




## Generative AI Adoption in Higher Education: Aligning Academic Tasks, Technology, and Learning

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### Abstract

Generative Artificial Intelligence (GenAI) is reshaping education by transforming teaching, learning, and assessment practices, making it vital to examine its effective integration within academic contexts. This study explores the adoption of GenAI tools and their impact on academic performance among ICT students at a private Australian higher education institute. Drawing on the Theory of Planned Behavior (TPB) and Task–Technology Fit (TTF) frameworks, it investigates how behavioural intentions, pedagogical factors, and technological characteristics collectively influence students' use of GenAI and academic performance. A positivist, quantitative design was adopted, using an anonymous self-administered questionnaire completed by 235 students across Melbourne and Sydney campuses. Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings highlight three insights. First, Perceived Behavioural Control emerged as the strongest predictor of students' intention to adopt GenAI, highlighting that confidence and a sense of control are critical drivers of adoption. Attitudes also positively influenced intention, while social influence was weaker, underscoring the need to strengthen students' self-efficacy and AI literacy. Second, TTF, shaped by pedagogical task variables and technological characteristics, directly affected both use and academic performance. Extending TTF to include learning outcomes and assessment methods demonstrates that curriculum design is central to technology-task alignment. Third, TTF emerged as the strongest driver of academic performance, exceeding both behavioural intention and actual use. Meaningful gains occur when GenAI is effectively aligned with tasks. By integrating TPB and TTF, this study provides a comprehensive framework for GenAI adoption and guidance for embedding AI into higher education.

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## Introduction

The launch of GPT-4 in 2023 marked a significant turning point in the integration of Generative AI (GenAI) into higher education (HE), prompting a rapid increase in its adoption by students for academic purposes. This surge in usage has been paralleled by growing scholarly attention, particularly since 2023, across multiple thematic areas. Recent studies have explored the opportunities and challenges of GenAI integration in HE (An et al., 2025; Cotton et al., 2024; Krause et al., 2024; C. Wang et al., 2025); the divergence in perspectives between students and educators (Cabellos et al., 2024; Khlaif et al., 2024; Smolansky et al., 2023); ethical concerns related to academic integrity (Cotton et al., 2024; Francis et al., 2025; Stahl & Eke, 2024; Tubella et al., 2024; C. Wang et al., 2025; Zlotnikova et al., 2025); and best practices for leveraging GenAI in educational contexts (Cotton et al., 2024; A. Nguyen et al., 2025; C. Wang et al., 2025).

Another research domain that has recently gained attention is how HE stakeholders perceive and adopt GenAI, often examined through behavioural intention frameworks such as TPB, TAM, and UTAUT (Ivanov et al., 2024; Schiavo et al., 2024; Zhang & Wang, 2025). While these frameworks explain adoption patterns, significant gaps remain in the related body of literature. In the educational context, limited research addresses how GenAI aligns with users' task expectations, (for example, achieving learning outcomes and meeting assessment requirements), and the technological features needed to support these tasks. The influence of behavioural and perception-related factors on academic performance is also underexplored (Aldreabi et al., 2025; Hsiao & Tang, 2025). Studies report positive effects of GenAI on learning performance (Al-Qaysi et al., 2025; Gökoğlu & Erdoğan, 2025; Liu et al., 2025), yet offer limited insight into why performance improves, particularly regarding alignment with task requirements. The Task-Technology Fit (TTF) framework suggests that performance improves when technological capabilities align with task demands, yet education task and technology characteristics remain underexplored. GenAI adoption is influenced by technological factors such as perceived usefulness, ease of use, enjoyment, interface design, and information quality (Ayyoub et al., 2025; Hsiao & Tang, 2025), yet performance also depends on alignment with task characteristics, a relationship rarely examined empirically, particularly in Australian contexts. Addressing these gaps are critical in today's era of GenAI transformation. Without understanding how GenAI aligns with the task characteristics students aim to fulfill, academic institutions risk inflated performance evaluations, compromised academic integrity, and misjudged skill attainment. Therefore, further exploration on aligning GenAI with academic tasks will contribute to understand optimal use of GenAI tools, for enhance academic performance, deepen learning, and support more efficient outcomes, offering both risk mitigation and improved performance outcomes.

In light of the above-mentioned research gaps, the primary aim of this research is to extend the widely accepted behavioural intention model, theory of planned behaviour (TPB) (Ajzen, 1991) with task-technology fit model (TTF) (Goodhue & Thompson, 1995). This is achieved by integrating behavioural dimensions and the technological fit of GenAI to investigate their influence on technology use intention, use behaviour, and performance. To address these objectives, the study is guided by the research question: To what extent do behavioural intentions, learning outcomes, assessment methods, and GenAI characteristics affect students' use of GenAI tools, and what is the impact of this use on their academic performance?

This study empirically examines a case of GenAI adoption in the context of an Australian higher education institute, focusing on ICT students at AQF levels 7–9 (AQF, 2013) across Melbourne and Sydney campuses. The ICT domain, as defined here, covers the use and management of information technologies and systems across diverse industries. Students typically specialise in areas such as computer science, cybersecurity, software development, data analytics, information systems, and machine learning. ICT graduates must develop core competencies and achieve learning outcomes in problem-solving, abstraction, design, ethics, professionalism, teamwork, and communication (ACS, 2015). This research investigates how GenAI supports ICT discipline-specific outcomes and how the forms of assessments influence students' ability to complete tasks using GenAI tools. The study also examines the combined influence of learning outcomes, assessment design, task-technology fit, and behavioural factors on GenAI adoption and academic performance.

This paper is structured as follows: the Introduction outlines research gaps and objectives; the Theoretical Background presents the conceptual foundation, literature, and hypotheses; the Methodology details sampling, data collection, questionnaire design, the conceptual model, and analysis procedures; the Results present the model estimation; and the Discussion interprets findings, addressing implications, limitations, and directions for future research in the conclusion.

## **Theoretical Background**

### **Theoretical Foundation**

The theoretical foundation of this study lies in the integration of the Theory of Planned Behaviour (TPB) (Ajzen, 1991) and the Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995). While TPB explains behavioural intentions and their influence on actual use, TTF provides a complementary perspective by capturing the fit between technological capabilities and task requirements. Therefore, this study intends to use the combined TTF–TPB framework to propose that GenAI is more likely to be adopted and enhance performance when well-aligned with tasks.

The Theory of Planned Behaviour (TPB) (Ajzen, 1991) is a widely respected cognitive theory, reflecting its broad influence across disciplines. TPB has been applied in psychology, education, technology adoption, and recent GenAI studies (Rejali et al., 2023; Y. Wang et al., 2020; Zhang & Wang, 2025). The theory posits that behavioural intention is the strongest predictor of action, shaped by attitude toward the behaviour, subjective norms, and perceived behavioural control, which together influence intentions and actual behaviour (Ajzen, 1991). Several recent studies have applied the TPB model to explain behavioural intentions regarding GenAI use. Recent studies have applied TPB to understand students' GenAI adoption. Ma (2024) and Falebita & Kok (2025) examined behavioural intentions, showing attitudes influenced intention. Huang et al. (2025) and Ivanov et al. (2024) highlighted how perceived benefits affect attitudes, subjective norms, and perceived control. Lenart et al. (2025) further integrated TPB with perceived usefulness, quality, and institutional support to identify key drivers of GenAI adoption. To enhance TPB's explanatory power, researchers have integrated it with complementary models. Zhang & Wang (2025) combined TPB with TAM and Trust Theory to identify factors influencing GenAI adoption. Nurtanto et al. (2025) integrated TPB, TAM, and UTAUT to examine students' intentions and learning

performance. Al-Qaysi et al. (2025) used Behavioural Reasoning Theory with TPB to study ChatGPT use, confirming positive effects on learning. Similarly, Al-Emran et al. (2025) combined TPB with TTF, showing that task and technology characteristics shape task-technology fit, enhancing GenAI use. Table 1 summarises recent studies integrating TPB with other models in educational contexts.

Table 1. Applications of TPB and Integrated Models in GenAI Education Research

Focus / Domain	Study	Integration
GenAI – Higher Education	Ivanov et al. (2024)	TPB only
GenAI – Chinese University Students	Wang et al. (2024)	TPB + AI literacy
GenAI – K-12 Mathematics Teachers	Y. Wang et al. (2025)	TAM + TPB + AI awareness
GenAI - Students Performance	Al-Emran et al. (2025)	TPB + TTF
GenAI – University Students (China)	Zhang & Wang (2025)	TPB + TAM + Trust Theory
GenAI – Student Intention & Performance	Nurtanto et al. (2025)	TPB + TAM + UTAUT
GenAI – ChatGPT Use	Al-Qaysi et al. (2025)	TPB + BRT

The Task-Technology Fit (TTF) model is particularly suitable for integration with TPB to address the research question, as demonstrated by Al-Emran et al. (2025), who showed that task and technology characteristics significantly shape task-technology fit. Introduced by Goodhue & Thompson (1995), TTF explains technology use by assessing how well a technology supports required tasks. Its core premise is that effective technology utilisation depends on alignment between task requirements and technology capabilities. Key TTF components include Task and Technology Characteristics, Task-Technology Fit, Individual Characteristics, Performance Impact, and Utilisation. Integrating TTF with TPB enables this study to capture both behavioural drivers and task-technology alignment, providing a comprehensive framework to understand GenAI adoption and its impact on academic performance.

