value
Direct effect	Output reliability → Adoption of GenAI	0.275	4.939	0.000
	Personalised learning experience → Adoption of GenAI	0.213	4.636	0.000
	Pedagogical drawbacks → Adoption of GenAI	-0.117	2.546	0.011
	Data security and privacy → Adoption of GenAI	-0.234	4.210	0.000
Moderating effect	Output reliability × Digital competence → Adoption of GenAI	0.163	2.819	0.005
	Personalised learning experience × Digital competence → Adoption of GenAI	-0.022	0.530	0.596
	Data security and privacy × Digital competence → Adoption of GenAI	-0.008	0.158	0.875

Discussion

Rather than viewing GenAI adoption as a purely instrumental decision, the findings indicate that students evaluate the technology primarily through its capacity to support or constrain their psychological needs for competence, autonomy and relatedness. In particular, the strong positive effects of output reliability and personalised learning experience suggest that students are more inclined to adopt GenAI when it is perceived as enabling effective learning and self-directed progress. Reliable outputs reduce cognitive uncertainty and help students feel capable of completing academic tasks, thereby strengthening their sense of competence. Similarly, personalised learning experiences enhance autonomy by allowing students to regulate pace, content and learning strategies in ways that align with their individual goals. This interpretation aligns with studies emphasising that GenAI is most educationally valuable when it supports learners' active engagement rather than merely increasing efficiency (Boguslawski et al., 2024; Chan & Hu, 2023; Tsai, 2025).

Beyond functional usefulness, these findings resonate with emerging GenAI adoption frameworks that emphasise hybrid human-AI collaboration and learner agency. Recent work on hybrid intelligent feedback argues that GenAI becomes educationally meaningful when embedded within pedagogical structures that preserve shared agency between learners, teachers and AI systems (Banihashem et al., 2024; Banihashem, Bond et al., 2025). In this sense, output reliability does not merely increase intention to use but also strengthens students' confidence to actively co-construct knowledge with AI tools, thereby reinforcing competence and autonomy simultaneously.

In contrast, the negative effects of pedagogical drawbacks and data security and privacy concerns highlight the conditions under which GenAI becomes need thwarting rather than need supportive. Notably, concerns related to data security and privacy exerted a substantially stronger negative impact on adoption than pedagogical drawbacks. This pattern suggests that perceived threats to autonomy, particularly the loss of control over personal data, weigh more heavily in students' decision-making than abstract concerns about skill development or instructional quality. As argued in research, when students are uncertain about how their data are collected, stored or reused, trust in the learning environment is undermined, which can reduce willingness to engage with digital technologies regardless of their pedagogical potential (Chan & Hu, 2023; Kshetri, 2024; Weng et al., 2024). This interpretation aligns with AI-self-regulated learning research, which stresses that trust, transparency and explainability are prerequisites for meaningful AI integration in higher education (Banihashem, Noroozi et al., 2025). Without transparent governance and ethical safeguards, students may experience diminished agency, thereby weakening the motivational foundations necessary for sustained engagement with GenAI.

This finding becomes especially meaningful when situated within the context of Vietnamese higher education. As a system undergoing rapid digitalisation, Vietnamese universities are still developing institutional policies, technical infrastructures, and shared norms governing the ethical use of GenAI

(Nguyen et al., 2025). In such contexts, students may experience heightened uncertainty regarding data governance and academic accountability, particularly in assessment-driven learning environments, where academic records carry high personal and institutional stakes. Consequently, data security and privacy concerns may directly undermine students' sense of autonomy, making these risks more salient than pedagogical considerations when evaluating GenAI adoption. This contextual explanation helps clarify why privacy-related concerns, rather than pedagogical drawbacks alone, emerged as the strongest deterrent in the present study.

Turning to pedagogical drawbacks, the weaker yet significant negative effect suggests a more ambivalent student stance. While concerns about overreliance, reduced critical thinking and diminished social interaction are present, these issues appear less immediately constraining than data-related risks. One possible explanation is that students perceive pedagogical drawbacks as manageable through individual strategies, such as selective use of GenAI, peer collaboration or instructor guidance. In contrast, data security risks are often viewed as beyond individual control, making them more threatening to students' sense of agency. This distinction reinforces the importance of examining not only whether risks exist but also how controllable students perceive those risks to be within their learning environment (Xu et al., 2025; Zhang et al., 2024).

