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Understanding students' perceptions of generative AI: Implications for pedagogy and graduate employability

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Abstract

As artificial intelligence (AI) transforms workplaces, understanding how future graduates engage with AI technologies is crucial for enhancing employability. This study investigates higher education students' familiarity with and perceptions of generative artificial intelligence (GenAI) in their learning. Using the Technology Acceptance Model (TAM) and incorporating personal innovativeness in information technology, we examined factors influencing students' adoption of GenAI. An online survey was conducted between April 30 and May 11, 2024, with 233 students from a college in northern Israel completing the questionnaire. Results revealed significant positive correlations, supporting the study's theoretical framework. Personal innovativeness was strongly related to TAM variables. Perceived usefulness, perceived ease of use, attitude toward use and behavioural intention to use the technology were each significant predictors of actual GenAI use. Gender and field of study influenced adoption, with both males and students studying information systems and economics showing higher usage rates. To the best of our knowledge, this study is the first to integrate TAM with personal innovativeness and demographic factors to assess student engagement with GenAI. The findings provide a theoretical and empirical foundation for understanding student responses to new technologies in higher education. The identified gender gap and field-based differences suggest that tailored approaches are necessary to enhance student engagement with GenAI tools. Overall, the findings imply that teaching practices should include scaffolded, inclusive strategies that foster GenAI literacy, adaptability and ethical awareness. Such approaches may strengthen students' preparedness for AI-enhanced workplaces and support higher education's role in assuring graduate employability.

Keywords
GenAI, TAM (Technology Acceptance Model), personal innovativeness in IT, employability, AI in education, workforce transformation, digital competencies, higher education policy

Introduction

Amid ongoing debates on the impact of technology in the sphere of education (Baytak, 2023; Tamim et al., 2011), the emergence of artificial intelligence (AI) presents transformative promise but also considerable challenges (Nguyen et al., 2023). With its ability to execute tasks that normally require human intelligence, by simulating cognitive processes using computers (Dwivedi et al., 2023), AI holds immense potential for education (Huang et al., 2023). Already, AI is used in realms such as language acquisition (Ali et al., 2023), mathematics education (Chu et al., 2021) and medical training (Wood et al., 2021). Beyond its immediate uses, the integration of AI in education not only enhances students' academic engagement but also has the potential to equip them with skills that are increasingly essential for employability in an AI-driven job market (Zouhaier, 2023). This facet of AI adoption within educational systems is highlighted by emerging concepts such as "AI readiness" (Karaca et al., 2021), "AI capabilities" (Markauskaite et al., 2022) and "AI literacy" (Long & Magerko, 2020), which capture the need to incorporate AI as part of students' preparation for their career futures. However, studies suggest these outcomes are not automatic. Without clear guidance, ethical awareness and appropriate teaching strategies, important learning goals may be missed, leaving some students struggling to use AI tools effectively and underprepared for AI-mediated workplaces (Alqahtani & Wafula, 2025; Alhammadi & Alhazmi, 2025; Selwyn, 2022; Ugwuozor & Egenti, 2024).

Generative AI (GenAI) is a type of AI that can produce original text, images and various forms of other media (Baytak, 2023). ChatGPT, an early GenAI tool (Bozkurt et al., 2023), was released in November 2022 (Lock, 2022). Since then, it has been followed by an increasing number of new GenAI tools serving a range of purposes (Chan & Hu, 2023). The rapid integration of GenAI within higher education holds potential to revolutionise student experiences and outcomes by offering personalised learning, adaptive support and scalable instruction (Baidoo-Anu & Ansah, 2023). At the same time, it raises concerns regarding precision, data privacy and ethical considerations (Lan & Chen, 2024; Sullivan et al., 2023).

Higher education must adapt if it is to equip graduates with the competencies and skills necessary to navigate the dynamics of modern employment environments, where GenAI is already reshaping professional practice and skill demands (Buck, 2024; Otermans et al., 2023). Indeed, while foundational GenAI models have existed for several years, the release of tools, such as ChatGPT, significantly increased public and educational engagement, prompting a surge in interest and experimentation in higher education settings (Barakat et al., 2024). Recent studies have examined the use of emerging technologies within higher education (e.g., Chowdhury & Singha, 2023; Granić, 2023; Jha et al., 2022; Waddill, 2023) and AI (e.g., Alotaibi, 2024; Laupichler et al., 2022). For example, Alotaibi (2024) highlights how AI-integrated learning platforms, when implemented with institutional support, can promote student adaptability, engagement and critical thinking – competencies aligned with graduate employability. Yet, while the need to prepare students for AI-driven workplaces is well acknowledged, the educational frameworks for doing so remain underdeveloped and in need of empirical grounding (Damaševičius, 2024) – all the more so with respect to the new challenges and evidence-based professional development required for the successful integration of GenAI (Dehouche, 2021; Dwivedi et al., 2023; Hwang & Chen, 2023).

Recent policy reviews have shown that universities globally are now actively developing guidelines to manage the integration of generative AI in learning and assessment, often shifting from restrictive to more supportive frameworks (Jin et al., 2025). This includes recent work on GenAI in teaching and learning, including its use in work-integrated learning and employability-focused contexts – an area increasingly relevant to curriculum design and institutional strategy (Dwyer et al., 2025; Greenwood, 2025; Harris-Reeves et al., 2023).

Student perspectives play a crucial role in discussions surrounding the adoption of GenAI, representing a fundamental element of institutional strategies, as outlined by Sullivan et al. (2023). Broadly speaking, students' views regarding their learning environments can significantly influence their approaches to learning and the results they achieve, with positive perceptions generally conducive to deep learning, and negative perceptions potentially limiting students to surface-level learning (Biggs, 1999). However, the adoption of GenAI within academic institutions has elicited mixed responses from faculty members and students alike (Smolansky et al., 2023). While some students express enthusiasm about GenAI's potential to enhance learning, others report discomfort, confusion or ethical concerns regarding its use in academic settings, as documented in both national and global studies (Kim et al., 2025; Ravšelj et al., 2025; Ugwuozor & Egenti, 2024). Experience, ability and interest in new technologies may all underpin these attitudes to some degree – a point noted by Haverila and Barkhi (2009), who identified a positive relationship between students' preparedness for e-learning and their perceived learning achievements. Al-Adwan and colleagues (2023) also emphasise the importance of considering factors, such as gender, academic expertise and age, to better understand their impact on students' readiness to adopt novel technologies.

Drawing on the technology acceptance model (TAM; Davis, 1989), this study explores higher education students' familiarity with and perceptions toward the incorporation of GenAI in academic learning, focusing on its perceived usefulness, ease of use and actual technology adoption. Specifically, we propose a model linking personal attributes with different perceptions toward the use of GenAI for learning, as well as actual use of GenAI itself, and we test eight hypotheses derived from our model with a sample of 233 Israeli students. The study has three main aims: (1) to identify individual factors that promote or impede students' acceptance of GenAI technology; (2) to support development of a potential strategic plan to enrich teaching by embedding GenAI-based technology within the academic environment; and (3) to identify factors influencing students' engagement with GenAI, and in turn, their readiness to join AI-driven workplaces. Importantly, although the study focused on students' general learning perceptions, these can offer insights into how students understand and approach GenAI as a learning tool—insights that may indirectly reflect their readiness to develop the digital adaptability, ethical reasoning and AI literacy required for the evolving world of work (Harris-Reeves et al., 2023; Waring & Evans, 2024). In this way, this study aims to support the development of pedagogical strategies that aim to bridge academic and professional readiness.

Literature review and hypotheses

AI and employability

The rapid integration of AI into the labour market is fundamentally transforming the essential skill sets required for employees to maintain their relevance and competitiveness (Hupfer, 2002; World Economic Forum, 2025). AI technologies, such as GenAI are capable of managing tasks that encompass decision-making, problem-solving and data analysis—the capacity to interpret and utilise data—to an extent that is remarkable (Ismail et al., 2024). This technological transformation demands a new level of technological literacy across diverse sectors (Bera et al., 2024). For example, while it is obvious that familiarity with machine learning – a subdivision of AI dedicated to enabling machines to acquire knowledge from data without explicit programming – has become particularly vital in disciplines, such as engineering and data science (Benriyene et al., 2024), employees in non-engineering careers also require an understanding of what AI offers (Ismail et al., 2024; Petropoulos, 2018).

Against this background, higher education must assume a fundamental role in cultivating AI-based competencies among students across fields of study. To develop employable graduates, institutions must revise their curricula to incorporate AI literacy, ensuring that students learn not only technical proficiencies but also the adaptability to navigate changing AI-enhanced work settings.

In parallel, recent scholarship has begun to explore how AI intersects with career development learning (CDL) and work-integrated learning (WIL). Pandya and Wang (2024) reviewed AI applications in career development and found that most are deployed in organisational settings – such as AI-powered coaching systems and data-driven career pathway tools – rather than in university-based teaching or learning contexts. Wahab et al. (2024), in a bibliometric analysis of graduate employability research, similarly identified a lack of focus on pedagogical interventions using AI. At the student level, Chaurasia and Veeriah (2023) showed that learners place high value on practical, job-aligned training, reinforcing the importance of teaching and learning approaches that embed real-world readiness. These studies point to an emerging opportunity for higher education to link GenAI with CDL and WIL in ways that support students' preparation for AI-mediated work environments.

GenAI in the era of educational datafication

GenAI, as defined by Chan and Hu (2023), encompasses a category of AI models that can produce novel data forms, like text, images, audio or code. The domain of GenAI is experiencing swift progression, characterised by the continuous emergence of fresh models and applications (García-Peñalvo & Vázquez-Ingelmo, 2023). At the time of writing, there were several prominent examples of GenAI technologies, falling into three main categories. The first, large-language-model chatbots, are designed to produce text to user inputs that resemble human-like responses. Examples include ChatGPT, developed by OpenAI (e.g., Strzelecki, 2024), Bard, developed by Google (Waisberg et al., 2024) and Claude, from Anthropic (Ali et al., 2023). The second main category comprises text-to-image systems, designed to generate high-quality visuals from natural-language textual descriptions. Examples include DALL-E and DALL-E 2, developed by OpenAI (e.g., Borji, 2022; Marcus et al., 2022) and Midjourney, developed by the lab of the same name (e.g., Wasielewski, 2023). The third main category is coding and the main system available is Codex, also from OpenAI, which can produce code in multiple programming languages (Idrisov & Schlippe, 2024).

The growing availability of GenAI has accelerated the phenomenon of "datafication" as described by Loosen (2018), where different components are converted into data, including information, behaviours and interactions (Flensburg & Lomborg, 2023). Within higher education, datafication entails an increased emphasis on the gathering, analysis and use of student data for a variety of objectives, including monitoring performance, identifying at-risk students, evaluating teaching strategies (Jarke & Breiter, 2019), simplifying administrative tasks, predicting enrolment trends, optimising resources (Szcyrek et al., 2024) and facilitating personalised learning pathways (Nguyen et al., 2023). However, datafication and GenAI also pose challenges. These include privacy concerns (Korir et al., 2023); the perpetuation of algorithmic biases, leading to disparities (Nguyen et al., 2023); excessive dependence on data-driven metrics, with concomitant loss of focus on educational goals such as critical thinking (Raffaghelli et al., 2020); and technical restrictions demanding specialised knowledge and resources (Szcyrek et al., 2024). Educators, therefore, face a dual imperative: to integrate datafication constructively into pedagogical design, while also equipping students with the skills to critically interpret and engage with data-driven systems (Raffaghelli et al., 2020). Without such preparation, graduates may struggle to navigate AI-mediated work environments where ethical reasoning and data literacy are essential (Nguyen et al., 2023). Moreover, higher education institutions must ensure that teaching staff are adequately supported to develop and deliver such competencies, especially as data use becomes increasingly embedded in both educational and professional domains (Szcyrek et al., 2024).