## Hypothesis Development

TPB framework posits that behaviour is primarily driven by behavioural intention, which is shaped by attitude, subjective norms, and perceived behavioural control (Ajzen, 1991). In this context, attitude reflects a person's perspective toward a phenomenon, influencing their actions. Studies show that students' attitudes toward using GenAI for academic purposes strongly predict their behavioural intention (Diao et al., 2024; Ivanov et al., 2024; Lenart et al., 2025). Positive attitudes, shaped by perceptions of usefulness, efficiency, or enjoyment, increase students' likelihood of integrating GenAI into academic work (Chiu, 2024; Ittefaq et al., 2025; Verma et al., 2025). Therefore, the first hypothesis proposed in this study is:

*H1: Attitude (AT) has a positive effect on Behavioural Intention (BI) to use GenAI.*

Subjective norms refer to perceived social pressure to perform or avoid a behaviour (Ajzen, 1985, 1991). In the context of GenAI, they reflect the influence of peers, teachers, and the academic community on students' adoption of AI tools (Ittefaq et al., 2025; C. Wang et al., 2024). Some studies suggest subjective norms have little effect on students' intentions, indicating that personal evaluations may outweigh social influence (Falebata & Kok, 2025;

Lenart et al., 2025; Ursavaş et al., 2025). However, substantial evidence shows that subjective norms significantly shape higher education students' intentions to use GenAI (Ivanov et al., 2024; Ma, 2025; Zhang & Wang, 2025). Accordingly, the hypothesis is proposed:

*H2: Subjective Norms (SN) have a positive effect on Behavioural Intention (BI) to use GenAI.*

Within TPB, perceived behavioural control refers to an individual's perception of how easy or difficult performing a behaviour will be, shaped by past experiences and anticipated challenges (Ajzen, 1991). In the context of GenAI, it reflects students' confidence in using AI tools to complete academic tasks. Higher perceived control positively influences intention to adopt GenAI (Ivanov et al., 2024). Some studies, however, report no significant effect on behavioural intentions (C. Wang, Wang, et al., 2024). Despite this, substantial evidence confirms that perceived behavioural control positively shapes higher education students' intentions to use GenAI for academic purposes (Falebita & Kok, 2025; Ivanov et al., 2024; Wu & Dong, 2025; Zhang & Wang, 2025). Accordingly, the present study proposes:

*H3: Perceived Behavioural Control (PBC) has a positive effect on Behavioural Intention (BI) to use GenAI.*

The core principle of the TPB posits that attitudes, subjective norms, and perceived behavioural control collectively shape behavioural intention, which, in turn, positively influences actual behaviour (Ajzen, 1985, 1991; Ajzen & Fishbein, 1980). In particular, several studies have identified a positive association between behavioural intention and the actual use of GenAI, indicating that the stronger the intention of higher education students to use GenAI, the greater their likelihood of engaging with these tools. Recent literature exploring this relationship has consistently reported a positive influence of behavioural intention on actual usage (Falebita & Kok, 2025; Ivanov et al., 2024; Nurtanto et al., 2025; Zhang & Wang, 2025). Therefore, this study proposes the next hypothesis as:

*H4: Behavioural Intention (BI) has a positive effect on the Actual Use of GenAI (AUG).*

In the TTF model, task characteristics refer to the attributes, requirements, and complexity of the tasks individuals must perform (Goodhue & Thompson, 1995). In this study, tasks represent the learning activities and assessments HE students complete to meet unit learning outcomes. These characteristics determine what must be done and influence how effectively a technology can support task completion. Prior research shows that task features shape the degree of task-technology fit in areas such as information systems, mobile learning, and education (Almusawi & Durugbo, 2024; Dahri et al., 2024; Wijayanti et al., 2024). However, limited work has examined this relationship in GenAI-supported academic contexts, with exceptions such as Al-Emran et al. (2025) and Al-Mamary et al. (2024), who reported positive effects of task characteristics on TTF in educational GenAI use.

Following Biggs' constructive alignment theory (Biggs et al., 2022), this study conceptualises learning outcomes and assessment types as the key task characteristics students must fulfil. TTF posits that these tasks influence how well a technology can support them; tasks that align closely with GenAI capabilities, for example, text-heavy analytical tasks, are more likely to benefit from GenAI support. When task demands fit the technology's strengths, students can achieve learning outcomes more efficiently and effectively. Accordingly, this study hypothesises that task characteristics, specifically unit learning outcomes and assessment design, shape how well tasks can be

accomplished using GenAI. As two types of tasks are considered, sub-hypotheses H5a and H5b are proposed under the main hypothesis H5.

*H5: Task Characteristics (TAC) of a unit/course influence how well the task can be achieved using GenAI (Task Technology Fit (TTF)).*

*H5a: Design of the Learning Outcomes (LO) of a unit/course influences how well the task can be achieved using GenAI (Task Technology Fit (TTF)).*

*H5b: Type of Assessment Methods (AM) of a unit/course influences how well the task can be achieved using GenAI (Task Technology Fit (TTF)).*

Biggs' Constructive Alignment framework (Biggs, 1996; Biggs et al., 2022) argues that effective curriculum design requires aligning intended Learning Outcomes (LOs), teaching and learning activities, and assessment methods (AMs). LOs specify the competencies students must demonstrate, while AMs evaluate those competencies. Well defined and measurable LOs shape the design of assessment tasks to ensure alignment. In the context of GenAI, this alignment influences how effectively AI tools can be used in completing assessments. For example, LOs requiring higher order skills such as critical analysis or synthesis often involve assessments such as essays or case studies that demand more complex and context aware GenAI use. Recent studies highlight the need to reconsider assessment design as GenAI becomes integrated into learning (Eyal, 2025; Perkins et al., 2024; Weng et al., 2024). Accordingly, the following hypothesis is proposed:

*H6: Design of Learning Outcomes (LO) for a unit/course influences the extent to which different Assessment Methods (AM) can be effectively completed using GenAI.*

Technology characteristics refer to the features and capabilities of a technology that determine how well it supports user tasks (Goodhue & Thompson, 1995). These include attributes such as speed, accessibility, ease of use, data handling capacity, and compatibility, which enable or constrain a technology's ability to meet task requirements. Prior studies show that these characteristics strongly influence task support, consistent with the Task Technology Fit (TTF) framework. For example, if GenAI can produce accurate summaries, it fits tasks involving summarisation. Empirical research confirms this relationship. Al-Mamary et al. (2024) and Saifi et al. (2025) found that GenAI technology characteristics positively affect task technology fit. Similar associations were reported for instructional technologies (Almusawi & Durugbo, 2024) and for accounting information systems (Wijayanti et al., 2024). Two commonly examined characteristics in TTF research are perceived usefulness and perceived ease of use, both of which show significant links to task technology fit and to each other (Alamri et al., 2020; Alturki & Aldraiweesh, 2023; Pal & Patra, 2021). Studies of e learning systems further confirm that perceived usefulness and ease of use significantly influence task technology fit (Kurniawan et al., 2021; Wang et al., 2024). Drawing on this evidence, the study proposes H7 and its sub hypotheses H7a and H7b:

*H7: Technology Characteristics (TEC) of GenAI influence how well the task can be achieved using GenAI (Task Technology Fit (TTF)).*

*H7a: Perceived Usefulness of GenAI influences how well the task can be achieved using GenAI (Task Technology Fit (TTF)).*

*H7b: Perceived Ease of Use of GenAI influences how well the task can be achieved using GenAI (Task Technology Fit (TTF)).*

In the TTF model, Goodhue and Thompson (1995) argue that when a technology aligns well with task requirements (high task technology fit), users are more likely to adopt it. Empirical studies support this, showing that task technology fit positively affects actual use. For example, Alamri et al. (2020) reported a positive link between task technology fit and the use of social networking applications. Some studies also suggest that behavioural intention can mediate this relationship, as seen in open online courses (Alturki & Aldraiweesh, 2023) and in e learning in healthcare (Abdekhoda et al., 2022). Additional research confirms this positive association across multiple contexts, including GenAI (Al Emran et al., 2025), virtual learning environments (Hizam et al., 2021) and e book usage (D'Ambra et al., 2013). Based on this evidence, the study proposes the following hypothesis:

*H8: How well an academic task can be achieved using GenAI (Task Technology Fit (TTF)) has a positive impact on the Actual use of GenAI (AUG).*

In educational technology research, actual system use is often linked to improved academic performance. Hizam et al. (2021) found that using Moodle enhanced teachers' performance, while Al-Qaysi et al. (2025) reported that students' use of GenAI positively affected learning outcomes. Y. Wang et al. (2020) showed that learning behaviour significantly shapes performance. In the GenAI context, Al-Emran et al. (2025) confirmed that its use directly improves academic performance, and Hasim et al. (2025) found similar effects in e learning environments. Together, these studies show that active, purposeful use of educational technologies can enhance learning achievements. Based on this evidence, the study proposes the following hypothesis:

*H9: Actual use of GenAI (AUG) for academic work has a positive impact on Academic Performance (AP).*

The Task Technology Fit (TTF) perspective argues that when a technology's capabilities match the needs of a task, performance improves. Studies across domains support this link. Wijayanti et al. (2024) found that TTF improved sustainability performance in microfinance, and Hizam et al. (2021) reported that TTF in virtual learning improved teacher performance. D'Ambra et al. (2013) also showed that TTF increased individual performance in e book use. In education, TTF has been directly tied to academic outcomes. Al-Rahmi et al. (2022) found that the TTF of social media supported better academic performance, while Ayyash et al. (2024) reported a significant positive effect of TTF on student achievement. Alyoussef (2021) showed that TTF in e learning improved learning performance in sustainability education, and Al-Maatouk et al. (2020) found that TTF in social media use enhanced university students' academic performance. Based on this evidence, this study proposes the following hypothesis:

*H10: How well an academic task can be achieved using GenAI (Task Technology Fit (TTF)) has a positive impact on Academic Performance (AP).*

## **Conceptual Model**

An analysis of the TPB and TTF models shows clear overlap in their use related constructs. In TPB, Actual Behavior refers to the action a person performs based on their behavioural intention (Ajzen, 1991). In TTF, the parallel construct is Utilisation, defined as the observable use of a technology to complete a task and the extent to which it supports task needs (Goodhue and Thompson, 1995). Because these constructs are conceptually similar,

they are combined into a single measure called Actual Use of Generative AI (AUG), which captures students practical use of GenAI tools in academic settings. The conceptual framework (Fig. 1) reflects this integration and brings together the ten earlier hypotheses. Appendix A defines all constructs and shows how TTF and TPB constructs align under AUG, offering a clear view of their coordination. This integration provides a strong basis for understanding user intentions, behaviours, and task technology alignment in the educational use of GenAI. It links students perceptions and behavioural drivers, their intentions to use GenAI, and the characteristics of tasks and technology with course learning outcomes, assessment needs, task technology fit, and academic performance.

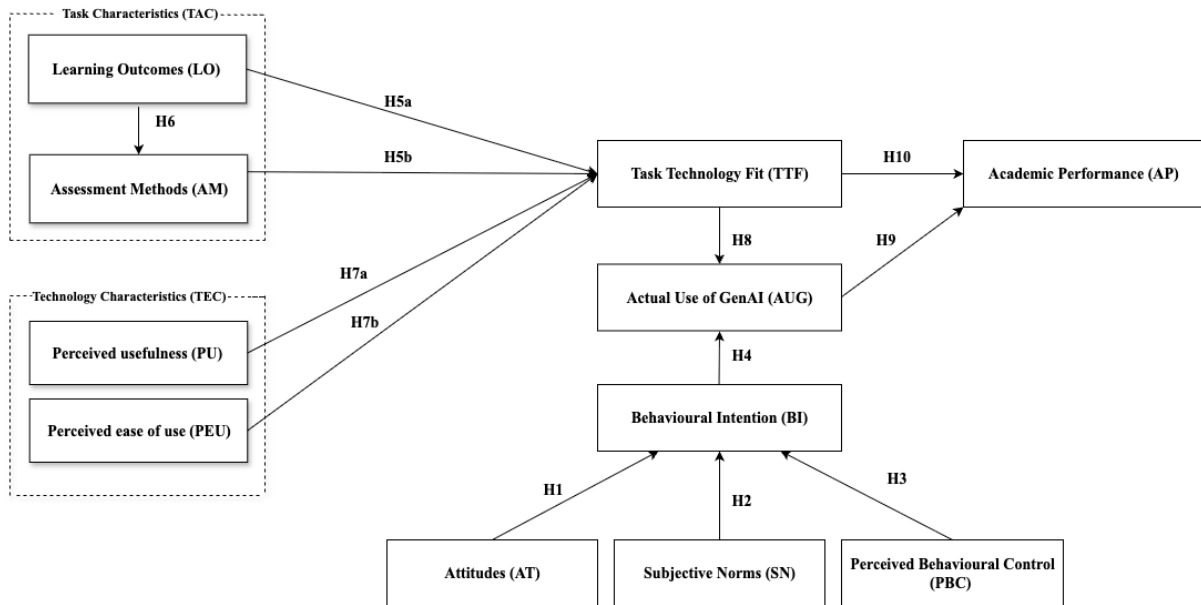


Figure 1. Conceptual Framework (Behavioural Intention-TTF Model) (Authors' work)

## Methodology

### Research Design

This study adopts a positivist paradigm with a quantitative stance to test the proposed conceptual framework. An ex post facto research design (Kerlinger, 1964) was employed, suitable for exploring causal relationships without manipulating independent variables. Aligned with this design, a deductive quantitative approach was used to validate the hypothesised relationships and assess the model's structural linkages.

### Sampling and Data Collection Procedures

Data were collected via an online survey (Google Forms) using a non-probabilistic strategy combining convenience and snowball sampling. The survey was distributed through institutional email lists, student platforms, and QR codes shared by academics; the authors did not distribute it in their own classes to minimise bias. Data collection occurred from March to June 2025. Approximately 1,200 students across the Melbourne and Sydney campuses were targeted, with a planned sample of 400. A total of 260 responses were received; 25 were excluded for incompleteness, non-ICT enrolment, or self-identified unfamiliarity. The final dataset comprised 235 valid responses, sufficient for the planned analyses. Participation was voluntary with informed consent, and all

responses were anonymised and non-identifiable. To ensure relevance, only students with prior experience using at least one GenAI tool were included. This screening ensured the dataset reflected students with genuine GenAI usage in academic contexts.

## Respondents

Participants were international undergraduate and postgraduate students enrolled in ICT programs at a private Australian higher education provider with campuses in Melbourne and Sydney. The final sample comprised 235 students (see Table 2).

Table 2.2 Sociodemographic Characteristics of Research Respondents

Attribute	Characteristics	Frequency	Percentage (%)
Level of study	Postgraduate	201	86%
	Undergraduate	34	14%
Gender	Female	87	37%
	Male	146	62%
	Prefer not to say	2	1%
Study Disciplines	Computer Science	2	1%
	Information Systems	2	1%
	Information Technology	201	86%
	Other related ICT specialisations	30	13%
Age	18 - 25	133	57%
	26 - 35	98	42%
	36 - 45	2	1%
	Prefer not to say	2	1%
Familiarity with GenAI tools	Extremely familiar and using frequently	49	21%
	Moderately familiar and using occasionally	115	49%
	Somewhat familiar and starting to use	71	30%
GenAI tools used	ChatGPT	146	62%
	Copilot	7	3%
	Google's Gemini	40	17%
	Grammarly	22	9%
	Other	10	4%
	Quillbot	10	4%

Most respondents were postgraduate students (86%), with undergraduates representing 14%. The majority studied Information Technology (86%), followed by other ICT specialisations (13%), with small proportions in Computer Science (1%) and Information Systems (1%). Gender distribution was 62% male ( $n = 146$ ) and 37% female ( $n = 87$ ). Age groups were mainly 18–25 years (57%) and 26–35 years (42%), with 1% aged 36–45 years or preferring

not to disclose. Familiarity with GenAI tools varied: 21% were highly familiar and frequent users, 49% reported moderate familiarity, and 30% were novice users. The most commonly used tools were ChatGPT (62%), Google Gemini (17%), Grammarly (9%), Copilot (3%), Quillbot (4%), and other platforms (4%).

### Questionnaire Design and Measures

The questionnaire was developed by adapting validated instruments from TPB and TTF. Although based on prior measures, several modifications were made to suit the GenAI context, improve methodological rigor, and align with the study aims. Following Ajzen's TPB guidelines (2002), behavioural items were adapted from earlier empirical studies (Appendix B). TTF constructs (Technology Characteristics, Task Technology Fit, Utilisation, and Performance Impact) required only minor adjustments, while Task Characteristics needed newly created items. These items reflected common learning outcomes and assessment practices in ICT education to ensure contextual relevance. The final instrument included 11 constructs measured by 33 items (Appendix B) on a 5 point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). It comprised a participant information sheet, eligibility screening questions (ICT students with GenAI experience), and socio demographic items (education level, discipline, age, gender) followed by construct measures. A pilot test with 20 students ( $\approx 5\%$  of intended sample) showed strong internal consistency (Cronbach alpha above 0.7). Content validity was supported through peer review and established literature. Of 260 collected responses, 235 were retained after removing incomplete or duplicate entries, meeting the guideline of at least 10 respondents per indicator and providing adequate power for structural analysis. Ethical approval was obtained from the authors university, and all procedures followed research ethics requirements.