Further insight emerges from the moderating role of digital competence. The finding that digital competence strengthens the relationship between output reliability and adoption suggests that digitally capable students are better equipped to engage critically with GenAI outputs. Building on this point, students with higher digital competence are likely more adept at evaluating the credibility of responses, refining prompts and integrating AI-generated content into their learning strategies. As a result, reliability becomes a more decisive factor for these students because it directly affects their ability to use GenAI as a meaningful learning aid rather than a passive shortcut. This helps explain why digital competence did not significantly buffer concerns related to data privacy but instead amplified the importance of reliable outputs as a foundation for competent and autonomous learning engagement (Grájeda et al., 2024; Tan et al., 2024).

Taken together, these findings help reconcile ongoing tensions in the GenAI literature. While some studies have emphasised the benefits of GenAI for efficiency and personalised learning, others have cautioned against risks related to academic integrity, learner dependency, and ethical governance (Almusharraf et al., 2025; Chan & Hu, 2023; Zhang et al., 2024). The present study demonstrates that these perspectives are not contradictory, but conditional. By integrating SDT with emerging GenAI adoption and hybrid intelligence frameworks, this study extends work that has predominantly focused on system performance or task outcomes. Instead, it demonstrates that sustainable GenAI adoption in higher education depends on whether institutional practices preserve learner agency, support competence development and ensure ethical transparency. From an SDT perspective (Ryan & Deci, 2017), GenAI supports student learning when it is experienced as need-supportive, particularly in terms of competence and autonomy, and undermines learning when it is perceived as threatening these needs. By foregrounding students' motivational experiences, this study shifts the discussion from whether GenAI should be adopted to how it should be designed, governed, and embedded within educational practice to support meaningful learning.

Implications for pedagogical practices

Our findings offer several practical implications for educators. First, because output reliability emerged as the strongest positive predictor of adoption, educators should design learning activities that require students to critically evaluate AI-generated outputs rather than passively accept them. For example, assignments may ask students to compare AI-generated responses with peer-reviewed academic sources, identify inaccuracies or fabricated references, and justify revisions. Such structured evaluation aligns with concerns regarding reliability and academic integrity (Boguslawski et al., 2024; Zhang et al., 2024) while strengthening students' sense of competence and autonomy. Importantly, these practices align with hybrid intelligent feedback frameworks, which recommend positioning GenAI outputs as an initial layer of feedback that is iteratively refined through human judgement (Banihashem et al., 2024). Educators may therefore adopt models such as human-led feedback with AI support or AI-led feedback with human enrichment, ensuring that GenAI complements rather than replaces instructional guidance.

Second, educators should be mindful of the pedagogical drawbacks and the data security and privacy issues when integrating GenAI into the curriculum. Given that data security concerns exerted a stronger negative impact than pedagogical drawbacks, institutions should provide transparent guidelines regarding acceptable AI use, data handling practices, and assessment expectations. Clear policies and open dialogue about AI governance can reduce uncertainty and restore students' sense of autonomy and trust (Chan & Hu, 2023; Kshetri, 2024). Although GenAI can enhance learning through personalised support, instant feedback, and accessibility, its use should be guided by established ethical academic practices to prevent plagiarism and ensure academic integrity (Chiu et al., 2023). Thus, institutions and educators may draw on responsible AI integration models that emphasise transparency, shared agency, and explicit alignment with learning objectives (Banihashem, Bond et al., 2025). For example, clarifying whether AI is used for formative feedback, drafting assistance, or summative evaluation can reduce ambiguity and reinforce students' perceived control over their learning process.

Moreover, while enhancing the advantages of GenAI, robust data security and privacy measures should be emphasised to ensure the safety of personally identifiable information and uphold the ethical use of GenAI in learning activities. To safeguard student data and promote ethical AI use in education, it is essential to implement strong security and privacy measures that protect user information while maximising the benefits of personalised learning through GenAI. Moreover, the moderating role of digital competence suggests that AI integration should be accompanied by explicit instruction in prompt formulation, source verification, and ethical AI literacy. Students with higher digital competence were more responsive to reliability perceptions, indicating that skill development enhances meaningful AI engagement. This finding aligns with calls for structured AI literacy development in higher education (Li et al., 2024). Embedding short training modules or scaffolded exercises within courses may therefore help students engage with AI tools more confidently and responsibly. This recommendation is consistent with AI-self-regulated learning frameworks, which advocate embedding AI tools within structured metacognitive scaffolding to enhance reflective use rather than superficial dependency (Banihashem, Noroozi et al., 2025).