Some researchers argue that failure to proficiently employ GenAI in higher education may limit the development of educational frameworks and the comprehensive preparation of workers in an artificial intelligence-dominated world (Saúde et al., 2024). It follows that understanding students' perceptions of learning tools, like GenAI, may provide insights that inform not only responsible integration of these tools, but also the design of teaching and learning strategies aimed at helping students develop the AI-related capabilities increasingly required in workplaces (Alqahtani & Wafula, 2025; Chen et al., 2025; Wut et al., 2025).

The technology acceptance model (TAM)

Merely providing technology in educational settings does not guarantee its effective use (Mei et al., 2018). Intended users must actively adopt the technology, defined as both accepting it and integrating it into relevant processes (Granić, 2023). We stress here that, for the effective adoption of any new technology, mere acceptance is not sufficient. Even if users are willing to employ new tools or systems, various factors may hinder their incorporation into existing routines or processes, including time constraints, resource limitations, lack of technical expertise or past negative encounters with technology (Al-Adwan et al., 2023). Thus, optimal decision-making by educational institutions must be based on insights into why and how users are likely to embrace emerging technologies (Alshammari & Rosli, 2020).

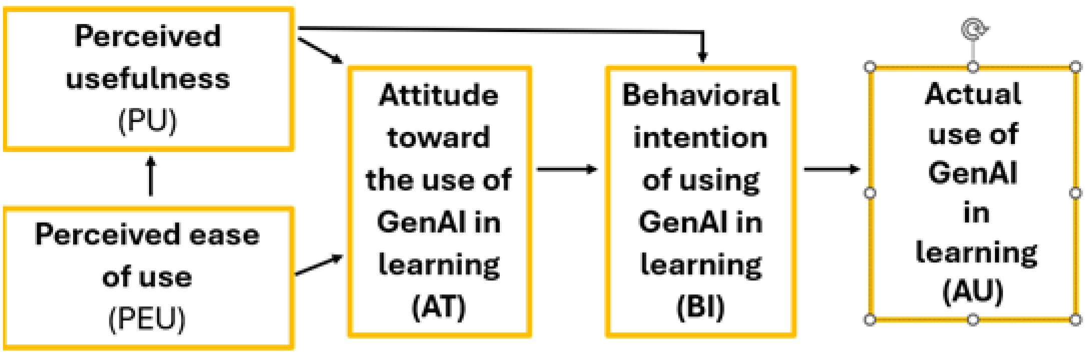
The technology acceptance model (TAM) (Davis, 1986) is a helpful starting point for understanding behaviour relating to the adoption of GenAI (Russo, 2024). The primary objective of the TAM (Figure 1) is to identify the cognitive and psychological determinants influencing users' inclination to embrace novel technologies (Granić & Marangunić, 2019). Initially developed to analyse computer usage, the TAM has been successfully applied to predict learners' acceptance of educational technologies (e.g., Al-Adwan, 2020; Padalia et al., 2023; Shen et al., 2022).

The TAM identifies a technology's perceived usefulness (PU) and perceived ease of use (PEU) as principal determinants of user acceptance (Stockless, 2018). In the current study, PU was defined as the degree to which students believe using GenAI will boost their academic performance. Prior research has found a positive relationship between PU, defined in this way, and an intention to embrace educational technology (Akour et al., 2022; Al-Rahmi et al., 2022). PEU reflects a user's expectation of how straightforward it will be to engage with the technology (Davis, 1989). Previous research into the adoption of educational technology has suggested that users' PEU considerably influences their assessment of PU (Mailizar et al., 2021) and is a precursor to adopting educational technology (Saleh et al., 2022).

The TAM has three additional parameters: attitude toward the technology (AT); behavioural intention (BI); and actual use (AU). AT refers to an individual's positive or negative feelings toward using a technology and is a function of PU and PEU. AT, in turn, helps influence behavioural intention to use a given technology (Yang & Yoo, 2004), which then predicts the AU of the technology in practice (Davis, 1989).

Figure 1 presents the relationships between the TAM parameters as applied in the current study, where the technology referred to is GenAI. The relationships between the TAM parameters are supported by evidence from a variety of studies within the higher educational context, including studies of e-learning (Al-Rahmi et al., 2019; Salloum et al., 2019), programming environments (Arpaci et al., 2019), use of Moodle (Teo et al., 2019), use of smartwatches (Al-Emran et al., 2021) and use of social media (Al-Qaysi et al., 2023). These findings have established the TAM as a leading scientific paradigm for studying the acceptance of learning technologies.

Figure 1: The technology acceptance model (TAM) as applied to students' use of GenAI in their learning



The cascade of effects captured in Figure 1 underpins our first five hypotheses:

H1: Perceived ease of use (PEU) of GenAI technologies will positively relate to their perceived usefulness (PU).

H2: Perceived usefulness (PU) and perceived ease of use (PEU) of GenAI will positively relate to attitudes toward using GenAI for learning.

H3: Perceived usefulness (PU) of GenAI will positively relate to behavioural intentions (BI) to use GenAI in learning.

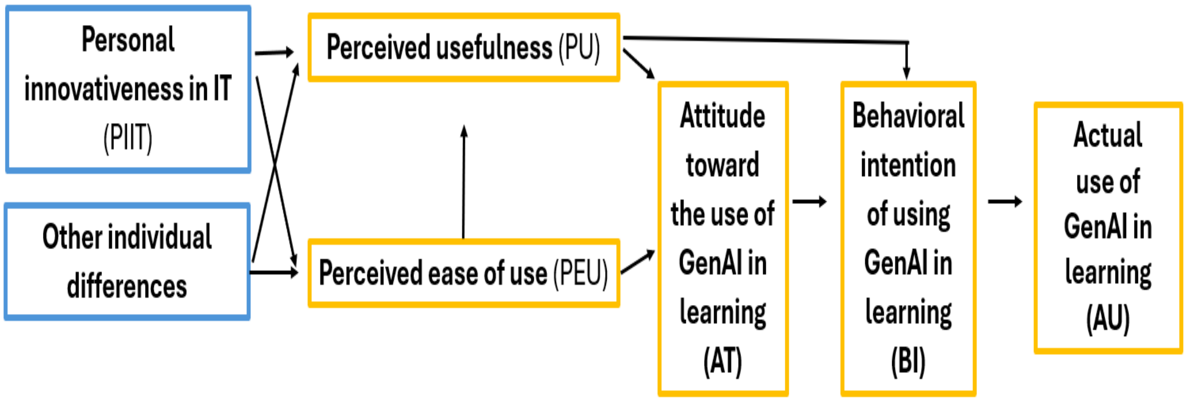
H4: Students' attitudes (AT) toward using GenAI in learning will positively relate to their behavioural intention (BI) to use GenAI in learning.

H5: Students' behavioural intention (BI) to use GenAI in learning will positively relate to their actual use (AU) of GenAI for learning purposes.

The diffusions of innovations theory

The TAM recognises that external variables can influence PU and PEU (Al-Adwan et al., 2023), and its flexibility allows the incorporation of additional factors (see Figure 2). The diffusion of innovations (DOI) theory (Rogers, 1983) can be used to supplement the TAM model by considering factors that may influence perceptions of a technology's usefulness and ease of use, and subsequent adoption of the technology by users. DOI theory elucidates the process by which an idea or product gradually gains traction and spreads across a particular population. It categorises users according to the timing at which they adopt an innovation: *innovators*, who pioneer in experimenting with novel concepts; *early adopters,* who serve as opinion leaders; the *early majority,* who precede the average person; the *late majority,* who harbour scepticism toward change; and *laggards,* who are notably conservative.

Figure 2: TAM model including external variables influencing students' use of GenAI (Authors, 2025)



According to DOI theory, individuals' reactions to a new technology—and thus where they are likely to fall in the DOI typology—vary according to their inherent inclination to adopt new technology (Fan et al., 2020). In turn, characteristics of different users could influence their acceptance of new technologies, including GenAI in educational contexts. In this research, we examine two types of individual differences that could affect PU and PEU in the context of GenAI: personal innovativeness in information technology (a personality trait) and demographic differences.

Personal innovativeness in IT (PIIT)

According to Agarwal and Prasad (1998), PIIT is a personality trait reflecting an individual's willingness to try out new technologies. In higher education contexts, PIIT has been shown to influence the adoption of e-learning platforms (Twum et al., 2022), animation usage (Dajani & Abu Hegleh, 2019), lecture capture systems (Farooq et al., 2017) and mobile learning during the COVID-19 pandemic (Sitar-Taut & Mican, 2021). Along the same lines, students who score higher in PIIT may be more open to trying and using GenAI and may use GenAI-based systems more frequently during their studies.

Based on the foregoing, we can expect that personal innovativeness in IT will influence how individuals view GenAI in terms of its PU and PEU (see Figure 2). We therefore propose our sixth hypothesis:

H6: Personal innovativeness in IT (PIIT) will be positively related to the perceived usefulness (PU) and perceived ease of use (PEU) of GenAI technology within a learning context.

Demographic differences (field of study, gender and age)

Beyond openness to innovation, as described above, our theoretical model suggests that academic characteristics (field of study) and demographics (age and gender) may serve as antecedents of PU and PEU (see Figure 2). Previous studies have suggested a positive correlation between knowledge of GenAI technologies and frequency of use (e.g., Chan & Hu, 2023). It is then reasonable to assume that students studying information systems may be more aware of such technologies than students in other fields of study. We also assume that, as economics curricula often involve data analysis, information processing and modelling, students in those fields will be relatively more aware of such technologies. We therefore hypothesised that:

H7: Students studying in technologically oriented fields (specifically, information systems or economics) will score higher in the perceived usefulness (PU) and perceived ease of use (PEU) of GenAI technology within the learning context compared to students in other fields.

Gender and age may also influence the adoption of new technologies. For example, a study investigating preferred sources of information regarding automated vehicle systems found that older respondents and women felt less technically sophisticated than their younger and male counterparts and were less willing to accept higher levels of automation (Greenwood & Baldwin, 2022). In a study by Fasbender (2022), age was negatively linked to attitudes toward new technology. Kourtesis et al. (2022) found that older participants were less aware of and held stronger prejudices against healthcare technologies than their younger counterparts, while male participants appeared to be more aware of such technologies than female participants. Other studies have also found differences in the use of information and communication technologies between men and women (e.g., Rispler & Luria, 2020). We therefore hypothesised that:

H8: Younger students and males will score higher in the perceived usefulness (PU) and perceived ease of use (PEU) of GenAI technology within the learning context compared to older students and females.