### Data Analysis

Partial Least Squares Structural Equation Modeling (PLS SEM) was used to analyse the data because it supports complex models with multiple variables. Unlike covariance-based SEM, which requires large samples that are normally distributed, PLS SEM is known to work well with small to medium samples and non-normal distributions (Ivanov et al., 2024), making it suitable for this analysis. The analysis was performed using SmartPLS 4 (Ringle et al., 2024), a common tool for modelling latent variable relationships. PLS SEM is widely used in technology adoption and digital learning studies due to its predictive power and ability to capture direct and indirect effects (Fayaza et al., 2025; Nurtanto et al., 2025), supporting its use for the proposed conceptual model.

PLS SEM analysis followed a two-step approach (Hair, 2014; Sarstedt et al., 2014). First, the measurement model was assessed to ensure construct reliability and validity. Constructs were evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity. Indicator reliability was assessed using outer loadings ( $\geq 0.70$ ), while internal consistency was assessed via Composite Reliability and Cronbach's alpha (0.70–0.95). Convergent validity was confirmed using Average Variance Extracted ( $AVE \geq 0.50$ ). Discriminant validity was examined through the Fornell–Larcker criterion, cross-loadings, and the Heterotrait–Monotrait (HTMT) ratio. Second, the structural model was assessed for collinearity ( $VIF < 5$ ), path coefficients,  $R^2$ , and  $f^2$  effect sizes (Hair

et al., 2021). Bootstrapping with 5000 resamples and a path weighting scheme (no sign changes) tested the significance of relationships and produced 95% confidence intervals. This procedure ensured robust, replicable results and allowed a comprehensive evaluation of factors considered.

## Results

### Measurement Model Assessment

Indicator reliability was assessed using outer loadings ( $\lambda$ ), with all items exceeding 0.70, indicating satisfactory individual reliability. Internal consistency was evaluated via Cronbach's alpha (CA) and Composite Reliability (CR), with acceptable values between 0.70 and 0.95. CA ranged from 0.866 to 0.957 and CR from 0.866 to 0.958; only two constructs slightly exceeded 0.95, still indicating adequate consistency. As shown in Table 3, convergent validity was confirmed using Average Variance Extracted ( $AVE > 0.50$ ), with values ranging from 0.815 to 0.922 (Hair, 2014; Hair et al., 2021).

Table 3.3 Evaluation of the Measurement Model (Indicator Reliability, Consistency reliability and Convergent Validity)

Variable	Construct	Indicator Reliability OL ( $\lambda > 0.70$ )	Consistency Reliability		Convergent Validity AVE ( $> 0.50$ )
			CA ( $\alpha > 0.70$ )	rho_A ( $\phi > 0.70$ )	
Academic Performance	AP1	0.962	0.957	0.958	0.922
	AP2	0.964			
	AP3	0.954			
Attitudes	AT1	0.939	0.919	0.924	0.861
	AT2	0.94			
	AT3	0.905			
Actual use of GenAI	AUG1	0.939	0.866	0.866	0.882
	AUG2	0.938			
Behavioural intention	BI1	0.908	0.912	0.913	0.85
	BI2	0.939			
	BI3	0.919			
Perceived Behavioural Control	PBC1	0.913	0.914	0.916	0.852
	PBC2	0.923			
	PBC3	0.934			
Subjective Norms	SN1	0.919	0.887	0.887	0.815
	SN2	0.896			
	SN3	0.894			
Assessment Methods	TAC-AM1	0.921	0.934	0.934	0.883

Variable	Construct	Indicator Reliability OL ( $\lambda > 0.70$ )	Consistency Reliability		Convergent Validity AVE ( $>0.50$ )
			CA ( $\alpha > 0.70$ )	rho_A ( $\phi > 0.70$ )	
	TAC-AM2	0.967			
	TAC-AM3	0.931			
Learning Outcomes	TAC-LO1	0.9	0.93	0.931	0.827
	TAC-LO2	0.913			
	TAC-LO3	0.926			
	TAC-LO4	0.897			
Perceived ease of use	TEC-PEU1	0.967	0.956	0.958	0.92
	TEC-PEU2	0.969			
	TEC-PEU3	0.941			
	TEC-PU1	0.953	0.944	0.945	0.899
Perceived usefulness	TEC-PU2	0.957			
	TEC-PU3	0.935			
Task-Technology Fit	TTF1	0.93	0.931	0.932	0.879
	TTF2	0.942			
	TTF3	0.941			

Discriminant validity was established through the Fornell-Larcker criterion, cross-loadings, and Heterotrait-Monotrait (HTMT) ratio. As shown in Table 4, Diagonal AVE square roots exceeded inter-construct correlations (e.g., Academic Performance 0.960 > Attitudes 0.575, Actual Use of GenAI 0.740). Cross-loading analysis further confirmed that each indicator loaded highest on its intended construct, supporting the discriminant validity of the measurement model.

Most HTMT values were below 0.90, supporting discriminant validity. The HTMT ratio between AP and TTF (0.923) slightly exceeded 0.90, but validity remains acceptable. Both constructs show high internal consistency (AP CR = 0.958, TTF CR = 0.932) and strong convergent validity (AP AVE = 0.922, TTF AVE = 0.879). Additionally, the square roots of their AVEs exceed their correlation, indicating each construct primarily explains its own variance. These results confirm the measurement model's validity.

Table 4.4 Discriminant Validity

Construct	Fornell-Larcker										
	AP	AT	AUG	BI	PBC	SN	TAC-AM	TAC-LO	TEC-PEU	TEC-PU	TTF
AP	0.96										
AT	0.575	0.928									

<b>AUG</b>	0.74	0.509	0.939									
<b>BI</b>	0.741	0.75	0.737	0.922								
<b>PBC</b>	0.654	0.787	0.609	0.808	0.923							
<b>SN</b>	0.633	0.73	0.604	0.711	0.733	0.903						
<b>TAC-AM</b>	0.76	0.543	0.689	0.668	0.627	0.568	0.94					
<b>TAC-LO</b>	0.807	0.673	0.682	0.796	0.757	0.647	0.722	0.909				
<b>TEC-PEU</b>	0.75	0.684	0.655	0.781	0.76	0.619	0.735	0.802	0.959			
<b>TEC-PU</b>	0.794	0.63	0.643	0.775	0.731	0.588	0.707	0.789	0.836	0.948		
<b>TTF</b>	0.873	0.627	0.714	0.781	0.738	0.638	0.76	0.81	0.813	0.807	0.938	

<b>Construct</b>	<b>HTMT Ratios</b>											
	AP	AT	AUG	BI	PBC	SN	TAC-AM	TAC-LO	TEC-PEU	TEC-PU	TTF	
<b>AP</b>												
<b>AT</b>	0.611											
<b>AUG</b>	0.812	0.568										
<b>BI</b>	0.792	0.818	0.828									
<b>PBC</b>	0.698	0.858	0.684	0.883								
<b>SN</b>	0.686	0.809	0.688	0.789	0.815							
<b>TAC-AM</b>	0.804	0.584	0.767	0.724	0.679	0.624						
<b>TAC-LO</b>	0.854	0.728	0.760	0.864	0.822	0.711	0.774					
<b>TEC-PEU</b>	0.784	0.729	0.720	0.837	0.813	0.673	0.778	0.851				
<b>TEC-PU</b>	0.835	0.676	0.711	0.836	0.785	0.644	0.752	0.842	0.880			
<b>TTF</b>	0.923	0.675	0.794	0.847	0.799	0.702	0.815	0.869	0.861	0.860		

\*Bold values show that the square roots of AVE exceed correlations with other constructs.

### Structural Model Assessment

With the measurement model validated, the study tested hypothesised relationships between latent constructs. The structural model assessment examined explanatory power and predictive accuracy. Collinearity among predictors was evaluated using Variance Inflation Factor (VIF) values, ideally below 5, with 3.3 as a conservative threshold to rule out common method bias (Kock, 2015). VIFs ranged from 1.000 to 4.308. Three paths slightly exceeded 3.3 (TAC-LO → TTF = 3.460, TEC-PEU → TTF = 4.308, TEC-PU → TTF = 3.900) but remained below 5, indicating moderate correlations without biasing estimates (Hair et al., 2021). Full collinearity VIFs confirmed no serious multicollinearity, supporting reliable path coefficients and robustness of data collected from a single survey source. These results indicate that the structural model meets required criteria, confirming the measurement model is valid and suitable for structural path analysis. The structural model was assessed through path coefficients and relationship relevance using 95% confidence intervals via bootstrapping with 5000 resamples to ensure reliability. Table 5 and Figure 2 show the results, with all hypothesised paths significant (p < 0.05), supporting

H1 to H10.