Third, educators should emphasise the paradigm shift from traditional learning methods to personalised online learning approaches. Students' perceptions of GenAI's reliability and personalised learning experiences are central to their self-determined motivations to adopt the technology. These findings highlight students' preferences for the diverse and innovative platforms provided by GenAI, which signifies a shift towards more personalised, engaging, and effective self-determined online learning methods tailored to meet students' evolving self-paced learning needs. In practice, this may involve integrating AI-supported drafting with peer review, using AI for formative feedback while retaining human evaluation for summative assessment or designing inquiry-based tasks where AI functions as a cognitive support rather than a substitute for reasoning (Weng et al., 2024; Yeh, 2024). Such approaches preserve learner agency while capitalising on AI's adaptive affordances. In countries where test-centric methodologies dominate traditional education, such as Vietnam, carefully structured AI use can help balance examination expectations with opportunities for autonomy and competence development (Minh et al., 2024). Therefore, GenAI should be embedded within pedagogical designs that explicitly support self-determined learning while safeguarding academic integrity and trust. Such hybrid configurations operationalise shared agency and complementarity principles within GenAI adoption models, allowing institutions to harness scalability while preserving pedagogical depth (Banihashem et al., 2024).

Final remarks

Drawing from SDT, this study addressed the research question by examining the factors that influence students' self-determined motivations to adopt GenAI in their learning activities. Our findings indicate that students perceive the reliability of GenAI applications and the personalised learning experiences they offer as key advantages, shaping their self-determined learning pathways and enhancing their learning capabilities. In contrast, concerns about data security, privacy, and pedagogical drawbacks were identified as limitations that hinder students' adoption of GenAI. Moreover, our results demonstrate that students' digital competence in using GenAI applications positively moderates their perception of the applications' reliability and strengthens their intention to adopt them for learning.

This study has two main limitations. First, it was conducted in an Eastern cultural context, where pedagogical practices, societal values, and attitudes towards GenAI adoption may differ from those in Western regions. As a result, our findings may not fully capture the perceptions of educators and students in Western contexts. Future research could expand this study by exploring GenAI integration across various pedagogical sectors, both horizontally (across different countries) and vertically (across pedagogical levels, from primary and secondary schools to transnational education programmes). This would help examine GenAI's effectiveness in diverse cultural, economic, and infrastructural contexts.

Second, given that GenAI is a relatively new digital technology, some students who participated in the research may have had a limited or partial understanding of GenAI. This lack of comprehensive knowledge could have led to biased or inaccurate survey responses, potentially affecting the overall validity of our findings. Future research could explore the long-term impact of GenAI on curricula delivered in different languages, providing insights into how sustained GenAI tool use influences students' self-determined motivation, engagement, and learning outcomes. Additionally, comprehensive studies of diverse teaching and learning pedagogies could assess GenAI's effectiveness in delivering adaptive learning modules and facilitating differentiated instruction.

Future research could also explore the development and implementation of GenAI-driven assessment and feedback mechanisms, examining their accuracy, effectiveness, and student reception compared to traditional evaluation methods. In doing so, scholars may build upon hybrid intelligent feedback and AI self-regulated learning frameworks to investigate how structured human-AI collaboration influences long-term motivation, agency, and learning quality across cultural contexts (Banihashem et al., 2024; Banihashem et al., 2025). The findings could inform the redesign of teacher training programmes to incorporate GenAI digital literacy, enabling educators to integrate AI effectively, evaluate its impact on classroom practices, and develop innovative teaching strategies tailored to students' specific needs.

Author contributions

Thu-Hang Hoang: Conceptualisation, Investigation, Writing – original draft, Writing – review and editing; **Stanley Teck Lee Yap:** Data curation, Investigation, Formal analysis, Writing – review and editing; **Minh Nhat Nguyen:** Conceptualisation, Formal analysis, Validation, Writing – review and editing; **Son Nguyen:** Investigation, Writing – review and editing; **Nguyen Canh Lam:** Investigation, Writing – review and editing; **Duy Dang:** Supervision, Methodology, Writing – review and editing; **Huy Truong Quang:** Supervision, Methodology, Writing – review and editing; **Duong An:** Methodology, Writing – review and editing.