Method

Participants and data collection

We analysed data obtained through a cross-sectional online survey of students at a college in northern Israel, conducted between April 30 and May 11, 2024. The questionnaire was sent to all students (4400) who study at the college. In total, 337 students responded. Of these, 104 questionnaires were incomplete, and so were removed from the analysis. Therefore, our final set comprised 233 student questionnaires.

The survey opened with a brief overview of the study's general purpose and content, its procedure and confidentiality. Participants were assured that the survey data would be used for research purposes only and that they could withdraw at any stage. All respondents agreed to participate voluntarily. The Max Stern Yezreel Valley college ethics committee approved the research protocol (Ethics Number: 2024-68).

The questionnaire was constructed based on several validated English-language questionnaires dealing with different types of technology (Al-Adwan et al., 2023; Khong et al., 2023; Stockless, 2018). We made slight adjustments by changing the type of technology described in the questionnaire to GenAI. The questionnaire was translated into Hebrew and then back translated into English to confirm the accuracy of the Hebrew translation (Brislin, 1980). The full questionnaire is provided in the Appendix.

Measures

Demographics

Participants were asked to provide their age, gender, the degree for which they were studying (bachelor's or master's degree), department (i.e., field of study) and year of study.

Personal innovativeness in IT (PIIT)

PIIT was measured using a four-item questionnaire developed by Al-Adwan et al. (2023), which tests students' willingness to explore new technologies and their capacity to adopt and utilise them. The questionnaire comprised three positive items (e.g., 'If I heard about a new information technology, I would look for ways to experiment with it') and one negative item: 'In general, I am hesitant to try out new information technologies.' Agreement with each item was measured on a Likert scale, with 1 = strongly disagree and 5 = strongly agree. The negative item was reverse scored. For each participant, ratings for the four items were then averaged to create a single PIIT score. A higher score indicates a tendency toward greater willingness to explore and adopt new technologies. Internal reliability in this study was $\alpha=0.811$, compared to $\alpha=0.918$ in Al-Adwan et al. (2023).

Perceived usefulness (PU)

PU was measured using Stockless' (2018) six-item questionnaire to test the degree to which students believed using GenAI would boost their academic performance. An example item from the scale is: 'Generative artificial intelligence can be useful for improving my learning.' Agreement with each item was measured on a Likert scale, with 1 = strongly disagree and 5 = strongly agree. For each participant, ratings for the six items were averaged to create a single PU score, with higher scores indicating a perception of GenAI as more beneficial. Internal reliability in this study was $\alpha=0.936$, compared to $\alpha=0.95$ in Stockless (2018).

Perceived ease of use (PEU)

PEU was also measured using Stockless' (2018) six-item questionnaire. A sample item is: 'It would be easy to access generative artificial intelligence and to do what I want to do.' Agreement with each item was measured on a Likert scale, with 1 = strongly disagree and 5 = strongly agree. For each participant, ratings for the six items were averaged to create a single PEU score, with higher scores indicating a perception of GenAI as easier to use. Internal reliability in this study was $\alpha=0.916$, compared to 0.95 in Stockless (2018).

Attitude toward use of GenAI (AT)

AT was measured using five items based on a questionnaire developed by Khong et al. (2023), which examines positive and negative feelings toward technology. The original questionnaire consists of four items, one reflecting a positive attitude (in our study, 'I am comfortable learning with generative artificial intelligence') and three reflecting negative attitudes (e.g., 'Learning with generative artificial intelligence is stressful'). In light of recent findings suggesting that ethical concerns—e.g., around possible bias, the need for transparency and potential misuse—significantly shape student attitudes toward GenAI in education (Al Zaidy, 2024; Barrientos et al., 2024; Mohamed, 2024), we added a fifth item addressing this dimension: 'The use of generative artificial intelligence for learning is accompanied by significant ethical concerns.' Agreement with each item was measured using a Likert scale, with 1 = strongly disagree and 5 = strongly agree. The negative items were reverse scored. For each participant, ratings for the five items were then averaged to create a single AT score, with high values indicating more positive attitudes. Internal reliability for the five items was $\alpha=0.805$, compared to $\alpha=0.92$ for the original four items in Khong et al. (2023).

Behavioural intention (BI)

BI was measured using Khong et al.'s (2023) four-item intention questionnaire. The questionnaire comprised three positive items (e.g., 'I will combine the use of generative artificial intelligence with other ways of learning whenever it is possible to do so') and one negative item: 'I will only use generative artificial intelligence if my college asks me to do so.' Agreement with each item was measured using a Likert scale, with 1 = strongly disagree and 5 = strongly agree. The negative item was reverse scored. For each participant, ratings for the four items were then averaged to create a single BI score, with higher scores indicating greater intentions to use GenAI for learning purposes. Internal reliability in our study was α=0.826, compared with α=0.75 in Khong et al. (2023).

Actual use of GenAI (AU)

To examine AU, participants were first asked to identify those GenAI tools they had used for learning purposes over the past 30 days, from a list of tools available at the time of the research (e.g., ChatGPT 3.5, ChatGPT 4.0, Claude, GEMINI, Perplexity, SciSpace, Copilot, Midjourney). For each tool, participants were then asked two sets of questions to assess their rate of use. One question elicited the number of times participants used the given GenAI tool for learning purposes in the past 30 days (an open-ended question). For the analysis, these responses were summed up to calculate the total number of times the participant had used GenAI for learning purposes over the past month. Second, for each tool, participants were asked to estimate the frequency with which they used that tool for each of four purposes (i.e., four items): summarising material; solving exercises; performing assessment tasks; and practicing for a test. Frequency was measured on a scale from 1 = never and 5 = most of the time. For each participant, one mean was calculated for each of the four items, with higher scores indicating more use of GenAI for that particular purpose. Internal reliability was α=0.762.

Data analysis procedure

Analyses were conducted using IBM SPSS Statistics 28.0 and AMOS 28.0. Because our final sample included only completed questionnaires, missing values represented less than 0.8% of the total and were not replaced. Cronbach's α coefficient was determined to verify the reliability of the measurement tools used in the study. We then calculated descriptive statistics for participants' socio-demographic characteristics. We used t-tests and ANOVA to compare the means of the research variables (PIIT, PU, PEU, AT, BI and AU) between genders, academic year and field of study. Pearson correlations were calculated to explore the relationships between age and the variables, and between the variables themselves.

Next, to provide preliminary insights into the relationships between variables, we conducted a hierarchical regression analysis to test the contribution of all variables for predicting the actual use of GenAI. For the regression model, we only entered socio-demographic variables that were significantly correlated with using GenAI. Significance was set at the .05 level and all significance tests were two-tailed.

Finally, the complete model was tested using structural equation modelling (SEM). In addition, the extent to which the theoretical model fitted the data was quantified using the $\chi 2$ test. A non-significant p-value (p >.05) and a ratio of $\chi 2$/df <2 were understood to represent an adequate model fit (Hu & Bentler, 1999). The root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker-Lewis index (TLI) and normed fit index (NFI) were also calculated, as recommended by Schreiber et al. (2006). A model is considered to fit the data well if the ratio of $\chi 2$ to df ≤2, TLI ≥0.95, CFI ≥0.95, NFI ≥0.95 and RMSEA ≤0.06. We used the bootstrap method to provide standard errors (SE) and significance tests of the indirect and total effects (Shrout & Bolger, 2002).

Results

Demographic characteristics

Our sample comprised 233 students, of whom 185 were studying for a bachelor's degree and 48 for a master's degree. Most were female (69.5%). Participants ranged in age from 20 to 74, with an average of 31.4 (SD=10.0). Demographic characteristics are reported in Table 1.

Table 1: Demographic characteristics of participants

Demographic characteristic	**Undergraduate students (*N*=185)**		**Graduate students (*N*=48)**		**Total (*N*=233)**	
	N	**%**	***N***	**%**	***N***	**%**
Gender						
Female	126	68.1%	36	75.0%	162	69.5%
Male	55	29.7%	12	25.0%	67	28.8%
Missing	4	2.2%	0	0.0%	4	1.7%
Academic year						
Year 1	83	44.9%				
Year 2	49	26.5%	25	52.1%		
Year 3	51	27.6%	23	47.9%		
Year 4	2	1.1%				
Field of study						
Information systems or economics	31	16.8%	0	0.0%	31	13.3%
Other social sciences	153	82.7%	48	100.0%	201	86.3%
Missing	1	0.5%	0	0.0%	1	0.5%
	Mean (SD)		**Mean (SD)**		**Mean (SD)**	
Age (years)	29.3 (8.6)		39.8 (11.0)		31.4 (10.0)	
Range	20–69		25–74		20–74	

Note: *N* = number of participants; *SD* = standard deviation.

Among the undergraduate students, 68.1% were female, with an average age of 29.3 (SD=8.6). Almost half (44.9%) were in their first year of study, 26.5% were in second year and 27.6% were in third year. Among the graduate students, 75.0% were female, with an average age of 39.8 (SD=11.0). More than half (52.1%) were in their first year of study, with the remainder (47.9%) in second year. Participants were enrolled in various academic study programmes (14 programmes for the bachelor's students and eight for the master's students). We grouped the programmes into two fields: (1) information systems or economics; and (2) other social science subjects (primarily social work, psychology, criminology, communication, human services, education and health systems management).

Actual use of GenAI technology

We tested the frequency with which students used GenAI for four purposes: summarising material; solving exercises; performing assessment tasks; and practicing for a test. Table 2, overleaf, shows the distribution of responses for this item.

Table 2: Frequency of use of GenAI (N=233)

Questionnaire item	**Likert scale**					
The frequency with which I use GenAI for learning purposes when:	**Never 1**	**Seldom 2**	**Sometimes 3**	**Often 4**	**Most of the time 5**	**No response**
Summarising material	76 32.6%	43 18.5%	52 33.2%	44 18.9%	17 7.3%	1 0.4%
Solving exercises	104 44.6%	54 23.2%	47 20.2%	23 9.9%	4 1.7%	1 0.4%
Performing assessment tasks	76 32.6%	42 18.0%	52 22.3%	39 16.7%	23 9.9%	1 0.4%
Practicing for a test	96 41.2%	39 16.7%	47 20.2%	34 14.6%	16 6.9%	1 0.4%

As Table 2 shows, 26.2% of the students used GenAI to summarise material often or most of the time, 26.6% used it to perform assessment tasks often or most of the time and 21.5% used it to practice for tests often or most of the time. Just 11.6% used GenAI to solve exercises often or most of the time.

We also asked students to report the number of times they had used GenAI for learning purposes during the preceding 30 days. Their responses ranged from 0 to 125 times, with 36% of the students not using GenAI at all for learning purposes in that period (0 times) and the remainder (64%) using it at least once. The average number of times the students used GenAI for learning during the preceding 30 days was 9.1 (SD=20.9).

In addition, we examined which GenAI tools the students used. The most-used tools were ChatGPT 3.5 (48.5%), ChatGPT 4.0 (27.5%), Claude (27.5%) and GEMINI (19.7%). Less-used tools were Perplexity (3.4%), SciSpace (2.6%), Copilot (1.7%), Midjourney (1.7%), Ruby Bot (0.9%), BlackBox (0.9%) and Firefly (0.9%). Thirty-nine percent of the students reported using multiple GenAI tools.