Table 5.5 Hypothesis Testing with Analysis of Direct Effects

Hypothesis	Original sample (O)/ $\beta$	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values	Assumption
H1 AT -> BI	0.228	0.23	0.08	2.843	0.004	Supported
H2 SN -> BI	0.181	0.187	0.066	2.717	0.007	Supported
H3 PBC -> BI	0.496	0.489	0.091	5.439	0	Supported
H4 BI -> AUG	0.461	0.461	0.062	7.406	0	Supported
H5a TAC-LO -> TTF	0.277	0.278	0.066	4.194	0	Supported
H5b TAC-AM -> TTF	0.225	0.226	0.067	3.344	0.001	Supported
H6 TAC-LO -> TAC-AM	0.722	0.723	0.038	18.872	0	Supported
H7b TEC-PEU -> TTF	0.22	0.219	0.085	2.584	0.01	Supported
H7a TEC-PU -> TTF	0.247	0.245	0.091	2.723	0.006	Supported
H8 TTF -> AUG	0.354	0.354	0.068	5.22	0	Supported
H9 AUG -> AP	0.238	0.241	0.067	3.577	0	Supported
H10 TTF -> AP	0.703	0.7	0.058	12.069	0	Supported

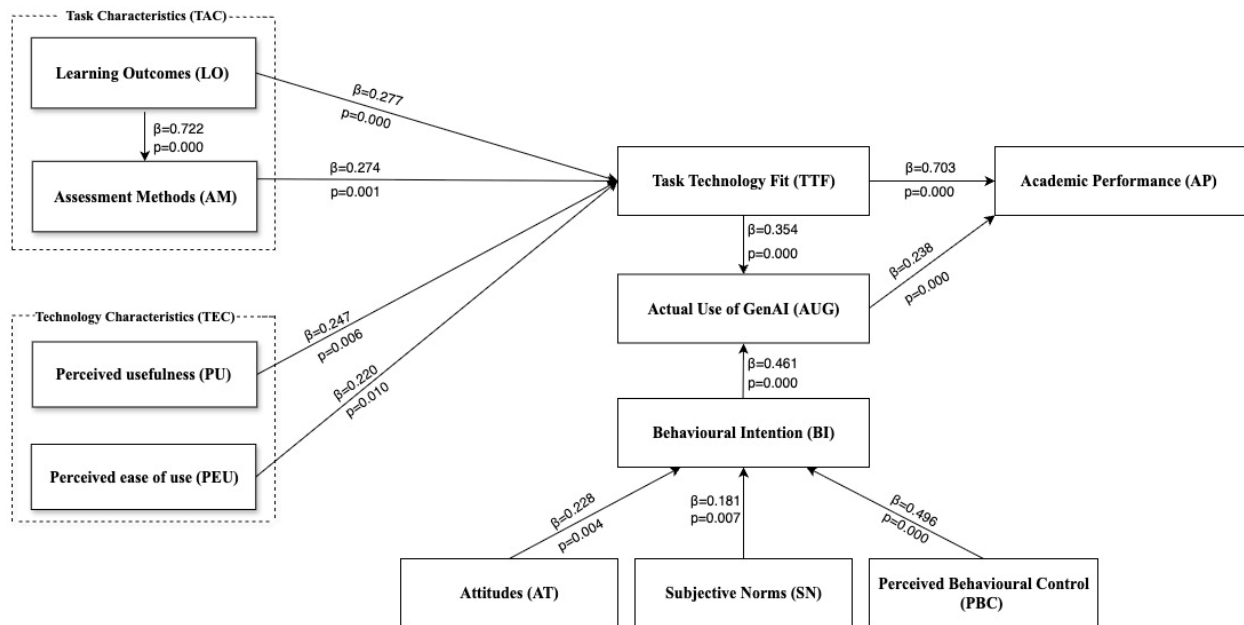


Figure 2. Structured Model (Authors' work)

Among predictors of *Behavioural Intention* (BI), *Perceived Behavioural Control* (PBC → BI,  $\beta = 0.496$ ,  $t = 5.439$ ,  $p < 0.001$ ) was strongest, followed by *Attitudes* (AT → BI,  $\beta = 0.228$ ,  $t = 2.843$ ,  $p = 0.004$ ) and *Subjective Norms* (SN → BI,  $\beta = 0.181$ ,  $t = 2.717$ ,  $p = 0.007$ ). BI significantly influenced *Actual Use of GenAI* (BI → AUG,  $\beta = 0.461$ ,  $t = 7.406$ ,  $p < 0.001$ ), providing empirical support for H1–H4 in line with TPB predictions. With respect to

*Task–Technology Fit (TTF)*, both *Learning Outcomes (TAC-LO → TTF,  $\beta = 0.277, t = 4.194, p < 0.001$ )* and *Assessment Methods (TAC-AM → TTF,  $\beta = 0.225, t = 3.344, p = 0.001$ )* were significant predictors, with *Learning Outcomes* also strongly influencing *Assessment Methods (TAC-LO → TAC-AM,  $\beta = 0.722, t = 18.872, p < 0.001$ )*. Similarly, both *Perceived Ease of Use (TEC-PEU → TTF,  $\beta = 0.220, t = 2.584, p = 0.010$ )* and *Perceived Usefulness (TEC-PU → TTF,  $\beta = 0.247, t = 2.723, p = 0.006$ )* significantly predicted TTF, supporting the TTF model. These outcomes provide empirical validation for the proposed relationships, reinforcing the applicability of the Task–Technology Fit (TTF) model. Finally, both *TTF (TTF → AUG,  $\beta = 0.354, t = 5.220, p < 0.001$ )* and *Actual Use of GenAI (AUG → AP,  $\beta = 0.238, t = 3.577, p < 0.001$ )* were significant predictors of *Academic Performance (AP)*. Notably, *TTF had the strongest effect on AP (TTF → AP,  $\beta = 0.703, t = 12.069, p < 0.001$ )*, underscoring its central role in driving academic outcomes. Overall, the findings confirm that the hypothesised structural relationships are robust, with *TTF and PBC (the key driver of intention) emerging as the most influential constructs* in explaining academic performance and behavioural intention, respectively.

The structural model's explanatory power was evaluated using  $R^2$  values, with 0.75, 0.50, and 0.25 considered substantial, moderate, and weak (Hair et al., 2021). As shown in Table 6, the model explains a large proportion of variance in *Academic Performance* ( $R^2 = 0.789$ ), *Task–Technology Fit* ( $R^2 = 0.773$ ), and *Behavioural Intention* ( $R^2 = 0.700$ ), indicating substantial explanatory power. *Actual Use of GenAI* ( $R^2 = 0.592$ ) and *Assessment Methods* ( $R^2 = 0.521$ ) show moderate explanatory power, suggesting additional factors may influence these constructs. Overall, the model demonstrates strong predictive accuracy for key outcomes and moderate power for use-related variables.

Table 6.6 Evaluation of Measurement based on  $R^2$  and  $f^2$ 

Variable	$R^2$		$f^2$ (Effect Size)				
	Value	Level	AP	AUG	BI	TAC-AM	TTF
Attitudes	–				0.057*		
Perceived Behavioural Control	–				0.269**		
Subjective Norms	–				0.044*		
Learning Outcomes	–					1.089^	0.098*
Perceived ease of use	–						0.049*
Perceived usefulness	–						0.069*
Academic Performance	0.789	Substantial					
Task-Technology Fit	0.773	Substantial	1.149^	0.12*			
Behavioural intention	0.7	Substantial		0.203**			
Actual use of GenAI	0.592	Moderate	0.132*				
Assessment Methods	0.521	Moderate					0.089*

Note:  $R^2$  (0.25 weak; 0.50 moderate; 0.75 substantial);  $f^2$  (0.02 small\*; 0.15 medium\*\*; 0.35 large^).

The  $f^2$  effect sizes assessed each exogenous construct's contribution to its endogenous construct, with 0.02, 0.15, and 0.35 representing small, medium, and large effects Cohen (2013). Large effects were observed for TTF → AP ( $f^2 = 1.149$ ) and TAC-LO → TAC-AM ( $f^2 = 1.089$ ), highlighting their strong influence on academic

performance and assessment task alignment with learning outcomes. Medium effects included BI → AUG ( $f^2 = 0.203$ ) and PBC → BI ( $f^2 = 0.269$ ), while other paths showed small effects, indicating more limited but significant contributions. Goodness-of-fit indices in Fig.2 and Table 7 confirmed that the model effectively represented relationships. Model fit was evaluated using SRMR, NFI, d\_ULS, d\_G, and chi-square differences. SRMR values met the  $<0.08$  threshold (Hu & Bentler, 1999) (saturated = 0.034, estimated = 0.079), d\_ULS (0.645 vs. 3.494) and d\_G (1.156 vs. 1.333) were within acceptable ranges, and NFI values (0.841, 0.837) approached the 0.90 cut-off. The chi-square difference between the saturated (1616.604) and estimated (1665.159) models was minimal, further supporting the adequacy of the model specification. Overall, Task–Technology Fit and task appropriateness (assessment task alignment with learning outcomes) were the strongest predictors, and the model demonstrates robust explanatory power, reliability, and acceptable goodness-of-fit, confirming its theoretical and empirical soundness.