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References

Ahmad, S. F., Han, H., Alam, M. M., Rehmat, M. K., Irshad, M., Arrano-Munoz, M., & Ariza-Montes, A. (2023). Impact of artificial intelligence on human loss in decision making, laziness and safety in education. *Humanities and Social Sciences Communications*, *10*(1), Article 311. https://doi.org/10.1057/s41599-023-01787-8

Almusharraf, A., Bailey, D., Almusharraf, N., & Alotaibi, T. (2025). Students' perceptions of generative AI in EFL writing: Strategies, self-efficacy, satisfaction and behavioural intention. A*ustralasian Journal of Educational Technology*, *41*(5), 18-36. https://doi.org/10.14742/ajet.10045

Annamalai, N., Bervell, B., Mireku, D. O., & Andoh, R. P. K. (2025). Artificial intelligence in higher education: Modelling students' motivation for continuous use of ChatGPT based on a modified self-determination theory. *Computers and Education: Artificial Intelligence*, *8*, Article 100346. https://doi.org/10.1016/j.caeai.2024.100346

Arpaci, I., & Kusci, I. (2025). A hybrid SEM-ANN approach for predicting the impact of psychological needs on satisfaction with generative AI use. *Technology, Knowledge and Learning, 30*(4), 2329–2350. https://doi.org/10.1007/s10758-025-09817-x

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science*, *40*(1), 8–34. https://doi.org/10.1007/s11747-011-0278-x

Banihashem, S. K., Bond, M., Bergdahl, N., Khosravi, H., & Noroozi, O. (2025). A systematic mapping review at the intersection of artificial intelligence and self-regulated learning. *International Journal of Educational Technology in Higher Education*, *22*, Article 50. https://doi.org/10.1186/s41239-025-00548-8

Banihashem, S. K., Kerman, N. T., Noroozi, O., Moon, J., & Drachsler, H. (2024). Feedback sources in essay writing: peer-generated or AI-generated feedback?. *International Journal of Educational Technology in Higher Education*, *21*, Article 23. https://doi.org/10.1186/s41239-024-00455-4

Banihashem, S. K., Noroozi, O., Khosravi, H., Schunn, C. D., & Drachsler, H. (2025). Pedagogical framework for hybrid intelligent feedback. *Innovations in Education and Teaching International. 63*(2), 554–570. https://doi.org/10.1080/14703297.2025.2499174

Bilquise, G., Ibrahim, S., & Salhieh, S. E. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies*, *29*(5), 6357–6382. https://doi.org/10.1007/s10639-023-12076-x

Boguslawski, S., Deer, R., & Dawson, M. G. (2024). Programming education and learner motivation in the age of generative AI: student and educator perspectives. *Information and Learning Sciences*, *126*(1/2), 91–109. https://doi.org/10.1108/ILS-10-2023-0163

Boubker, O. (2024). From chatting to self-educating: Can AI tools boost student learning outcomes? *Expert Systems with Applications*, *238,* Article 121820. https://doi.org/10.1016/j.eswa.2023.121820

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, *20*, Article 38. https://doi.org/10.1186/s41239-023-00408-3

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*, Article 43. https://doi.org/10.1186/s41239-023-00411-8

Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, *10*, Article 60. https://doi.org/10.1186/s40561-023-00269-3

Chan, C. K. Y., & Zhou, W. (2023). Deconstructing student perceptions of generative AI (GenAI) through an expectancy value theory (EVT)-based instrument. arXiv. https://doi.org/10.48550/arXiv.2305.01186

Chen, L., Ifenthaler, D., Yau, J. Y.-K., & Sun, W. (2024). Artificial intelligence in entrepreneurship education: a scoping review. *Education + Training*, *66*(6), 589–608. https://doi.org/10.1108/ET-05-2023-0169

Chiu, T. K. F. (2021a). Applying the self-determination theory (SDT) to explain student engagement in online learning during the COVID-19 pandemic. *Journal of Research on Technology in Education*, *54*(sup1), S14–S30. https://doi.org/10.1080/15391523.2021.1891998

Chiu, T. K. F. (2021b). Digital support for student engagement in blended learning based on self-determination theory. *Computers in Human Behavior*, *124,* Article 106909. https://doi.org/10.1016/j.chb.2021.106909

Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *4*, Article 100118. https://doi.org/10.1016/j.caeai.2022.100118

