The relationship between students’ self-regulated learning skills and technology acceptance of GenAI

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Generative artificial intelligence (GenAI) has quickly become prolific in our daily lives, including the higher education sector. Although an AI-fuelled world is unpredictable, there is an urgent need to understand how university students use GenAI to support their learning and the factors influencing GenAI adoption. In this study, underpinned by self-regulated learning (SRL) theory and the technology acceptance model, we examined how university students’ adoption of GenAI is influenced by their SRL skills. Given the importance of SRL skills on students’ selection of study strategies, we hypothesised that SRL constructs would have a strong association with their adoption of GenAI. To explore this, we conducted an international survey-based study of 435 students from two universities in Australia and Canada to capture students’ use of GenAI within the first year of its wider adoption. Our findings reveal that SRL constructs of self-efficacy and social support predict the perceived ease of use of GenAI. Intrinsic motivation and effort regulation also predicted the perceived usefulness of GenAI, with a stronger association for students using GenAI for university learning than those who used it for non-academic purposes such as work or personal use. We discuss implications of our findings for educators.

Implications for practice or policy:

- University teachers should demonstrate and model GenAI use that fosters SRL skill development, such as self-efficacy, social support, intrinsic motivation and effort regulation.
- University administrators should prioritise academic development to equip instructors with skills for fostering SRL with GenAI tools.
- The institution should provide guidance on GenAI tool usage and SRL strategies through social support strategies.

Keywords: GenAI, self-regulated learning, technology acceptance model, self-efficacy, motivation, survey

Introduction

The rapid evolution of artificial intelligence (AI) technology has significantly impacted the global higher education, functioning not only as a tool for instructional delivery and institutional management (Hannan & Liu, 2021) but also to augment and advance the possibilities of teaching and learning through AI-powered tools such as chatbots (Popenici & Kerr, 2017). Australia’s higher education institutions are actively embracing the global trend of incorporating generative AI (GenAI) into the learning process, as evidenced by a growing consensus on the productive use of ChatGPT (Sullivan et al., 2023) and given the widespread availability and free access to AI technologies, making them an integral part of people’s daily lives (Rudolph et al., 2023).

The global workforce increasingly relies on AI-driven solutions, leading to a growing imperative for students to develop AI literacy to ensure they are future-ready (Gabriel et al., 2022). The integration of GenAI in workplaces is transforming job roles and creating new career opportunities, necessitating a comprehensive understanding of AI technologies among future professionals. Educational institutions must, therefore, prioritise not only the incorporation of GenAI tools in their curricula but also the fostering of critical skills required to navigate an AI-augmented work environment (Bankins et al., 2024). Understanding the factors influencing students' adoption and use of GenAI is essential for educators to design effective pedagogical strategies and technical support systems. Research into students' motivations, perceived benefits and barriers to GenAI usage can inform the development of tailored instructional methods that enhance AI literacy and readiness for future careers (Chan & Hu, 2023; Tierney et al., 2024). This underscores the need for an educational approach that not only integrates GenAI into learning processes but also equips students with the competencies necessary to leverage AI in their professional lives.

It is paramount for educators to gain a deeper understanding of students' use and adoption of GenAI through validated research measures. Prior studies (Al Shamsi et al., 2022; Strzelecki, 2023; Zhou et al., 2024) have used the technology acceptance model (TAM) to interrogate the factors that influence students' use or behavioural intentions to use AI tools, revealing a positive relationship between ease of use and perceived usefulness on behavioural intention to use AI tools, aligning with TAM assumptions (Davis, 1989) and much of the research on technology adoption. There is also a growing body of research (Guan et al., 2025) conducted in understanding how AI tools can enhance students' self-regulated learning (SRL) approaches such as monitoring and adapting their learning processes, setting goals or managing their motivations. However, although the focus has been on how AI tools can support the development of students' SRL approaches, little is known about how their SRL influences their adoption of AI tools or the interplay between SRL and TAM, a gap in the literature that this study addresses. Such investigation may provide useful insight for universities looking at how to best encourage students to use AI tools responsibly and to equip them with the skills needed when they enter the workforce. A recent study investigated how SRL can be a mediator between students' perceptions of the ease of use of AI and enhancing their critical thinking and problem solving skills suggesting the potential of a synergistic relationship between SRL, AI and TAM (Zhou et al., 2024). Hence, our study aimed to better understand this relationship and investigates whether students' SRL approaches can influence AI adoption, alongside previously established TAM constructs shedding light on the considerations needed by higher education institutions to support AI adoption.