Relationships between demographic characteristics and research variables

Differences between genders

T-tests comparing the variables between genders found a significant difference (medium effect) between men's and women's PIIT, PEU, BI and AU (Table 3). Male students perceived themselves to be more technologically innovative, perceived GenAI as easier to use, had higher intention to use GenAI and actually used GenAI more, compared to female students. However, no significant differences were found between men's and women's PU and AT.

Table 3: Mean differences in variables between genders

Variable	**Female (N=162)**		**Male (N=67)**		***t* (*df*=227)**	***p-value***	***D***
	M	***SD***	***M***	***SD***			
Personal innovativeness in IT (PIIT)	3.32	0.98	3.74	0.88	-3.22	**.002**	-0.45
Perceived usefulness (PU)	3.65	1.10	3.92	0.98	-1.77	.078	-0.26
Perceived ease of use (PEU)	3.17	1.00	3.71	0.93	-3.77	**<.001**	-0.55
Attitude toward use (AT)	3.51	0.99	3.70	0.96	-1.36	.175	-0.20
Behavioural intention (BI)	3.29	1.09	3.72	0.87	-3.03	**.003**	-0.40
Actual use (AU)	2.21	0.93	2.60	1.03	-2.80	**.006**	-0.41

Note: *M* = mean; *SD* = standard deviation; *D* = effect size (Cohen's D); *df* = degrees of freedom. Significant effects are in bold.

Differences by fields of study

Table 4 presents the results of the independent samples t-tests used to test differences in the means of the research variables among students in technologically oriented fields (information systems or economics) versus those studying other social science subjects.

Table 4: Mean differences in variables between fields of study

Variable	Information systems or economics (N=31)		Other social sciences (N=202)		t (df=231)	*p-value*	*D*
	M	*SD*	*M*	*SD*			
Personal innovativeness in IT (PIIT)	3.78	0.64	3.39	1.00	2.91	**.005**	0.41
Perceived usefulness (PU)	3.83	1.00	3.71	1.08	0.57	.569	0.11
Perceived ease of use (PEU)	3.86	0.85	3.25	1.01	3.21	**.002**	0.62
Attitude toward use (AT)	3.61	0.97	3.56	0.99	0.28	.783	0.05
Behavioural intention (BI)	3.78	0.78	3.34	1.07	2.79	**.007**	0.43
Actual use (AU)	2.85	0.97	2.25	0.95	3.23	**.001**	0.62

Note: *M* = mean; *SD* = standard deviation; *D* = effect size (Cohen's D); *df* = degrees of freedom. Significant effects are in bold.

Significant differences (a medium effect) were found between the fields of study for PIIT, PEU, BI and AU. That is, students who studied information systems or economics perceived themselves to be more technologically innovative, perceived GenAI as easier to use, had a higher intention of use and actually used GenAI more, compared to students in other social science fields. No significant differences were found between the fields of study in terms of PU and AT.

Differences by academic years

Differences between the years of study were examined separately for undergraduate and graduate students. ANOVAs were used to compare the research variables between undergraduates in their first, second or third years, and t-tests were used to compare the variables between graduate students in years one and two. No statistically significant differences were found in any of these analyses.

Correlations between age and variables

Pearson correlations were calculated to test for correlations between age and the research variables. All correlations were found to have a weak and non-significant effect, except for that between age and PEU, which exhibited a weak but statistically significant effect ($r=-.15$, $p<.05$).

Correlations between research variables

Table 5 presents the correlations between the research variables. As can be seen, all correlations were positive and significant ($p<.001$). In particular, there were significant positive correlations between PIIT and PU ($r=.58$), between PIIT and PEU ($r=.60$), between PU and AT ($r=.69$), between PU and BI ($r=.78$), between PEU and AT ($r=.49$), between AT and BI ($r=.67$) and between BI and AU ($r=.60$).

Table 5: Pearson correlations, Cronbach's alpha, means and SDs of the research variables (N=233)

Variable	**1**	**2**	**3**	**4**	**5**	**Cronbach's alpha**	***M***	***SD***
1. Personal innovativeness in IT (PIIT)	1					.811	3.44	0.97
2. Perceived usefulness (PU)	.58*	1				.936	3.73	1.07
3. Perceived ease of use (PEU)	.60*	.63*	1			.916	3.33	1.01
4. Attitude toward use (AT)	.54*	.69*	.49*	1		.805	3.57	0.98
5. Behavioural intention (BI)	.55*	.78*	.65*	.67*	1	.826	3.40	1.05
6. Actual use (AU)	.50*	.60*	.57*	.45*	.60*	.762	2.33	0.97

Note: M = mean; SD = standard deviation; *p < .001.

Hierarchical linear regression analysis for predicting actual use of GenAI

Hierarchical linear regression was used to predict the actual use of GenAI (AU). In the first step, the demographic variables found to be significantly related to AU were entered into the model: gender (1, female; 0, male); and field of study (1, other social sciences; 0, information systems or economics). In the second step, the remaining research variables (PIIT, PU, PEU, AT and BI) were entered into the model. The results of these analyses are presented in Table 6.

Table 6: Hierarchical regression analysis for predicting the actual use of GenAI (N=228)

Predictor variable	***B***	***SE***	***β***	***t***	***p-value***	***R^2***
Step 1: (constant)	3.00	.18		16.37	<.001	.07
Gender (1 = female)	-.31	.14	-.14	-2.18	**.031**	
Field of study (1 = other social sciences)	-.54	.19	-.19	-2.81	**.005**	
Step 2: (constant)	0.21	.27		0.77	.442	.46
Gender (1 = female)	-.06	.11	-.03	-0.50	.615	
Field of study (1 = other social sciences)	-.32	.15	-.11	-2.13	**.035**	
Personal innovativeness in IT (PIIT)	.12	.07	.12	1.68	.094	
Perceived usefulness (PU)	.24	.08	.26	2.90	**.004**	
Perceived ease of use (PEU)	.17	.07	.18	2.48	**.014**	
Attitude toward use (AT)	-.04	.07	-.04	-0.57	.571	
Behavioural intention (BI)	.21	.08	.23	2.54	**.012**	

Note: B = unstandardised coefficient; SE = standard error; β = standard coefficient. Significant effects are in bold.

In step one, gender and field of study were shown to be significant predictors of AU, with male students and those studying information systems or economics using GenAI more, compared to female students. These variables explained 7% of the variance in the actual use of GenAI.

In step two, PU, PEU and BI emerged as significant predictors of AU. That is, the more students perceived GenAI as being useful and easy to use, and the higher their usage intentions and the more they used GenAI. These variables added 39% to the explained variance.

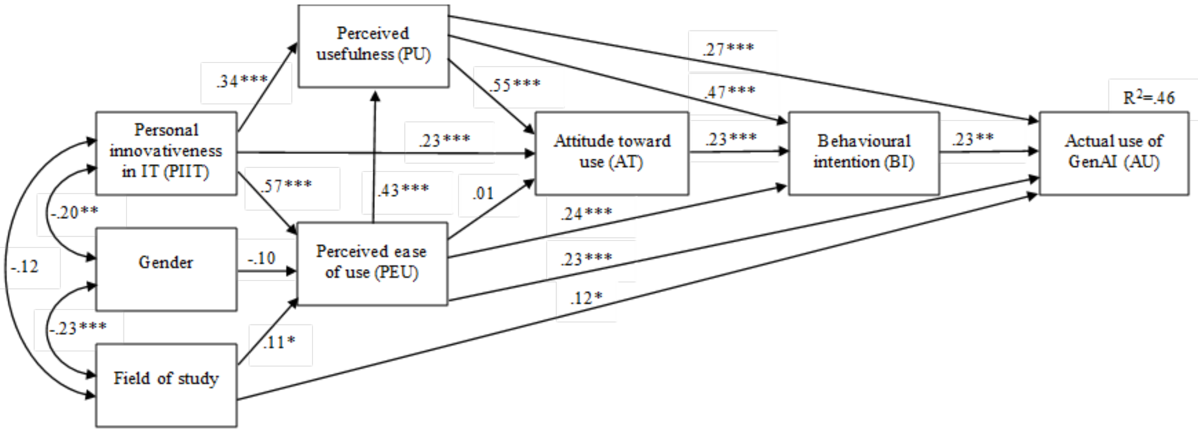
In total, our model explained 46% of the variance of the actual use of GenAI. The model was statistically significant (F(7,220)=27.19, p<.001).

Structural equation modelling

Structural equation modelling was used to examine the research model while controlling for the two background variables (gender and field of study) that were significant predictors in the regression model. The results of the analysis are presented in Figure 3. The model fits the observed data well, as seen in the goodness-of-fit indices: $\chi 2$=13.2; df=10; p=.212; $\chi 2$/df=1.3; RMSEA=.038; CFI=.996; TLI=.989; and NFI=.985.

As depicted in Figure 3, PIIT was positively related to PU (β=0.34, p<.001), PEU (β=0.57, p<.001) and AT (β=0.23, p<.001). Moreover, PEU was positively related to PU (β=0.43, p<.001), BI (β=0.24, p<.001) and AU (β=0.23, p<.001). While PEU had no direct effect on AT (β=0.01, p=.926), it did have an indirect effect through PU (indirect effect=0.23, SE=0.05 CI=[0.14, 0.34]). These results indicate that PU fully mediated the association between PEU and AT. Furthermore, PU was positively related to AT (β=0.55, p<.001), BI (β=0.47, p<.001) and AU (β=0.27, p<.001). A positive relationship between AT and BI was also found (β=0.23, p<.001). Finally, BI was positively related to AU (β=0.23, p<.01). In aggregate, the combined effects of all paths in the model accounted for 46% of the variance in the actual use of GenAI.

Figure 3: Results of the Structural Equation Model (N=228)



Note: Numbers next to the single-headed arrows reflect standardised regression weights; *p < .05, **p < .01, ***p < .001.

Discussion

As employers place greater emphasis on AI proficiency and data analysis capabilities across sectors, students who demonstrate mastery of GenAI tools will have a competitive edge in the workforce (Jacques et al., 2024). Employers expect graduates to navigate complex AI-enhanced workflows, perform data-driven decision-making and collaborate seamlessly with AI systems to optimise business outcomes (Ejjami, 2024). Therefore, fostering familiarity with GenAI within educational contexts directly contributes to improving students' employability by preparing them to meet these growing demands (Ismail et al., 2024). The present study advances this agenda by examining student perceptions toward and use of GenAI in their higher education context. Consistent with the TAM literature (Davis, 1989; Saif et al., 2024), our findings support the favourable impact of perceived usefulness and perceived ease of use on both attitudes toward and intentions to use GenAI.

Furthermore, our research revealed gender and academic discipline as critical predictors of GenAI adoption. Although gender was not significant in the SEM model, it was significant in the bivariate analysis (t-test) and in the hierarchical regression in the first step, when the other research variables had not yet been entered into the model. Male students and those specialising in information systems or economics displayed heightened levels of innovativeness and greater intentions to use GenAI. The latter observation is consistent with prior research that indicates a higher comfort level with technology in disciplines focused on business and technology (e.g., Dowling-Hetherington et al., 2020), economics (e.g., Leão & Ferreira, 2021) and information systems (e.g., Naveh & Shelef, 2021). The identified gender disparity corresponds with previous findings with respect to technology adoption generally (Rola-Rubzen et al., 2020) and the use of GenAI in particular (Draxler et al., 2023). Daher and Hussein (2024) found gender differences in perceptions of AI tools specifically in educational settings. Addressing these disparities is imperative to guarantee equitable access to AI technologies for all student demographics to ensure equitable preparation for the workforce.