Table 7.7 Model Fit Summary

	Saturated model	Estimated model
SRMR	0.034	0.079
d_ULS	0.645	3.494
d_G	1.156	1.333
Chi-square	1616.604	1665.159
NFI	0.841	0.837

The saturated model showed excellent fit (SRMR = 0.034), capturing indirect pathways that has not captured in the estimated model. Mediation analysis (Table 8) revealed significant indirect effects. Within TPB, *Attitude* (AT) influenced both *Academic Performance* (AP;  $\beta = 0.025$ ,  $t = 2.085$ ,  $p = 0.037$ ) and *Actual Use of GenAI* (AUG;  $\beta = 0.105$ ,  $t = 2.656$ ,  $p = 0.008$ ), stronger for AUG. *Behavioural Intention* (BI) indirectly affected AP ( $\beta = 0.110$ ,  $t = 3.078$ ,  $p = 0.002$ ), and *Perceived Behavioural Control* (PBC) had strong indirect effects on AP ( $\beta = 0.054$ ,  $t = 2.702$ ,  $p = 0.007$ ) and AUG ( $\beta = 0.229$ ,  $t = 4.373$ ,  $p < 0.001$ ). *Subjective Norms* (SN) only indirectly predicted AUG ( $\beta = 0.083$ ,  $t = 2.488$ ,  $p = 0.013$ ).

TTF and task-related constructs also showed substantial indirect effects. *Learning Outcomes* (TAC-LO) strongly influenced AP ( $\beta = 0.346$ ,  $t = 5.799$ ,  $p < 0.001$ ) and AUG ( $\beta = 0.155$ ,  $t = 3.684$ ,  $p < 0.001$ ), while *Assessment Methods* (TAC-AM) affected AP ( $\beta = 0.177$ ,  $t = 3.249$ ,  $p = 0.001$ ) and AUG ( $\beta = 0.079$ ,  $t = 2.725$ ,  $p = 0.006$ ). TAC-LO also indirectly contributed to TTF ( $\beta = 0.162$ ,  $t = 3.168$ ,  $p = 0.002$ ). Technology constructs, *Perceived Ease of Use* (TEC-PEU) and *Perceived Usefulness* (TEC-PU), were significant indirect predictors of AP ( $\beta = 0.173$ ,  $t = 2.594$ ,  $p = 0.010$ ;  $\beta = 0.194$ ,  $t = 2.696$ ,  $p = 0.007$ ) and AUG ( $\beta = 0.078$ ,  $t = 2.296$ ,  $p = 0.022$ ;  $\beta = 0.087$ ,  $t = 2.482$ ,  $p = 0.013$ ). TTF itself mediated the effect on AP ( $\beta = 0.084$ ,  $t = 2.936$ ,  $p = 0.003$ ).

Indirect effects showed that Attitude, PBC, and SN influenced actual use of GenAI mainly through Behavioural Intention, with PBC emerging as the strongest contributor. Among task-related factors, Learning Outcomes had the largest indirect effect on *Academic Performance* ( $\beta = 0.346$ ,  $p < 0.001$ ), followed by *Assessment Methods*.

*Perceived Ease of Use* and *Perceived Usefulness* also indirectly shaped *Academic Performance* and *Actual use* through TTF, which in turn significantly predicted *Academic Performance* ( $\beta = 0.084$ ,  $p = 0.003$ ), underscoring its central role in aligning technology with learning outcomes.

Table 8.8 Hypothesis Testing with Analysis of Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ( O/STDEV )	P values	Assumption
AT -> AP	0.025	0.025	0.012	2.085	0.037	Supported
AT -> AUG	0.105	0.106	0.04	2.656	0.008	Supported
BI -> AP	0.11	0.111	0.036	3.078	0.002	Supported
PBC -> AP	0.054	0.054	0.02	2.702	0.007	Supported
PBC -> AUG	0.229	0.226	0.052	4.373	0	Supported
SN -> AP	0.02	0.021	0.011	1.801	0.072	Not Supported
SN -> AUG	0.083	0.086	0.033	2.488	0.013	Supported
TAC-AM -> AP	0.177	0.177	0.054	3.249	0.001	Supported
TAC-AM -> AUG	0.079	0.08	0.029	2.725	0.006	Supported
TAC-LO -> AP	0.346	0.346	0.06	5.799	0	Supported
TAC-LO -> AUG	0.155	0.157	0.042	3.684	0	Supported
TAC-LO -> TTF	0.162	0.163	0.051	3.168	0.002	Supported
TEC-PEU -> AP	0.173	0.172	0.067	2.594	0.01	Supported
TEC-PEU -> AUG	0.078	0.078	0.034	2.296	0.022	Supported
TEC-PU -> AP	0.194	0.193	0.072	2.696	0.007	Supported
TEC-PU -> AUG	0.087	0.086	0.035	2.482	0.013	Supported

## Discussion

Grounded in the Theory of Planned Behaviour (TPB), this study extends Ajzen's (1991) framework to examine GenAI adoption in HE contexts, using higher education as the empirical case. Consistent with TPB, our findings confirm that Attitude (AT), Subjective Norms (SN), and Perceived Behavioural Control (PBC) significantly influence Behavioural Intention (BI), aligning with prior research on GenAI adoption in educational settings (Ahadzadeh et al., 2024; Al-Emran et al., 2025; C. Wang et al., 2024).

One interesting finding emerged from this study is that among the predictors of Behavioural Intention (BI), *PBC emerged as the strongest determinant* ( $\beta = 0.496$ ). Attitudes ( $\beta = 0.228$ ) and Subjective Norms ( $\beta = 0.181$ ) showed comparatively smaller impacts. This indicates that users' confidence in their ability to use GenAI tools (i.e., Perceived Behavioural Control) is the strongest driver of their intention to adopt them. This highlights that when the GenAI users feel capable and in control, they are much more likely to intend to use them. Attitudes toward GenAI, whether users' perceive it as useful, beneficial, or positive, also significantly increase intention, while social influence plays a meaningful but weaker role. Overall, confidence and perceived control matter most, followed by attitudes, then social influence, with intention acting as the bridge between these psychological factors

and actual GenAI use. These results align with prior studies. Ivanov et al. (2024) reported PBC ( $\beta = 0.58$ ), AT ( $\beta = 0.22$ ), and SN ( $\beta = 0.16$ ), confirming PBC as the strongest predictor of BI. Similarly, Falebita and Kok (2025) found PBC ( $\beta = 0.431$ ), followed by AT ( $\beta = 0.348$ ) and SN ( $\beta = 0.040$ ). These findings strengthen the evidence that building users' confidence through training and developing AI literacy is critical for fostering GenAI adoption. While attitudes and social influence remain relevant, they exert smaller effects compared to PBC. While these results highlight a greater impact of PBC and relative importance of AT, and SN in predicting Behavioural Intention, and in turn predicting Actual Use of GenAI, the model does not explain all the variance. This suggests that additional factors, not captured in the current model, may also influence why users adopt and use GenAI. Therefore, further research should be directed toward identifying these factors

Behavioural intention was found to have a strong and significant effect on the actual use of GenAI ( $\beta = 0.461$ ,  $p < 0.001$ ). This finding aligns with prior literature in higher education (Falebita & Kok, 2025; Ivanov et al., 2024; Nurtanto et al., 2025; Zhang & Wang, 2025) as well as in other contexts, such as AI adoption in Korean SMEs (Kim et al., 2024) and AI-based CRM systems (Chatterjee et al., 2023), which consistently demonstrate that behavioural intention is a key predictor of technology usage across different information systems. Proposed model examined Learning Outcomes and Assessment Methods as key task characteristics shaping Task–Technology Fit (TTF) in the education context. Both Learning Outcomes ( $\beta = 0.277$ ,  $p < 0.001$ ) and Assessment Methods ( $\beta = 0.225$ ,  $p = 0.001$ ) significantly predicted TTF, with Learning Outcomes exerting particularly strong influence. Learning Outcomes also strongly predicted Assessment Methods ( $\beta = 0.722$ ,  $p < 0.001$ ), indicating that assessment design is predominantly driven by intended learning goals. Introducing Learning Outcomes and Assessment Methods as task characteristics represents a key contribution, demonstrating that these pedagogical elements are central drivers of fit in educational settings. When tasks are framed through clearly defined outcomes that users are expected to achieve, GenAI tools are perceived as a better fit for user needs, thereby extending the TTF framework to reflect GenAI-specific task requirements. Similar patterns appear across other IS domains: task characteristics predict TTF in GenAI-based shopping platforms (Chakraborty et al., 2025), in routine and creative organisational tasks (Przegalinska et al., 2025), and in data-intensive legal research (Nosrati et al., 2025), where GenAI shows strong alignment with the task characteristics. In AI-based clinical decision support systems, clinicians were found to be sceptical of AI-generated judgements when contextual information is missing, yet they value AI's ability to identify patient trends, consolidate large datasets, detect patterns, and compare similar cases (Parsons et al., 2025). This reinforces that GenAI's effectiveness and acceptance depend on how well its capabilities align with task characteristics, a principle consistent across educational, organisational, legal, and clinical contexts.