AI in higher education

To examine the adoption of GenAI in higher education, a range of studies have recently been published. For example, a wide-scale survey was conducted in 2023 in the United States of America with 727 university student respondents from across the country, revealing 55% of students were unfamiliar with GenAI, approximately 30% acknowledged using it to edit or submit generated materials for assignments, generating ideas or entertainment and a quarter used it for in-class activities, as discussion prompts or for completing assignments (Muscanell & Robert, 2023). In a parallel context in Australia, a survey was conducted at a mid-size university in early 2023, exploring students' awareness of GenAI tools (Kelly et al., 2023). With 1,135 responses, the study revealed that, at the time, most students were unaware of GenAI or had heard very little about it, with significant disparities among students from different disciplines with science students more aware of it and medical and health students exhibiting the lowest awareness. This trend extended to the actual utilisation of GenAI tools, with engineering and science students reporting more frequent use than students in other areas.

Although GenAI tools offers considerable benefits for supporting teaching and learning, they lack the ability to encode higher-order thinking skills; instead, they rely solely on recognising statistical patterns in language to produce the most likely response. As a result, they cannot truly understand or engage in complex reasoning, critical thinking or deep analysis, which are essential for advanced learning and teaching. This brings significant challenges and difficulties in evaluating the quality of responses (Farrokhnia et al., 2023), given the tendency of GenAI tools to produce different responses every time, as well as sometimes produce completely incorrect responses (known as hallucinations) (Perković et al., 2024). Such issues pose significant limitations to the effective use of GenAI and were critical in informing the current study. We posit that navigating such limitations requires effective SRL skills that would allow for the effective use of GenAI technologies (Lodge, De Barba, & Broadbent, 2023).

SRL

SRL is a theoretical framework focusing on learners' motivation, metacognitive awareness and the learning strategies that they deploy, as well as aspects that can influence their learning behaviour. Although there are many models of SRL (see Panadero, 2017, for a review), they share similar phases and processes of planning, goal setting, monitoring and modifying and sustaining learning strategies aligned with learning goals (Broadbent et al., 2022; Pintrich, 2000; Zimmerman, 1986). These models involve self-assessment at each phase, allowing learners to gauge their abilities and set goals, continuously monitor their progress and reflect on their learning strategies. For example, Zimmerman's (2002) concept of academic self-regulation outlines a three-phase cyclical process occurring before, during and after learning, consisting of *forethought, performance and self-reflection.* In the forethought phase, learners set goals and plan their learning strategies underpinned by their self-efficacy and motivation towards learning. In the performance phase, learners complete their learning tasks using the plans they determined in the prior phase and self-control strategies such as help-seeking, time management and task strategies along with self-recording their learning and monitoring their performance. In the final and third phase, learners judge their academic performance and reflect on the strategies they had chosen influencing the goals and plans they make in the forethought phase of the next SRL cycle. Pintrich (2000) has a similar approach to SRL with four key phases: *forethought, planning and activation; monitoring; control;* and *reaction and reflection.* In the first phase, learners activate their prior knowledge and set goals, while in the second phase, learners engage in metacognitive awareness monitoring their learning, effort, affect and motivations. In the third phase, learners select and adapt strategies to manage their learning, motivation and affect and adapt the effort required to complete or modify their task. In the fourth and final phase, learners evaluate their learning and reflect on their performance and emotional reactions.

A recent systematic literature review highlighted a growing interest in using chatbots to scaffold and support students' SRL processes (Guan et al., 2025). Chatbots are a type of large language models that utilise AI and natural language processing to engage in dynamic and adaptive conversations with humans. For example, education chatbots can support students in setting personal learning goals (Hew et al., 2023) or scaffold their planning and metacognitive monitoring through guided prompts (Zhang et al., 2023). Unlike educational chatbots that can be developed to support students' SRL, GenAI tools such as ChatGPT are not typically programmed to engage in proactively aiding learners with their SRL. However, according to Lodge, Yang et al., 2023 (2023), humans can initiate indirect co-regulation from GenAI by prompting it for feedback or to explain concepts. However, high levels of SRL are necessary for effective co-regulation with GenAI, particularly when the reliability and accuracy of GenAI responses may be questionable (Lodge, Yang et al., 2023). Hence, learners' need to draw on their SRL processes to continuously monitor learning goals, evaluate responses from GenAI and adapt their learning strategies.