Chu, H. C., Hwang, G. H., Tu, Y. F., & Yang, K. H. (2022). Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. *Australasian Journal of Educational Technology*, *38*(3), 22–42. https://doi.org/10.14742/ajet.7526

Cong-Lem, N., Tran, T. N., & Nguyen, T. T. (2024). Academic integrity in the age of generative AI: Perceptions and responses of Vietnamese EFL teachers. *Teaching English with Technology*, *24*(1), 28–47. https://doi.org/10.56297/FSYB3031/MXNB7567

Dai, Y., Lai, S., Lim, C. P., & Liu, A. (2023). ChatGPT and its impact on research supervision: Insights from Australian postgraduate research students. *Australasian Journal of Educational Technology*, *39*(4), 74–88. https://doi.org/10.14742/ajet.8843

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Duong, C. D., & Vu, T. N. (2025). Entrepreneurial education and higher education students'e-entrepreneurial intention: a moderated mediation model of generative AI incorporation and e-entrepreneurial self-efficacy. *Higher Education, Skills and Work-Based Learning*, *15*(5), 1024–1048. https://doi.org/10.1108/HESWBL-12-2024-0390

Ferrara, E. (2024). GenAI against humanity: nefarious applications of generative artificial intelligence and large language models. *Journal of Computational Social Science*, *7*(1), 549–569. https://doi.org/10.1007/s42001-024-00250-1

Gao, Z., Cheah, J.-H., Lim, X.-J., & Luo, X. (2024). Enhancing academic performance of business students using generative AI: An interactive-constructive-active-passive (ICAP) self-determination perspective. *The International Journal of Management Education*, *22*(2), Article 100958. https://doi.org/10.1016/j.ijme.2024.100958

Grájeda, A., Burgos, J., Córdova, P., & Sanjinés, A. (2024). Assessing student-perceived impact of using artificial intelligence tools: Construction of a synthetic index of application in higher education. *Cogent Education*, *11*(1), Article 2287917. https://doi.org/10.1080/2331186X.2023.2287917

Hair, J. F., Gabriel, M., & Patel, V. (2014). AMOS covariance-based structural equation modeling (CB-SEM): Guidelines on its application as a marketing research tool. *Brazilian Journal of Marketing*, *13*(2), 44–55. https://doi.org/10.5585/remark.v13i2.2718

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, *53*(4), 566–584. https://doi.org/10.1108/EJM-10-2018-0665

Han, I. (2022). Contextualization of communicative language teaching in confucian heritage culture: Challenging pedagogic dichotomization. *SAGE Open*, *12*(1), Article 21582440221079895. https://doi.org/10.1177/21582440221079895

Ho, S. (2020). Culture and learning: Confucian heritage learners, social-oriented achievement, and innovative pedagogies. In C. S. Sanger & N. W. Gleason (Eds.), *Diversity and inclusion in global higher education: Lessons from across Asia* (pp. 117–159). Springer Nature. https://doi.org/10.1007/978-981-15-1628-3

Kapasi, I., & Grekova, G. (2018). What do students think of self-determined learning in entrepreneurship education? *Education+ Training, 60*(7/8), 841–856. https://doi.org/10.1108/ET-02-2017-0028

Kline, T. J. (2005). *Psychological testing: A practical approach to design and evaluation.* Sage Publications. https://doi.org/10.4135/9781483385693

Knight, S., Dickson-Deane, C., Heggart, K., Kitto, K., Kozanoğlu, D. C., Maher, D., Narayan, B, & Zarrabi, F. (2023). Generative AI in the Australian education system: An open data set of stakeholder recommendations and emerging analysis from a public inquiry. *Australasian Journal of Educational Technology, 39(*5), 101–124. https://doi.org/10.14742/ajet.8922

Kshetri, N. (2024). The academic industry's response to generative artificial intelligence: An institutional analysis of large language models. *Telecommunications Policy, 48*(5), Article 102760. https://doi.org/10.1016/j.telpol.2024.102760

Larson, B. Z., Moser, C., Caza, A., Muehlfeld, K., & Colombo, L. A. (2024). Critical thinking in the age of generative AI. *Academy of Management Learning & Education*, *23*(3), 373–378. https://doi.org/10.5465/amle.2024.0338