Technology-related constructs also contributed meaningfully: *Perceived Ease of Use (PEU)* and *Perceived Usefulness (PU)* significantly predicted TTF, highlighting the importance of aligning technological characteristics with tasks. These task technology factors, PEU ( $\beta = 0.220$ ,  $p = 0.010$ ) and PU ( $\beta = 0.247$ ,  $p = 0.006$ ) also significantly predicted TTF, highlighting the importance of GenAI tools being both functional and user-friendly. While integrating pedagogically grounded task variables with classical technology constructs offers a more holistic understanding of TTF, the model does not fully explain all variance, suggesting that individual learner characteristics and contextual factors may further shape perceptions of fit. These gaps open avenues for future

research to refine and extend the TTF framework within education. These findings demonstrate that both task-related and technology-related factors jointly determine TTF, reinforcing the central premise of the TTF framework (Goodhue & Thompson, 1995) and aligning with recent GenAI-related literature in similar education research (Al-Emran et al., 2025; Al-Mamary et al., 2024; C. Wang, Dai, et al., 2024), AI based shopping platforms (Chakraborty et al., 2025), and Chatbot usage (V. T. Nguyen & Nguyen, 2023). TTF also showed a positive effect on Actual Use of GenAI ( $\beta = 0.354$ ,  $p < 0.001$ ), suggesting that students benefit most when the technology effectively supports their learning tasks. Similar findings were reported by Prasad et al. (2025), who showed that TTF positively affects the usage intention of GenAI tools among information technology employees, as well as in AI-based supply chain management (Chen et al., 2025).

Importantly, TTF exerted the strongest direct effect on Academic Performance ( $\beta = 0.703$ ,  $p < 0.001$ ), exceeding even the influence of Actual Use of GenAI. This finding underscores that the alignment between tasks and technology is more critical for academic success than the mere intention of tool use. Actual Use of GenAI ( $\beta = 0.238$ ,  $p < 0.001$ ) was also a significant predictor on Academic Performance (AP), indicating that meaningful engagement with the tools can enhance learning performance, particularly when the technology is well-aligned with tasks. The relatively larger effect of TTF compared to Actual Use highlights the practical importance of task-technology fit, suggesting that simply using GenAI without ensuring alignment with learning objectives may not yield optimal results. These findings further reinforce TTF theory by highlighting that performance gains depend on how well technology aligns with core tasks, not simply on its adoption. This pattern is consistent across domains, including social media use (Al-Maatouk et al., 2020; Al-Rahmi et al., 2022), organisational performance (Przegalinska et al., 2025), and business management outcomes (Song et al., 2025). Cross-sector evidence also suggests that while GenAI fits many data-intensive tasks, its performance is weaker for judgment-based tasks such as clinical decision-making (Parsons et al., 2025) and legal reasoning (Nosrati et al., 2025). Future research could examine interactions between TTF and Actual Use, as users may experience the highest performance benefits when both fit and engagement are strong.

The mediation analysis revealed several important indirect effects, showing that GenAI adoption influences users' performance through complex pathways rather than simple direct effects, consistent with Venkatesh et al. (2003). According to their UTAUT model, technology adoption and usage are shaped by multiple factors, such as performance expectancy, effort expectancy, social influence, and facilitating conditions, that indirectly influence behavioural intention and actual use. Users' confidence in using GenAI (PBC) not only shapes behavioural intention but also translates into actual use, highlighting intention as a key mediating mechanism (Ajzen, 1991). Task–Technology Fit (TTF) further serves as a critical bridge, converting perceptions of usefulness and task-related factors into both usage and performance outcomes (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). The chain from Learning Outcomes → Assessment Methods → TTF → Academic Performance demonstrates that well-aligned pedagogical design amplifies GenAI's effectiveness in supporting learning. Subjective norms and attitudes influence performance primarily through indirect pathways, suggesting that social pressures and personal evaluations alone are insufficient unless they foster actual engagement with the technology (Fishbein & Ajzen, 2010).

Overall, the findings show that GenAI enhances user performance through the combined effects of intention, actual use, and task alignment, with TTF emerging as the central mechanism. However, they also highlight a critical concern for organisations adopting GenAI for key tasks. If assessments or task requirements are not intentionally designed with GenAI's capabilities in mind, users may appear to perform better in ways that distort genuine ability or integrity, as seen in higher education (Cotton et al., 2024; Smolansky et al., 2023). Similar risks have been reported in organisational performance (Przegalinska et al., 2025) clinical decision-making (Parsons et al., 2025), and AI-supported legal judgments (Nosrati et al., 2025). Thus, GenAI presents both an opportunity and a challenge. When meaningfully integrated into academic or organisational settings, it can enrich learning and performance, but it also demands realignment of tasks and practices to match GenAI's affordances. To fully harness its potential, organisations must adopt integrity-focused approaches that leverage GenAI's strengths while protecting the credibility of outcomes. Ultimately, the future of performance quality and work integrity will depend on how effectively organisations embed GenAI within task design and task characteristics.

## Conclusions

### Theoretical Contribution

This study contributes theoretically by extending and integrating TPB and TTF models to examine GenAI adoption in a case of higher education. First, it extends the TPB to GenAI in higher education, a novel application given GenAI's unique dynamics including creativity support, content generation, and academic integrity concerns. Aligned with recent research (Falebita & Kok, 2025; Ivanov et al., 2024), PBC emerges as the strongest predictor of GenAI adoption intentions, suggesting self-efficacy outweighs attitudinal and social influences. This highlights that users' confidence in using GenAI is critical for adoption decisions. The strong intention–behaviour link extends TPB's explanatory scope to performance outcomes, refining Ajzen's framework for disruptive technologies. While Attitude and Subjective Norms contribute significantly, PBC's dominance demonstrates that perceived behavioural control plays a disproportionately important role in rapidly evolving technologies, enriching theoretical understanding of technology adoption in academic settings.

Second, the study advances the TTF framework by introducing pedagogical task variables. For the first time, Learning Outcomes and Assessment Methods are modelled as task characteristics, demonstrating that curriculum design elements drive technology–task alignment in higher education. This confirms constructive alignment (Biggs, 1996) in the GenAI context and broadens TTF's explanatory power into education. By integrating pedagogical variables with technological constructs (Perceived Ease of Use and Perceived Usefulness), the research offers a holistic understanding of GenAI adoption, highlighting that effective integration depends on both curriculum-aligned tasks and technology usability.

Third, the study shows that TTF predicts academic performance more strongly than behavioural intention or usage, extending Goodhue and Thompson's (1995) framework and emphasizing that performance gains arise primarily from technology–task fit rather than adoption alone. This pattern aligns with evidence from prior studies where GenAI delivers the greatest performance benefits when the technology closely matches students' task demands. Finally, integrating TPB and TTF creates a dual-pathway model where perceptual and behavioural

factors shape intentions and use, while task-based and technological factors determine fit, which drives academic performance. TTF serves as a bridge between adoption constructs and performance, offering a comprehensive account that neither framework could capture alone.

### **Practical Implications**

From a practical standpoint, this study shows that universities and educators aiming to integrate GenAI should prioritise building user' GenAI literacy and capability. Since PBC is the strongest predictor of intention to use GenAI, institutions should focus on boosting users' confidence through training, hands-on workshops, and clear guidelines. Positive attitudes can be strengthened by demonstrating GenAI's benefits, such as creativity, efficiency, and personalised learning, while addressing risks and ethical concerns. Although Subjective Norms play a smaller role, peer support and supervisors' encouragement can help normalise responsible GenAI use. Overall, practical GenAI strategies should emphasise strengthening perceived control through skills and guidance, while fostering supportive attitudes and social norms.

From a pedagogical perspective, aligning learning tasks with GenAI tools, Task-Technology Fit, is essential for effective outcomes. Learning outcomes and assessment methods should be designed to leverage GenAI appropriately, ensuring the technology supports rather than replaces learning. Assignments should promote critical thinking, creativity, and higher-order skills that GenAI cannot complete alone, and assessments should measure genuine learning rather than simple tool use. Technology choices should prioritise usability and usefulness to optimise task fit. Scaffolded integration, starting with guided use and gradually increasing independence, can build confidence and reduce misuse.

To maximise GenAI's benefits, organisations should implement monitoring and feedback systems that guide users on effective use. Training should include AI literacy, ethics, and integrity so users use GenAI both competently and responsibly. Clear organisational policies on acceptable GenAI use are essential to protect work integrity while supporting meaningful engagement. By combining psychological, pedagogical, and technological strategies, organisations can ensure GenAI adoption is effective, responsible, and aligned with high-quality outcomes.

### **Limitations and Future Work**

While this study offers valuable insights into GenAI adoption, several limitations must be acknowledged. Although Attitude, Subjective Norms, and PBC significantly predict Behavioural Intention, they do not fully capture users' intentions or actual usage. Additional factors, such as trust, ethical concerns, perceived risks, digital literacy, and organisational policies are likely to influence GenAI adoption and warrant future investigation. The cross-sectional design limits causal inference, and longitudinal research is needed to understand how perceptions, intentions, and behaviours evolve over time. As data were drawn from a single Australian higher-education institution, generalisability to other sectors remains limited. Notably, current GenAI adoption research across knowledge-intensive domains, particularly in examining how behavioural, task-related, and technological factors

jointly shape GenAI-enabled performance. Conducting comparable studies in diverse sectors, disciplines, and cultural contexts would strengthen external validity. Self-reported usage data of this study may introduce social desirability bias; future work could incorporate behavioural usage logs or experimental designs to enhance accuracy.