The gender and discipline disparities identified in our study also have significant implications for workforce preparedness. The observed gender gap – where male students showed higher comfort with GenAI – mirrors broader technology industry trends, with employers increasingly advocating for diversity in technology and AI literacy across genders (Draxler et al., 2023). This is not only a matter of equity, but essential to improving the quality, fairness and accountability of AI systems as gender-diverse teams have been shown to produce more robust and reliable AI outcomes (Cynthia & Roy, 2025). Addressing these gaps in educational settings will contribute to greater workforce inclusivity and ensure that female students and those from underrepresented disciplines are well-prepared for AI-enhanced roles (Daher & Hussein, 2024).

Beyond the demographic factors, the significance of PIIT as an external determinant underscores the relevance of individual technological comfort levels. In our study, students exhibiting higher levels of PIIT demonstrated a more pronounced positive correlation with PU and PEU. These findings are in line with those of Teo et al. (2019), who identified analogous relationships between attitudes and behavioural intentions in the context of students' willingness to use Moodle. Teo et al. (2019) argued that students with higher PIIT are more likely to embrace AI technologies in professional environments. This is particularly true in fields like information systems and economics, where data-driven decision-making and the integration of AI into everyday business practices are now fundamental skills for workforce success. However, employers increasingly seek AI literacy across all disciplines, including non-technical fields such as marketing, management and education (Benriyene et al., 2024). Therefore, enhancing PIIT through academic engagement with GenAI can help prepare graduates to transition smoothly into AI-enhanced roles (Damaševičius, 2024; Segbenya et al., 2023).

Recent reporting suggests that universities are racing to adapt their teaching to prepare students for AI-integrated workplaces, reflecting growing institutional awareness of the urgency (Jin, 2025; Surjadi, 2024). Insights from our study offer several points of guidance for institutions seeking to adapt. First, our findings support prior research (e.g., Greenwood, 2025; Harris-Reeves et al., 2023; Krusberg, 2025) showing that novel teaching and assessment strategies – based, for example, on scaffolded tool use, student-led inquiry and structured ethical reflection – may help students engage more meaningfully with AI. Embedding such strategies into curricula could foster GenAI literacy, supporting graduate employability by ensuring students develop technical proficiency, adaptability and ethical judgement (Jacoby et al., 2024; Wut et al., 2025). Such strategies could also help address students' differential adoption of GenAI based on gender and field of study by introducing more inclusive, discipline-sensitive GenAI training. Second, our findings join with previous work on the broader institutional discourses that shape how GenAI is framed and perceived in higher education settings (Gonsalves & Acar, 2025), suggesting a parallel need for institutional capacity building, including professional development for staff involved in employability support, particularly in higher degree research contexts (O'Connor, 2024).

While GenAI has the potential to transform learning environments, it also carries significant challenges, including workforce displacement, equity concerns and algorithmic biases, which require careful consideration through comprehensive institutional policies (Saidakhror, 2024). In particular, there exists a risk of over-reliance on AI at the expense of human interaction, potentially intensifying feelings of isolation (Crawford et al., 2024). Therefore, higher education organisations must advocate for responsible AI implementation that enhances rather than displaces human interaction while ensuring equitable access to these technological tools across all student demographics.

In conclusion, higher education institutions must take an active role in shaping the future workforce by embedding AI literacy and employability skills into their curricula (Ramirez-Montoya et al., 2023). In particular, institutions can better prepare graduates for roles where AI tools are reshaping job functions, such as in business analysis, marketing and operations management (Ejjami, 2024), by ensuring all students have access to the AI-focused education that employers increasingly prioritise when hiring (Jacques et al., 2024). In this respect, our findings provide significant insights for educational policymakers and institutions endeavouring to integrate GenAI into higher education frameworks. While apprehensions regarding excessive dependence on technology persist, these can be alleviated through responsible usage protocols and a well-defined comprehension of GenAI's limitations (Choudhury & Shamszare, 2023). Moving forward, higher education institutions must prioritise developing AI literacy across all student demographics, ensuring that graduates are well-prepared for an AI-driven workplace. This holistic approach to technology adoption will enhance students' employability while promoting inclusive participation in the ongoing digital transformation of work.

Practical implications

Several practical implications emerge from our findings for institutions, employers, policy makers, students and graduates. We consider each in turn.

For higher education institutions, our findings have implications in areas including curriculum development and assessment, personalised learning and faculty training. First, our findings showing that students' perceptions of GenAI are shaped by its perceived usefulness and ease of use point to the importance of integrating AI literacy and data skills across disciplines. To enhance these competencies, institutions could embed AI-related skills into course assessments and regularly update curricula to stay aligned with emerging AI applications in the workforce. At the same time, given our findings on the importance of openness to innovativeness as a personality trait, institutions should support students with diverse technological comfort levels by offering personalised learning approaches that encourage responsible engagement with AI tools, with the aim of ensuring that all students have the opportunity to develop AI competency. Finally, faculty must be enlisted to help achieve both these goals—i.e., integrating AI into course curricula and assessments while supporting students with differing levels of readiness and comfort with technology. Toward this end, institutions should strengthen faculty training in AI literacy, helping faculty to incorporate AI tools thoughtfully while being mindful of students' individual-level differences. Indeed, recent research highlights the importance of training educators in AI to ensure they can effectively incorporate these technologies into curricula, thus preparing students for the challenges of the AI-driven workplace (Ramírez-Montoya et al., 2023). This approach will support the effective adoption of AI technologies across varied student demographics, helping all students build confidence in using these tools and preparing them for technology-driven roles in diverse fields.

For employers, our findings point to the need for skill feedback and clear role requirements. Specifically, by providing targeted feedback on AI-related skills and clearly communicating the specific digital competencies required for various roles, employers can guide students in refining the skills most in demand. Collaborating with higher education institutions to align curricula with industry needs can help bridge the skills gap, ensuring that educational programmes equip students with the competencies valued in the AI-driven workplace.

For policy makers, our findings highlight how attitudes toward GenAI adoption vary based on students' backgrounds, with differences observed across gender and academic discipline. Policy initiatives that incentivise industry–education collaboration could help ensure that AI-centred curricula and hands-on training programmes are accessible to all students, regardless of background. Targeted funding for collaborative projects can bridge the gap between academic preparation and job requirements by offering practical AI experiences that reflect industry standards, thus addressing diverse student needs.

Finally, for students and graduates, our findings underscore the pivotal role played by personal innovativeness in AI adoption. Students with higher PIIT show a greater likelihood of embracing GenAI, suggesting that proactive engagement with AI tools can build essential competencies. By seeking AI learning opportunities, students can improve their readiness for technology-enhanced roles and develop the adaptability and critical thinking skills increasingly needed across a range of careers (Krause et al., 2025). At the same time, success in an AI-driven workplace requires a blend of technical and adaptive skills, suggesting the value of interdisciplinary learning. Students are encouraged to complement their AI competencies with problem-solving, communication and teamwork skills, preparing them for the complexities of an evolving workplace (Wei et al., 2025). Integrating AI competencies into diverse disciplines can help students build a robust, adaptable skill set suited to dynamic professional environments (Babashahi et al., 2024).

These implications highlight the need for a coordinated and multipronged approach to enhance graduates' preparedness for an AI-driven workplace. The successful implementation of these recommendations requires ongoing collaboration and commitment from all parties to ensure graduates can effectively engage with and leverage GenAI technologies throughout their careers.

Limitations and future directions

This investigation was conducted through a cross-sectional survey. Despite findings from regression and SEM analyses hinting at possible causal relationships among the variables, it is important to recognise that the model applied in this study validates a plausible interpretation of the connections between variables yet cannot confirm causation.

The current study also has methodological limitations, in that the survey was exclusively distributed to students from a single college in Israel. While the students sampled had varied academic backgrounds, future studies should employ random sampling across various disciplines and periods to enhance the validity of the conclusions. In addition, conducting similar research in other geographical regions would enable comparative analyses and help identify region-specific implications for GenAI integration in education. The global survey by Ravšelj et al. (2025) highlights the value of cross-national designs for uncovering how institutional, cultural and policy contexts shape student perceptions. Future research and practice might build on such approaches to inform the development of inclusive AI integration strategies in diverse educational settings. The degree level of students has also been found to influence student perceptions of Gen AI tools (Daher & Hussein, 2024) and should be studied further, especially in terms of how it relates to employability and career development.

In addition, this study focused on student perspectives. Future research should explore the perspectives of academic staff, to facilitate teaching adapted to a GenAI environment and adequately prepare graduates for the rapidly changing job market. Finally, the current study may serve as a foundation for more targeted investigations into one or more of the practical implications identified, such as ethical awareness, skill development, or the evolving student–instructor relationship.

Conflict of interests

The authors declare no conflicting interests to declare, regarding the publication of this manuscript.

Declaration on the use of AI in the writing process

The authors of this manuscript declare that in the writing process of this work, no generative artificial intelligence (AI) or AI-assisted technologies were used to generate content, ideas, or theories. AI was utilised solely for the purpose of enhancing literature searching, translation, readability and refining language.

CReDIT authorship contribution statement

Clara Rispler: Conceptualisation, Methodology, Writing- Original draft preparation and Editing**,** Project administration. **Michal Mashiach Eizenberg**: Conceptualisation, Methodology, Funding acquisition, Formal analysis, Visualization, Writing-Methods and results preparation. **Gila Yakov**: Conceptualisation, Methodology.