Lee, H. Y., Chen, P. H., Wang, W. S., Huang, Y. M., & Wu, T. T. (2024). Empowering ChatGPT with guidance mechanism in blended learning: Effect of self-regulated learning, higher-order thinking skills, and knowledge construction. *International Journal of Educational Technology in Higher Education*, *21*, Article 16. https://doi.org/10.1186/s41239-024-00447-4
Li, Y., Zhou, X., & Chiu, T. K. F. (2024). Systematic review on artificial intelligence chatbots and ChatGPT for language learning and research from self-determination theory (SDT): what are the roles of teachers? *Interactive Learning Environments*, *33*(3), 1850–1864. https://doi.org/10.1080/10494820.2024.2400090
Lodge, J. M., Thompson, K., & Corrin, L. (2023). Mapping out a research agenda for generative artificial intelligence in tertiary education. *Australasian Journal of Educational Technology*, *39*(1), 1–8. https://doi.org/10.14742/ajet.8695
Major, L., Francis, G. A., & Tsapali, M. (2021). The effectiveness of technology-supported personalised learning in low- and middle-income countries: A meta-analysis. *British Journal of Educational Technology*, *52*(5), 1935–1964. https://doi.org/10.1111/bjet.13116
Minh, L. C., Dung, N. T. M., Hieu, P. N. V., Linh, N. T., Han, N. T. N., & Trong, H. (2024). The impact of students' using generative AI for learning on self-learning motivation: A study based on self-determination theory. *Proceedings of the 2nd International Conference - Resilience by Technology and Design*, 362–382). https://doi.org/10.2991/978-94-6463-583-6_19
Monisha Thangam, K. S., Anju, S., Madhavan, S. P., & Gupta, D. (2024). Innovativeness or competence: A self-determination theory model of how students use generative AI in higher education. In M. Tuba, S. Akashe, & A. Joshi (Eds.), *Lecture notes in networks and systems: Vol. 1163*. *ICT systems and sustainability* (pp. 321–328). Springer. https://doi.org/10.1007/978-981-97-8537-7_29
Morselli, D. (2018). Teaching a sense of initiative and entrepreneurship with constructive alignment in tertiary non-business contexts. *Education+ Training*, *60*(2), 122–138. https://doi.org/10.1108/ET-06-2017-0093
Nguyen, A., Duong, A. T., Nguyen, D. T. B., Lai, V. T. T., & Dang, B. (2025). Guidelines for learning design and assessment for generative artificial intelligence-integrated education: A unified view. *Information and Learning Sciences*, *126*(7-8), 491-512. https://doi.org/10.1108/ILS-11-2024-0148
Park, Y., & Doo, M. Y. (2024). Role of AI in blended learning: A systematic literature review. *The International Review of Research in Open and Distributed Learning*, *25*(1), 164–196. https://doi.org/10.19173/irrodl.v25i1.7566
Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford publications. https://doi.org/10.1007/978-3-031-17299-1
Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology* , *25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020
Saihi, A., Ben-Daya, M., Hariga, M., & As'ad, R. (2024). A structural equation modeling analysis of generative AI chatbots adoption among students and educators in higher education. *Computers and Education: Artificial Intelligence*, *7,* Article 00274. https://doi.org/10.1016/j.caeai.2024.100274
Schumacker, R. E., & Lomax, R. G. (2016). *A beginner's guide to structural equation modeling (4th ed.).* Routledge. https://doi.org/10.4324/9781315749105
Tan, C. N., Tee, M., & Koay, K. Y. (2024). Discovering students' continuous intentions to use ChatGPT in higher education: a tale of two theories. *Asian Education and Development Studies*, *13*(4), 356–372. https://doi.org/10.1108/aeds-04-2024-0096
Terblanche, N., Molyn, J., Williams, K., & Maritz, J. (2022). Performance matters: students' perceptions of Artificial Intelligence Coach adoption factors. *Coaching: An International Journal of Theory, Research and Practice*, *16*(1), 100–114. https://doi.org/10.1080/17521882.2022.2094278
Thompson, K., Corrin, L., & Lodge, J. M. (2023). AI in tertiary education: Progress on research and practice. *Australasian Journal of Educational Technology, 39*(5), 1–7. https://doi.org/10.14742/ajet.9251
Tsai, S. C. (2025). Online EFL business writing with GenAI-generated templates: Students' performance and perceptions. *Australasian Journal of Educational Technology*, *41*(6), 82–97. https://doi.org/10.14742/ajet.10743

Weng, X., Qi, X. I. A., Gu, M., Rajaram, K., & Chiu, T. K. (2024). Assessment and learning outcomes for generative AI in higher education: A scoping review on current research status and trends. *Australasian Journal of Educational Technology*. 40(6), 37–55. https://doi.org/10.14742/ajet.9540