With respect to the TTF framework, integrating pedagogical task variables with traditional technology constructs offers a broader understanding of fit. However, the model does not account for all variance in TTF. Individual characteristics, discipline-specific contexts, institutional policies, and peer or instructor influences may also shape perceptions of fit. Task characteristics were defined narrowly, centred on learning outcomes and assessment methods, while other task components, such as instructional activity design, were not assessed. Moreover, task requirements differ significantly across industries, suggesting the need for sector-specific TTF models grounded in the unique workflows and performance criteria of each domain.

Overall, these limitations highlight opportunities for future research to broaden both the TPB and TTF frameworks in educational contexts. Future studies could explore additional psychological, contextual, and institutional factors, as well as individual learner differences, to better explain the complexity of GenAI adoption and optimise its integration into higher education. Recognising these gaps emphasises the need to expand the TTF framework, particularly in the rapidly evolving landscape of GenAI adoption.

## Statements and Declarations

**Acknowledgments/Notes:** The original text was written collectively by the author team, and GenAI tools were used only in limited instances to improve grammar and expression.

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**Informed Consent:** Informed consent was obtained from all subjects involved in the study.

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## Appendix A. Construct Definitions and Comparison of TPB and TTF Factors

Constructs of the proposed research model (Behavioural Intention-TTF)	Constructs of TPB	Constructs of TTF
Attitudes (AT) (The degree to which a HE student has a favourable or unfavourable assessment of the using GenAI for academic purposes)	Attitude toward the behavior (The degree to which a person has a favourable or unfavourable assessment of the behavior)	
Subjective Norms (SN) (Perceived social pressure for a HE student to use GenAI for HE purposes. It involves the influence of others in the student's social circle)	Subjective Norms (The perceived social pressure to perform or not perform the behavior. It involves the influence of others in the individual's social circle)	
Perceived Behavioural Control (PBC) (A student's belief in the ability to use GenAI effectively for HE purposes. This refers to the degree to which resources, and support available, that enable them to use GenAI)	Perceived Behavioural Control (An individual's belief in their ability to perform a specific behavior, which can either help or hinder its execution)	
Behavioural intention (BI) (A student's readiness or plan to use GenAI. It is the most immediate and direct predictor of whether the student will engage in a behavior of using GenAI for academic purposes.)	Behavioural intention (An individual's plan or readiness to perform a behavior, directly predicting whether they will engage in it)	
Actual use of GenAI (AUG) (The extent to which a HE student utilises GenAI technology for academic purposes, indicating the real, observed usage)	Actual Behaviour (The execution of a specific action that an individual intends to perform, resulting from behavioural intention and shaped by various internal and external factors)	Utilisation (The actual use of the technology by individuals to perform tasks, reflecting whether the technology is applied in practice)
Task Characteristics (TAC) (This refers to the specific requirements, complexity, and nature of the tasks that users need to accomplish. It includes what needs to be done, how it is done, and the processes involved in completing the tasks. In this study, learning		Task Characteristics (Attributes or requirements of a task that determine what actions or processes are needed to accomplish it effectively)

<b>Constructs of the proposed research model (Behavioural Intention-TTF)</b>	<b>Constructs of TPB</b>	<b>Constructs of TTF</b>
<p>outcomes and assessment methods are identified as the specific task characteristics which HE students must accomplish)</p> <p>Learning Outcomes (LO) (The measurable skills, abilities, knowledge or values that students should be able to demonstrate because of a completing a course, or a unit)</p> <p>Assessment Methods (EM) (various techniques and tools used to assess and measure the extent to which students have achieved the intended learning outcomes of a course, or unit)</p>		
<p>Technology Characteristics (TEC) (The features, capabilities, and functionalities of GenAI technologies, including features such as ease of use, and ability to support the tasks. Following specific factors are used).</p> <p>Perceived usefulness (PU) (The degree to which a student believes that using GenAI would enhance their academic performance)</p> <p>Perceived ease of use (PEU) (This degree to which a student feels that GenAI is easy to use and can be operated with minimal effort.)</p>		<p>Technology Characteristics (Features and capabilities of a technology that enable or constrain its use in performing tasks. This includes functionality, ease of use, reliability, and flexibility)</p>
<p>Task-Technology Fit (TTF) (This is a measure of how well GenAI technology's characteristics align with the academic task requirements of HE students).</p>		<p>Task-Technology Fit (The degree to which a technology's capabilities match the requirements of a task. Higher fit indicates that the technology effectively supports task performance)</p>
<p>Academic Performance (AP) (This is the degree to which the task-technology fit of GenAI influences students' academic performance, as reflected in their grades, marks, and feedback received)</p>		<p>Performance Impact (The effect of technology use on task or organisational performance, representing outcomes such as efficiency, accuracy, or effectiveness)</p>

## Appendix B. Constructs, Measurement Items, and Sources of the Questionnaire

Variables	Questionnaire Items	Source
<b>(Behavioural Intention-TTF Model)</b>		
Attitudes (AT)	AT1: My experience with using GenAI for academic purposes is a pleasant one AT2: I prefer to use GenAI for academic purposes currently or in the near future. AT3: I enjoy my learning process more when I use GenAI	(Al-rahmi et al., 2021; Ivanov et al., 2024; Rejali et al., 2023)
Subjective Norms (SN)	SN1: My classmates and friends believe that I should be using GenAI for academic purposes SN2: My lecturers and unit coordinators believe that I should be using GenAI for academic purposes SN3: I'm experiencing a push from my social networks these days to use GenAI for academic purposes.	(Ivanov et al., 2024)
Perceived Behavioural Control (PBC)	PBC1: I have the ability to incorporate GenAI in my academic work efficiently. PBC2: I have resources, time, and opportunities to use GenAI for my academic work. PBC3: I am confident that, if I choose to, I can make profound use of GenAI in my academic work.	(Ivanov et al., 2024)
Behavioural intention (BI)	BI1: Given the opportunity, I would use GenAI for academic activities. BI2: I plan to use GenAI for academic activities in the future frequently. BI3: I will recommend others to use GenAI for their academic work.	(Humida et al., 2022; Y. H. Lee et al., 2011)
Actual use of GenAI (AUG)	AUG1 – I spend a lot of time each day using GenAI for higher education learning. AUG2 – I frequently use GenAI to prepare my assessments.	(Al-rahmi et al., 2021; Ivanov et al., 2024)
Task Characteristics (TAC) Learning Outcomes (LO) Assessment Methods (AM)	TAC-LO1: GenAI supports me in deriving solutions for critical thinking assessments, such as analysing research papers, case studies, tackling projects. TAC-LO2: GenAI assists me in solving complex problems, including coding, computational challenges, system analysis, database design, and other design projects. TAC-LO3: GenAI assists me deriving high quality academic reports and preparing for oral presentations. TAC-LO4: GenAI helps me to derive solutions that adhere to ethical principles, safeguard privacy, and maintain security in academic settings. TAC-EM1: GenAI assist me in preparing/answering for quizzes,	Developed by authors

Variables	Questionnaire Items	Source
<b>(Behavioural Intention-TTF Model)</b>	structured tests, and unstructured exams. TAC-EM2: GenAI assist me in preparing/answering answers for written assessments, case studies, lab work and projects. TAC-EM3: GenAI assist me in preparing/answering for oral presentations, viva, and classroom discussions.	
Technology Characteristics (TEC)	TEC-PU1: GenAI is a useful tool for me to find information related to my academic tasks instantly.	(Humida et al., 2022; B. Wu & Chen, 2017)
Perceived usefulness (PU)	TEC-PU2: GenAI is a useful tool for me to improve the quality of my academic work.	and expanded by the authors
Perceived ease of use (PEU)	TEC-PU3: GenAI is useful to me as it provides learning support for my academic needs without time restrictions. TEC-PEU1: I find it is easy to interact and access GenAI to accomplish my academic tasks. TEC-PEU2: I find it is easy to understand the instructions or prompts needed to interact with GenAI. TEC-PEU3: I find it is easy to start using GenAI with minimal effort and no training.	
Task-Technology Fit (TTF)	TTF1: I believe GenAI is well matched tool to carry out my academic tasks. TTF2: In helping to achieve my unit/course learning outcomes, the functions of GenAI are sufficient. TTF3: Using generative AI fits well with my preferred methods for completing academic tasks.	(D. Y. Lee & Lehto, 2013; B. Wu & Chen, 2017) and expanded by the authors
Academic Performance (AP)	AP1: I've noticed an improvement in my assessment marks since I started using GenAI. AP2: I've received positive feedback for my academic work since I started using GenAI. AP3: With the help of GenAI, I can produce high-quality academic work that meets the criteria of the marking rubric.	(Al-Emran et al., 2025) and expanded by the authors