References

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in information technology. *Information Systems Research*, *9*(2), 204–215. https://doi.org/10.1287/isre.9.2.204

Akour, I. A., Al-Maroof, R. S., Alfaisal, R., & Salloum, S. A. (2022). A conceptual framework for determining metaverse adoption in higher institutions of gulf area: An empirical study using hybrid SEM-ANN approach. *Computers and Education: Artificial Intelligence*, *3*, 100052. https://doi.org/10.1016/j.caeai.2022.100052

Al-Adwan, A. S. (2020). Investigating the drivers and barriers to MOOC adoption: The perspective of TAM. *Education and Information Technologies, 25*(6), 5771–5795. https://doi.org/10.1007/s10639-020-10250-z

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model (TAM) to predict university students' intentions to use metaverse-based learning platforms. *Education and Information Technologies*, *28*(11), 15381–15413. https://doi.org/10.1007/s10639-023-11816-3

Al-Emran, M., Granić, A., Al-Sharafi, M. A., Ameen, N., & Sarrab, M. (2021). Examining the roles of students' beliefs and security concerns for using smartwatches in higher education. *Journal of Enterprise Information Management*, *34*(4), 1229–1251. https://doi.org/10.1108/JEIM-02-2020-0052

Al Zaidy, A. (2024). The impact of generative ai on student engagement and ethics in higher education. *Journal of Information Technology, Cybersecurity, and Artificial Intelligence*, *1*(1), 30–38. https://doi.org/10.70715/jitcai.2024.v1.i1.004

Ali, A. H., Alajanbi, M., Yaseen, M. G., & Abed, S. A. (2023). ChatGPT4, DALL· E, Bard, Claude, BERT: Open possibilities. *Babylonian Journal of Machine Learning*, 17–18. https://doi.org/10.58496/BJML/2023/003

Ali, J. K. M., Shamsan, M. A. A., Hezam, T. A., & Mohammed, A. A. (2023). Impact of ChatGPT on learning motivation: Teachers and students' voices. *Journal of English Studies in Arabia Felix*, *2*(1), 41–49. https://doi.org/10.56540/jesaf.v2i1.51

Alhammadi, Y., & Alhazmi, A. K. (2025). Towards effective AI adoption in higher education: A comprehensive conceptual model. *Journal of Science and Technology*, *30*(3). https://doi.org/10.20428/jst.v30i3.2758

Alotaibi, N. S. (2024). The impact of AI and LMS integration on the future of higher education: Opportunities, challenges, and strategies for transformation. *Sustainability*, *16*(23), 10357. https://doi.org/10.3390/su162310357

Alqahtani, N., & Wafula, Z. (2025). Artificial intelligence integration: Pedagogical strategies and policies at leading universities. *Innovative Higher Education*, *50*(2), 665–684. https://doi.org/10.1007/s10755-024-09749-x

Al-Qaysi, N., Granić, A., Al-Emran, M., Ramayah, T., Garces, E., & Daim, T. U. (2023). Social media adoption in education: A systematic review of disciplines, applications, and influential factors. *Technology in Society*, 102249. https://doi.org/10.1016/j.techsoc.2023.102249

Al-Rahmi, A. M., Al-Rahmi, W. M., Alturki, U., Aldraiweesh, A., Almutairy, S., & Al-Adwan, A. S. (2022). Acceptance of mobile technologies and m-learning by university students: An empirical investigation in higher education. *Education and Information Technologies*, pp. *27*, 7805–7826. https://doi.org/10.1007/s10639-022-10934-8

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use e-learning systems. *IEEE Access*, *7*, 26797–26809. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8643360

Alshammari, S. H., & Rosli, M. S. (2020). A review of technology acceptance models and theories. *Innovative Teaching and Learning Journal*, *4*(2), 12–22. https://itlj.utm.my/index.php/itlj/article/view/51

Arpaci, I., Durdu, P. O., & Mutlu, A. (2019). The role of self-efficacy and perceived enjoyment in predicting computer engineering students' continuous use intention of Scratch. *International Journal of E-Adoption*, *11*(2), 1–12. https://doi.org/10.4018/IJEA.2019070101

Babashahi, L., Barbosa, C. E., Lima, Y., Lyra, A., Salazar, H., Argôlo, M., de Almeida, M. A., & Souza, J. M. D. (2024). AI in the workplace: A systematic review of skill transformation in the industry. *Administrative Sciences, 14*(6), 127. https://doi.org/10.3390/admsci14060127

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, *7*(1), 52–62. http://dx.doi.org/10.2139/ssrn.4337484

Barakat, M., Salim, N. A., & Sallam, M. (2024). Perspectives of university educators regarding ChatGPT: A validation study based on the technology acceptance model. Preprint available at Research Square. https://doi.org/10.21203/rs.3.rs-3919524/v1

Barrientos, A., Del Mundo, M. A., Inoferio, H. V., Adjid, M. A., Hajan, H. B., Ullong, M. M., Alih, D. R. S., Abdulmajid, B. P., & Espartero, M. M. (2024). Discourse analysis on academic integrity generative AI: Perspectives from science and mathematics students in higher education. *Environment & Social Psychology*, *9*(9). https://doi.org/10.59429/esp.v9i9.2927

Baytak, A. (2023). The acceptance and diffusion of generative artificial intelligence in education: A literature review. *Current Perspectives in Educational Research*, *6*(1), 7–18. https://doi.org/10.46303/cuper.2023.2

Benriyene, S., Ismaili, B. A., & Bakkali, S. (2024, October). Artificial Intelligence and Employability: A Literature Review of Engineer's Competencies. In *International Conference on Advanced Intelligent Systems for Sustainable Development* (pp. 215-224). Cham: Springer Nature Switzerland.

Bera, S., Pillai, S., & Pathak, D. P. (2024, June 2). *Navigating the AI Impact: Job Markets and Evolving Skillsets*. [Paper presentation]. In Proceedings of the International Conference on Innovative Computing & Communication (ICICC), New Delhi, India. https://dx.doi.org/10.2139/ssrn.4851647

Biggs, J. (1999). What the student does: Teaching for enhanced learning. *Higher Education Research & Development*, *18*(1), 57–75. https://doi.org/10.1080/0729436990180105

Borji, A. (2022). Generated faces in the wild: Quantitative comparison of Stable Diffusion, Midjourney and DALL-E 2. arXiv preprint. http://arxiv.org/abs/2210.00586

Bozkurt, A., Junhong, X., Lambert, S., Pazurek, A., Crompton, H., Koseoglu, S., Farrow, R., Bond, M., Nerantzi, C., Honeychurch, S., Bali, M., Dron, J., Mir, K., Stewart, B., Costello, E., Mason, J., Stracke, C. M., & RomeroHall, E. (2023). Speculative futures on ChatGPT and generative artificial intelligence (AI): A collective reflection from the educational landscape. *Asian Journal of Distance Education*, 18(1), 53–130. https://doi.org/10.5281/zenodo.7636568

Brislin, R. W. (1980). Translation and content analysis of oral and written materials. In H. C. Triandis & J. W. Berry (Eds.), *Handbook of cross-cultural psychology: Vol. 2. Methodology* (pp. 137–164). Allyn and Bacon.
Buck, A. (2024). Transdisciplinary employability practitioners: Engaging with skills for the future and redefining professional identity. *Journal of Teaching and Learning for Graduate Employability, 15*(2), 41–44. https://doi.org/10.21153/jtlge2024vol15no2art2017
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*(43). https://doi.org/10.1186/s41239-023-00411-8
Chaurasia, D., & Veeriah, P. (2023). Skill development opportunities and its influence on employability of students. *Indian Journal of Vocational Education*, *35*(1), 1–15. https://ejournals.ncert.gov.in/index.php/ijve/article/view/4628
Chen, K., Tallant, A. C. and Selig, I. (2025). Exploring generative AI literacy in higher education: Student adoption, interaction, evaluation and ethical perceptions. *Information and Learning Sciences*, *126(*1/2), 132–148. https://doi.org/10.1108/ILS-10-2023-0160
Choudhury, A., & Shamszare, H. (2023). Investigating the impact of user trust on the adoption and use of ChatGPT: Survey analysis. *Journal of Medical Internet Research*, *25*, e47184. https://doi.org/10.2196/47184
Chowdhury, R. R., & Singha, A. K. (2023). Importance of integration modern technology in higher education. *Knowledgeable Research: A Multidisciplinary Journal*, *1*(09), 71–82. https://doi.org/10.57067/kr.v1i09.78
Chu, H. C., Chen, J. M., Kuo, F. R., & Yang, S. M. (2021). Development of an adaptive game-based diagnostic and remedial learning system based on the concept-effect model for improving learning achievements in mathematics. *Educational Technology & Society*, *24*(4), 36–53. https://www.jstor.org/stable/10.2307/48629243
Crawford, J., Allen, K. A., Pani, B., & Cowling, M. (2024). When artificial intelligence substitutes humans in higher education: The cost of loneliness, student success, and retention. *Studies in Higher Education, 49*(5), 883–897. https://doi.org/10.1080/03075079.2024.2326956
Cynthia, S. T., & Roy, B. (2025). An empirical study on the impact of gender diversity on code quality in AI systems. *arXiv preprint arXiv:2505.03082*. https://doi.org/10.48550/arXiv.2505.03082
Daher, W., & Hussein, A. (2024). Higher education students' perceptions of GenAI tools for learning. *Information, 15*(7), 416. https://doi.org/10.3390/info15070416
Dajani, D., & Abu Hegleh, A. S. (2019). Behavior intention of animation usage among university students. *Heliyon*, *5*(10), e02536. https://doi.org/10.1016/j.heliyon.2019.e02536
Damaševičius, R. (2024). Commentary on artificial intelligence and graduate employability: What should we teach Generation AI? *Journal of Applied Learning and Teaching*, *7*(2). https://doi.org/10.37074/jalt.2024.7.2.39
Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. [Doctoral thesis]. Sloan School of Management, Massachusetts Institute of Technology. http://hdl.handle.net/1721.1/15192
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008
Dehouche, N. (2021). Plagiarism in the age of massive generative pre-trained transformers (GPT-3). *Ethics in Science and Environmental Politics*, *21*, 17–23. https://doi.org/10.3354/esep00195
Dowling-Hetherington, L., Glowatz, M., McDonald, E., & Dempsey, A. (2020). Business students' experiences of technology tools and applications in higher education. *International Journal of Training and Development*, *24*(1), 22–39. https://doi.org/10.1111/ijtd.12168
Draxler, F., Buschek, D., Tavast, M., Hämäläinen, P., Schmidt, A., Kulshrestha, J., & Welsch, R. (2023). Gender, age, and technology education influence the adoption and appropriation of LLMs. arXiv preprint. arXiv:2310.06556. https://doi.org/10.48550/arXiv.2310.06556
Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., Carter, L.… & Wright, R. (2023). "So, what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Dwyer, N., Dempsey, N., Brown, D., & Watt, A. (2025). Employer perspectives on the importance of help-seeking as a key skill of higher education graduates. *Journal of Teaching and Learning for Graduate Employability*, *16*(1), 1–17. https://doi.org/10.21153/jtlge2025vol16no1art2015

Ejjami, R. (2024). AI's impact on vocational training and employability: Innovation, challenges, and perspectives. *International Journal for Multidisciplinary Research*, *6*(4), 24967. https://doi.org/gt43r9

Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2020). Investigating the impacting factors for healthcare professionals to adopt artificial intelligence-based medical diagnosis support systems (AIMDSS). *Annals of Operations Research*, *294*(1), 567–592. https://doi.org/10.1007/s10479-018-2818-y

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies. *Interactive Technology and Smart Education*, *14*(4), 329–348. https://doi.org/10.1108/ITSE-06-2016-0015

Fasbender, U. (2022). Age and technology use: A dual pathway model of motivation and capability. In *Academy of Management Proceedings* (Vol. 2022, No. 1). Academy of Management. https://doi.org/10.5465/AMBPP.2022.10532abstract

Flensburg, S., & Lomborg, S. (2023). Datafication research: Mapping the field for a future agenda. *New Media & Society*, *25*(6), 1451–1469. https://doi.org/10.1177/146144482110466

García-Peñalvo, F. J., & Vázquez-Ingelmo, A. (2023). What do we mean by GenAI? A systematic mapping of the evolution, trends, and techniques involved in Generative AI. International Journal of Interactive Multimedia and Artificial Intelligence, *8*(4), 7-16. http://dx.doi.org/10.9781/ijimai.2023.07.006

Gonsalves, C., & Acar, O. A. (2025). Identifying discourses of generative AI in higher education. In K. Pulk & R. Koris (Eds.), *Generative AI in Higher Education* (pp. 28-44). Edward Elgar Publishing. https://doi.org/10.4337/9781035326020.00012

Granić, A. (2023). Technology acceptance and adoption in education. In O. Zawacki-Richter & I. Jung (Eds.), *Handbook of open, distance and digital education* (pp. 183-197). Springer, Singapore. https://doi.org/10.1007/978-981-19-2080-6_11