Xia, Q., Chiu, T. K. F., Lee, M., Sanusi, I. T., Dai, Y., & Chai, C. S. (2022). A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education. *Computers & Education*, *189,* Article 104582. https://doi.org/10.1016/j.compedu.2022.104582

Xiao, Y., Cai, Y., Ge, Q., & Yang, Y. (2022). The potential of using formative assessment to enhance academic achievement in the Confucian-heritage culture: A comparison between Hong Kong and Shanghai. *The Asia-Pacific Education Researcher*, *32*(6), 867–876. https://doi.org/10.1007/s40299-022-00702-0

Xu, J., Shen, R., Li, J., & Hu, D. (2025). Artificial intelligence literacy among Chinese Master of Education students: Current situation, influencing factors and generative pathways. *Australasian Journal of Educational Technology*, *41*(6), 1–17. https://doi.org/10.14742/ajet.10656

Yeh, H. -C. (2024). The synergy of generative AI and inquiry-based learning: transforming the landscape of English teaching and learning. *Interactive Learning Environments*, *33*(1), 88–102. https://doi.org/10.1080/10494820.2024.2335491

Zhang, L., Amos, C., & Pentina, I. (2024). Interplay of rationality and morality in using ChatGPT for academic misconduct. *Behaviour & Information Technology*, *44*(3), 491–507. https://doi.org/10.1080/0144929x.2024.2325023

Zhang, L., & Zhang, W. (2024). Integrating large language models into project-based learning based on self-determination theory. *Interactive Learning Environments*, *33*(5), 3580–3592. https://doi.org/10.1080/10494820.2024.2446535

Zheng, Y., Wang, Y., Liu, K. S.-X., & Jiang, M. Y.-C. (2024). Examining the moderating effect of motivation on technology acceptance of generative AI for English as a foreign language learning. *Education and Information Technologies*, *29*(17), 23547–23575. https://doi.org/10.1007/s10639-024-12763-3

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Appendix

Table A1
Measurement items for each factor and source

Constructs	Codes	Measurement items	Sources
Perceived reliability	OR1	I think I would have faith in the information provided by the GenAI applications.	Bilquise et al. (2024)
	OR2	I think that the GenAI applications provide unbiased and accurate information and recommendations.	
	OR3	I think that the GenAI applications would be honest and trustworthy.	
	OR4	I think that the GenAI applications would provide reliable support.	
Personalised learning experience	PL1	GenAI applications can provide personalised guidance for coursework as effectively as human teachers.	Chan and Zhou (2023)
	PL2	If a fully online programme with the assistance of a personalised AI tutor was available, I would be willing to pursue my degree through this option.	
	PL3	I think GenAI applications can provide me with personalised and immediate feedback and suggestions for my assignments.	
	PL4	I think GenAI is a great tool for student support services due to anonymity.	
Pedagogical drawbacks	PD1	Using GenAI applications to complete assignments undermines the value of university education.	Chan and Hu (2023)
	PD2	GenAI applications will limit my opportunities to interact with others and socialise while completing coursework.	
	PD3	GenAI applications will hinder my development of generic or transferable skills such as teamwork, problem-solving and leadership skills.	
	PD4	I can become overreliant on GenAI applications.	
Data security and privacy	DS1	The GenAI applications policy ensures that my data will not be used improperly.	Guida (2021)
	DS2	The GenAI application’s policy reflects the data control commitment to privacy.	
	DS3	The GenAI application's policy states that my data will be treated with due confidentiality.	
Digital competence	DC1	I had no difficulties formulating the prompts in the GenAI applications to support learning.	Grájeda et al. (2024)
	DC2	I found it easy to use GenAI applications to formulate my questions to support learning.	
	DC3	The GenAI applications used to support learning were easy to use to solve problems.	
	DC4	I frequently used GenAI applications to support learning.	
	DC5	I mastered GenAI applications applied to my learning.	
	DC6	I mastered the use of the GenAI tool in learning.	
Adoption of GenAI	AG1	I envision integrating GenAI applications into my teaching and learning practices in the future.	Chan and Zhou (2023); Boubker (2024)
	AG2	I use GenAI applications daily.	
	AG3	I use GenAI applications frequently.	
	AG4	I visit GenAI applications often.	