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, *50*(5), 2572–2593. https://doi.org/10.1111/bjet.12864

Greenwood, P. M., & Baldwin, C. L. (2022). Preferred sources of information, knowledge, and acceptance of automated vehicle systems: Effects of gender and age. *Frontiers in Psychology*, *13*, 806552. https://doi.org/10.3389/fpsyg.2022.806552

Greenwood, S. (2025). Using student conferences as a form of authentic assessment to develop and enhance transferable communication skills in quantitative and data-driven disciplines: Evidence from a postgraduate public health program. *Journal of Teaching and Learning for Graduate Employability*, *16*(1), 18–38. http://dx.doi.org/10.21153/jtlge2025vol16no1art2100

Harris-Reeves, B. E., Pearson, A. G., Vanderlelie, J. J., & Massa, H. M. (2023). The value of employability-focused assessment: Student perceptions of career readiness. *Journal of Teaching and Learning for Graduate Employability*, *14*(1), 186–204. https://doi.org/10.21153/jtlge2024vol15no1art1903

Haverila, M., & Barkhi, R. (2009). The influence of experience, ability, and interest on e-learning effectiveness. *The European Journal of Open, Distance and E-Learning*, *1*. https://eric.ed.gov/?id=EJ911761

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indices in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huang, X., Zou, D., Cheng, G., Chen, X., & Xie, H. (2023). Trends, research issues and applications of artificial intelligence in language education. *Educational Technology & Society*, *26*(1), 112–131. http://index.j-ets.net/Published/26_1/ETS_26_1_09.pdf

Hupfer, S. (2020, March 3rd). *Talent and workforce effects in the age of AI: Insights from Deloitte's State of AI in the Enterprise, 2nd Edition survey*. Deloitte Insights. https://tinyurl.com/473352we

Hwang, G. J., & Chen, N. S. (2023). Editorial position paper: Exploring the potential of generative artificial intelligence in education: Applications, challenges, and future research directions. *Educational Technology & Society*, *26*(2), 18. http://index.j-ets.net/Published/26_1/ETS_26_1_09.pdf

Idrisov, B., & Schlippe, T. (2024). Program code generation with generative AIs. *Algorithms*, *17*(2), 62. https://doi.org/10.3390/a17020062

Ismail, A., Aliu, A., Ibrahim, M., & Sulaiman, A. (2024). Preparing teachers of the future in the era of artificial intelligence. *Journal of Artificial Intelligence, Machine Learning and Neural Network*, *4*(04), 31–41. https://doi.org/10.55529/jaimlnn.44.31.41

Jacques, P. H., Moss, H. K., & Garger, J. (2024). A synthesis of AI in higher education: Shaping the future. *Journal of Behavioral and Applied Management, 24*(2), 103–111. https://doi.org/10.21818/001c.122146

Jacoby, D., Savage, S., & Coady, Y. (2024, May). Remote possibilities: Where there is a WIL, is there a way? AI education for remote learners in a new era of work-integrated-learning. In *Proceedings of the AAAI Symposium Series* (Vol. 3, No. 1, pp. 478-485). https://doi.org/10.1609/aaaiss.v3i1.31261

Jarke, J., & Breiter, A. (2019). Editorial: The datafication of education. *Learning, Media and Technology*, *44*(1), 1–6. https://doi.org/10.1080/17439884.2019.1573833

Jha, M., Jha, S., Thakur, S., & Xu, J. (2022, December 18-20). Student engagement and learning through digital educational technology. In *2022 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, (pp. 1-6). Gold Coast, Australia. https://ieeexplore.ieee.org/document/10089226

Jin, Y., Yan, L., Echeverria, V., Gašević, D., & Martinez-Maldonado, R. (2025). Generative AI in higher education: A global perspective of institutional adoption policies and guidelines. *Computers and Education: Artificial Intelligence*, *8*, 100348. https://doi.org/10.1016/j.caeai.2024.100348

Karaca, O., Çalışkan, S. A., & Demir, K. (2021). Medical artificial intelligence readiness scale for medical students (MAIRS-MS) – development, validity and reliability study. *BMC Medical Education*, *21*(1). https://doi.org/10.1186/s12909-021-02546-6

Khong, H., Celik, I., Le, T. T., Lai, V. T. T., Nguyen, A., & Bui, H. (2023). Examining teachers' behavioural intention for online teaching after the COVID-19 pandemic: A large-scale survey. *Education and Information Technologies*, *28*(5), 5999–6026. https://doi.org/10.1007/s10639-022-11417-6

Kim, J., Klopfer, M., Grohs, J. R., Eldardiry, H., Weichert, J., Cox II, L. A., & Pike, D. (2025). Examining faculty and student perceptions of generative AI in university courses. *Innovative Higher Education, 50*, 1–33. http://dx.doi.org/10.1007/s10755-024-09774-w

Korir, M., Slade, S., Holmes, W., Héliot, Y., & Rienties, B. (2023). Investigating the dimensions of students' privacy concerns in the collection, use and sharing of data for learning analytics. *Computers in Human Behavior Reports*, *9*, 100262. https://doi.org/10.1016/j.chbr.2022.100262

Kourtesis, P., Whear, S. A., Wilson, G., & Parra, M. A. (2022). Factors influencing acceptance of technology across age: Amid the COVID-19 pandemic. *Alzheimer's & Dementia*, *17*(Suppl 7). https://doi.org/10.1002/alz.055102

Krause, S., Dalvi, A., & Zaidi, S. K. (2025). Generative AI in education: Student skills and lecturer roles. *arXiv preprint arXiv:2504.19673*. https://doi.org/10.48550/arXiv.2504.19673

Krusberg, Z. (2025). Where's the line? A classroom activity on ethical and constructive use of generative AI in physics. *arXiv preprint arXiv:2506.00229*. https://doi.org/10.48550/arXiv.2506.00229

Lan, Y.-J., & Chen, N.-S. (2024). Teachers' agency in the era of LLM and generative AI: Designing pedagogical AI agents. *Educational Technology & Society*, *27*(1), I-XVIII. http://index.j-ets.net/Published/27_1/ETS_27_1_PP01.pdf

Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. *Computers and Education: Artificial Intelligence, 3*, 100101. https://doi.org/10.1016/j.caeai.2022.100101

Leão, C.P., & Ferreira, A .C. (2021). Engineering student attitude towards new technologies employed in active teaching. In: M. E. Auer, T. Rüütmann (Eds.), *Educating engineers for future industrial revolutions*. ICL 2020. Advances in Intelligent Systems and Computing, vol 1329. Springer, Cham. https://doi.org/10.1007/978-3-030-68201-9_63

Lock, S. (2022, December 5). What is the AI chatbot phenomenon ChatGPT, and could it replace humans? *The Guardian*. https://tinyurl.com/32bjxe24

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *CHI '20: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Honolulu, USA. https://doi.org/10.1145/3313831.3376727

Loosen, W. (2018). Four forms of datafied journalism: Journalism's response to the datafication of society (Communicative Figurations Working Paper No. 18). University of Bremen, Centre for Media, Communication and Information Research (ZeMKI). https://zemki.uni-bremen.de/en/publikation/working-papers-no-18/

Mailizar, M., Burg, D., & Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model. *Education and Information Technologies*, *26*(6), 7057–7077. https://doi.org/10.1007/s10639-021-10557-5

Marcus, G., Davis, E., & Aaronson, S. (2022). A very preliminary analysis of DALL-E 2. arXiv preprint arXiv:2204.13807. https://doi.org/10.48550/arXiv.2204.13807

Markauskaite, L., Marrone, R., Poquet, O., Knight, S., Martinez-Maldonado, R., Howard, S., Tondeur, J., de Laat, M., Buckingham Shum, S., Gašević, D., & Siemens, G. (2022). Rethinking the entwinement between artificial intelligence and human learning: What capabilities do learners need for a world with AI? *Computers & Education: Artificial Intelligence*, *3*. https://doi.org/10.1016/j.caeai.2022.100056

Mei, B., Brown, G. T., & Teo, T. (2018). Toward an understanding of preservice English as a foreign language teachers' acceptance of computer-assisted language learning 2.0 in the People's Republic of China. *Journal of Educational Computing Research*, *56*(1), 74–104. https://doi.org/10.1177/0735633117700144

Mohamed, M. S. P. (2024). Exploring ethical dimensions of AI-enhanced language education: A literature perspective. *Technology in Language Teaching & Learning*, *6*(3), 1813–1813. https://doi.org/10.29140/tltl.v6n3.1813

Naveh, G., & Shelef, A. (2021). Analyzing attitudes of students toward the use of technology for learning: Simplicity is the key to successful implementation in higher education. *International Journal of Educational Management*, *35*(2), 382–393. https://doi.org/10.1108/IJEM-04-2020-0204

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies*, *28*(4), 4221–4241. https://doi.org/10.1007/s10639-022-11316-w

O'Connor, M. (2024). Reconceptualising and supporting graduate employability practitioners for higher degree research candidates. *Journal of Teaching and Learning for Graduate Employability*, *15*(2), 76–79. http://dx.doi.org/10.21153/jtlge2024vol15no2art2043

Otermans, P. C., Aditya, D., & Pereira, M. (2023). A study exploring soft skills in higher education. *Journal of Teaching and Learning for Graduate Employability*, *14*(1), 136–153. https://doi.org/10.21153/jtlge2023vol14no1art1665

Padalia, A., Jamilah, A., Syakhruni, S., Rini, Y. S., & Idkhan, A. M. (2023). E-learning application usage in higher education with technology acceptance model (TAM) for students' assessment. *International Journal on Advanced Science, Engineering and Information Technology*, *13*(3), 1059–1067. https://doi.org/10.18517/ijaseit.13.3.18691

Pandya, S. S., & Wang, J. (2024). Artificial intelligence in career development: A scoping review. *Human Resource Development International*, *27*(3), 324–344. https://doi.org/10.1080/13678868.2024.2336881

Petropoulos, G. (2018). The impact of artificial intelligence on employment. In J. O'Reilly, F. Ranft, & M. Neufeind (Eds.), *Work in the digital age: Challenges of the fourth industrial revolution* (pp. 119-132). Rowman & Littlefield International. https://tinyurl.com/nwxbehrp

Raffaghelli, J. E., Manca, S., Stewart, B., Prinsloo, P., & Sangrà, A. (2020). Supporting the development of critical data literacies in higher education: Building blocks for fair data cultures in society. *International Journal of Educational Technology in Higher Education*, *17*(58). https://doi.org/10.1186/s41239-020-00235-w

Ramírez-Montoya, M.S., Oliva-Córdova, L. M., & Patiño, A. (2023). Training teaching personnel in incorporating generative artificial intelligence in higher education: A complex thinking approach. In *Proceedings of the 11th International Conference on Technological Ecosystems for Enhancing* Multiculturality (TEEM 2023). Braganca, Portugal. https://doi.org/10.1007/978-981-97-1814-6_16

Ravšelj, D., Keržič, D., Tomaževič, N., Umek, L., Brezovar, N., A. Iahad, N., ... & Aristovnik, A. (2025). Higher education students' perceptions of ChatGPT: A global study of early reactions. *PloS One*, *20*(2), e0315011. https://doi.org/10.1371/journal.pone.0315011

Rispler, C., & Luria, G. (2020). Employee perseverance in a "no phone use while driving" organizational road-safety intervention. *Accident Analysis and Prevention*, *144*, 105689. https://doi.org/10.1016/j.aap.2020.105689

Rogers, E. M. (1983). *Diffusion of innovations*. University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship. https://ssrn.com/abstract=1496176

Rola-Rubzen, M. F., Paris, T., Hawkins, J., & Sapkota, B. (2020). Improving gender participation in agricultural technology adoption in Asia: From rhetoric to practical action. *Applied Economic Perspectives and Policy*, *42*(1), 113–125. https://doi.org/10.1002/aepp.13011

Russo, D. (2024). Navigating the complexity of generative AI adoption in software engineering. *ACM Transactions on Software Engineering and Methodology*, *5*(33), 1–50. https://doi.org/10.1145/3652154

Saidakhror, G. (2024). The impact of artificial intelligence on higher education and the economics of information technology. *International Journal of Law and Policy*, *2*(3), 1–6. https://doi.org/10.59022/IJLP.125

Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024). Chat-GPT; validating technology acceptance model (TAM) in education sector via ubiquitous learning mechanism. *Computers in Human Behavior, 154*, 108097. https://doi.org/10.1016/j.chb.2023.108097

Saleh, S. S., Nat, M., & Aqel, M. (2022). Sustainable adoption of e-learning from the TAM perspective. *Sustainability*, *14*(6), 3690. https://doi.org/10.3390/su14063690.

Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access, 7*, 128445–128462. https://doi.org/10.1109/ACCESS.2019.2939467

Saúde, S., Barros, J. P., & Almeida, I. (2024). Impacts of generative artificial intelligence in higher education: Research trends and students' perceptions. *Social Sciences, 13*(8), 410. https://doi.org/10.3390/socsci13080410

Schreiber, J. B., Stage, F. K., King, J., Nora, A., & Barlow, E. A. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research*, *99*(6), 323−337. https://doi.org/10.3200/JOER.99.6.323-338

Segbenya, M., Bervell, B., Frimpong-Manso, E., Otoo, I. C., Andzie, T. A., & Achina, S. (2023). Artificial intelligence in higher education: Modelling the antecedents of artificial intelligence usage and effects on 21st century employability skills among postgraduate students in Ghana. *Computers and Education: Artificial Intelligence*, *5*, 100188. https://doi.org/10.1016/j.caeai.2023.100188

Selwyn, N. (2022). The future of AI and education: Some cautionary notes. *European Journal of Education, 57*(4), 620–631. https://doi.org/10.1111/ejed.12532

Shen, S., Xu, K., Sotiriadis, M., & Wang, Y. (2022). Exploring the factors influencing the adoption and usage of augmented reality and virtual reality applications in tourism education within the context of the COVID-19 pandemic. *Journal of Hospitality, Leisure, Sport & Tourism Education*, *30*, 100373. https://doi.org/10.1016/j.jhlste.2022.100373

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods*, *7*(4), 422–445. http://dx.doi.org/10.1037/1082-989X.7.4.422

Sitar-Taut, D.-A., & Mican, D. (2021). Mobile learning acceptance and use in higher education during social distancing circumstances: An expansion and customization of UTAUT2. *Online Information Review*, *45*(5), 1000–1019. https://doi.org/10.1108/OIR-01-2021-0017

Smolansky, A., Cram, A., Raduescu, C., Zeivots, S., Huber, E., & Kizilcec, R. F. (2023). Educator and student perspectives on the impact of generative AI on assessments in higher education. In Proceedings of the Tenth Association for Computing Machinery (ACM) Conference on Learning @ Scale (L@S '23): Copenhagen, Denmark, July 20–22, 2023 (pp. 378–382). https://doi.org/10.1145/3573051.3596191

Stockless, A. (2018). Acceptance of learning management system: The case of secondary school teachers. *Education and Information Technologies*, *23*, 1101–1121. https://doi.org/10.1007/s10639-017-9654-6

Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments, 32*(9), 5142–5155. https://doi.org/10.1080/10494820.2023.2209881

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning & Teaching*, *6*(1), 1–10. https://doi.org/10.37074/jalt.2023.6.1.17

Surjadi, M. (2024, August 5). Colleges race to ready students for the AI workplace. *The Wall Street Journal*. https://www.wsj.com/us-news/education/colleges-race-to-ready-students-for-the-ai-workplace-cc936e5b

Szcyrek, S., Stewart, B., & Miklas, E. (2024). Educators' understandings of digital classroom tools and datafication: Perceptions from higher education faculty. *Research in Learning Technology*, *32*, 3040. https://doi.org/10.25304/rlt.v32.3040

Tamim, R. M., Bernard, R. M., Borokhovski, E., Abrami, P. C., & Schmid, R. F. (2011). What forty years of research says about the impact of technology on learning: A second-order meta-analysis and validation study. *Review of Educational Research*, *81*(1), 4–28. https://doi.org/10.3102/0034654310393361

Teo, T., Zhou, M., Fan, A. C. W., and Huang, F. (2019). Factors that influence university students' intention to use Moodle: A study in Macau. *Educational Technology Research and Development*, *67*, 749–766. https://doi.org/10.1007/s11423-019-09650-x

Twum, K. K., Ofori, D., Keney, G., & Korang-Yeboah, B. (2022). Using the UTAUT, personal innovativeness and perceived financial cost to examine student's intention to use e-learning. *Journal of Science and Technology Policy Management*, *13*(3), 713–737. https://doi.org/10.1108/JSTPM-12-2020-0168

Ugwuozor, F. O., & Egenti, M. C. (2024). Artificial intelligence and the future of work: Recent graduates' perspective. *Creative Artist: A Journal of Theatre and Media Studies*, *18*(1), 1–19. https://www.ajol.info/index.php/cajtms/article/view/267136

Waddill, D. (2023). Applied learning strategy using technology to connect higher education students with workplace opportunities. In ICERI2023 Proceedings: 16th annual International Conference of Education, Research and Innovation, Seville, Spain, 13–15 November 2023 (pp. 7187). IATED. https://doi.org/10.21125/iceri.2023.1786

Wahab, M. H. S., Hosen, M., Islam, M. A., Chowdhury, M. A. M., Jantan, A. H., & Wahab, S. A. (2025). Graduate employability: A bibliometric analysis. *Global Business and Organizational Excellence*, *44*(2), 38–57. https://doi.org/10.1002/joe.22267

Waisberg, E., Ong, J., Masalkhi, M., Zaman, N., Sarker, P., Lee, A. G., & Tavakkoli, A. (2024). Google's AI chatbot "Bard": A side-by-side comparison with ChatGPT and its utilization in ophthalmology. *Eye*, *38*(4), 642–645. https://doi.org/10.1038/s41433-023-02760-0

Waring, M., & Evans, C. (2024). Facilitating students' development of assessment and feedback skills through critical engagement with generative artificial intelligence. In *Research Handbook on Innovations in Assessment and Feedback in Higher Education* (pp. 330-354). Edward Elgar Publishing. https://doi.org/10.4337/9781800881600.00027

Wasielewski, A. (2023). "Midjourney can't count": Questions of representation and meaning for text-to-image generators. *The Interdisciplinary Journal of Image Sciences*, *37*(1), 71–82. https://doi.org/10.1453/1614-0885-1-2023-15454

Wei, X., Wang, L., Lee, L. K., & Liu, R. (2025). The effects of generative AI on collaborative problem-solving and team creativity performance in digital story creation: an experimental study. *International Journal of Educational Technology in Higher Education*, *22*(1), 23. https://doi.org/10.1186/s41239-025-00526-0

Wood, E. A., Ange, B. L., & Miller, D. D. (2021). Are we ready to integrate artificial intelligence literacy into medical school curriculum: Students and faculty survey. *Journal of Medical Education and Curricular Development*, *8*. https://doi.org/10.1177/23821205211024078

World Economic Forum. (2025, January). *The Future of Jobs Report 2025*. https://www.weforum.org/publications/the-future-of-jobs-report-2025/

Wut, T. M., Chan, E. A. H., Wong, H. S. M., & Chan, J. K. (2025). Perceived artificial intelligence literacy and employability of university students. *Education+ Training*, *67*(2), 258–274. https://doi.org/10.1108/ET-06-2024-0272

Yang, H. D., & Yoo, Y. (2004). It's all about attitude: Revisiting the technology acceptance model. *Decision Support Systems*, *38*(1), 19–31. https://doi.org/10.1016/S0167-9236(03)00062-9

Zouhaier, S. (2023). The impact of artificial intelligence on higher education: An empirical study. *European Journal of Educational Sciences*, *10*(1), 17–33. https://doi.org/10.19044/ejes.v10no1a17

Appendix: The research questionnaire

Personal innovativeness in IT (PIIT):

1. If I heard about a new information technology, I would look for ways to experiment with it.
2. Among people my age, I am usually the first to try out new information technologies.
3. In general, I am hesitant to try out new information technologies. (Reverse question)
4. I like to experiment with new information technologies.

Perceived usefulness (PU):

1. Generative artificial intelligence can be useful for achieving learning goals faster.
2. Generative artificial intelligence can be useful for improving my learning.
3. Generative artificial intelligence can be useful for increasing my learning productivity.
4. Generative artificial intelligence can be useful for effective implementation of my learning.
5. Generative artificial intelligence can be useful by allowing me to learn more easily.
6. Generative artificial intelligence can be useful to enable me to do my work as a teacher more easily.

7. I find generative artificial intelligence useful in my learning as a student.

Perceived ease of use (PEU):

1. It is easy for me to learn how to use generative artificial intelligence.
2. It would be easy to access generative artificial intelligence and to do what I want to do.
3. It is easy for me to navigate generative artificial intelligence technologies.
4. What I can do with generative artificial intelligence will be clear and understandable to others.
5. It is easy for me to develop good skills in using generative artificial intelligence.
6. I believe that most of my friends will be able to easily use generative artificial intelligence.

Attitude toward use of GenAI (AT):

1. I am comfortable learning with generative artificial intelligence.
2. Learning with generative artificial intelligence is stressful. (Reverse question)
3. I don't like learning with generative artificial intelligence. (Reverse question)
4. In general, I am not satisfied with my use of technology in learning over the past two years. (Reverse question)
5. The use of generative artificial intelligence for learning is accompanied by significant ethical concerns. (Reverse question)

Behavioural intention (BI):

1. I will only use generative artificial intelligence if my college asks me to do so. (Reverse question)
2. I will combine the use of generative artificial intelligence with other ways of learning whenever it is possible to do so.
3. I am willing to support my classmates in using generative artificial intelligence in learning.
4. I am willing to use generative artificial intelligence even when it is not required at my college.

Actual use of GenAI (AU):

Which AI tools do you use? (Check all that apply)

1. ChatGPT 3.5
2. ChatGPT 4.0
3. Claude
4. Consensus
5. SciSpace
6. GEMINI
7. Perplexity
8. Other: ________

Please indicate how often you use generative AI for the following learning-related purposes (1: Never – 5: Very Frequently):

1. Summarising material.
2. Solving exercises.
3. Performing assessment tasks.
4. Practicing for a test.