The Self-Regulation for Learning Online (SRL-O) questionnaire developed by Broadbent et al. (2022) psychometrically measures a wide range of SRL approaches commonly employed in online or blended learning contexts where students are using digital tools, such as AI, to support their learning. Grounded in Zimmerman and Moylan's (2009) work that emphasised the role of motivational beliefts in the forethought phase and during the entire SRL cycle and after rigorous review of Pintrich et al.'s (1991) Motivated Strategies for Learning Questionnaire, the SRL-O includes 10 subscales that assess a range of motivational and learning strategies. Although it is a comprehensive instrument, our study focused on six key subscales: self-efficacy, intrinsic motivation, extrinsic motivation, effort regulation, planning and time management, and social support. These subscales encompass both motivational strategies, such as learners' beliefs in their ability to succeed (self-efficacy), their intrinsic reasons for learning (e.g., interest and curiosity), and extrinsic drivers (e.g., grades and rewards), as well as key learning strategies, including persistence in the face of challenges (effort regulation), structured approaches to time and planning (planning and time management) and help seeking or collaboration with others (social support).

Although the SRL-O is a relatively new questionnaire, it has begun to be used across a number of recent studies. For example, Mejia-Domenzain et al. (2024) used four subscales of the SRL-O to measure students' self-reported SRL approaches, with their behavioural trace data when using an intelligent tutoring system, while Karakaš and Helic (2023) adopted the SRL-O to measure students' SRL approaches and the extent they influence students' use of version control systems in a programming course and their academic performance.

Although SRL can potentially equip students with the skills to navigate the complexities of using GenAI to support learning effectively and the SRL-O can help with collecting students' self-reports about their motivational and learning strategies informing their SRL approaches, it is not yet known how specific dimensions of SRL influence students' use and perceived value of GenAI.

TAM

TAM is a well-established and effective framework widely used in investigating the acceptance of new technology. Initially developed by Davis (1989), TAM serves to predict individuals' attitudes towards adopting a particular technology. The model posits that two fundamental personal beliefs, namely perceived usefulness and perceived ease of use, are influenced by external and system-specific factors. These beliefs, in turn, impact the actual use of the technology (Al Shamsi et al., 2022; Salloum et al., 2019). Perceived usefulness represents the degree to which individuals believe adopting a particular technology will enhance their performance or productivity in achieving specific tasks (Al Shamsi et al., 2022; Davis, 1989). This perception is influenced by external factors, such as the educational environment and societal expectations, as well as system-specific factors, including the functionality and features of the technology in question. Perceived ease of use refers to individuals' perceptions of the simplicity and user-friendliness of the technology (Al Shamsi et al., 2022; Davis, 1989). It reflects students' evaluations of the ease in interacting and navigating technology.

Al Shamsi et al. (2022) used an adapted version of TAM to investigate the factors influencing university students' use of AI-based voice assistants to support their learning. The findings indicate that, overall, students' perceived ease of use had a positive impact on the perceived usefulness of the AI-based voice assistants, while factors such as enjoyment and trust towards the tool increased both perceived usefulness and perceived ease of use. Similarly, Kim et al.'s (2020) study used a TAM-based survey at a university in the United States of America to identify the perceptions of 349 university students' towards using AI teaching assistants. Findings revealed that positive attitudes associated with perceived ease of use for communicating with the AI teaching assistant subsequently led to students' intentions to use the AI teaching assistants. However, Kim et al.'s research was limited to students learning about AI teaching assistants through reading a short article and not direct interaction. The researchers emphasised the urgency of gathering empirical data on students' use of AI technologies.

Aim of the study

Collectively, the studies above highlight students' perceptions of AI-based tools and the use of survey instruments, such as TAM, to reveal factors that influence students' AI adoption. Earlier, we noted the importance of students' SRL in effectively using GenAI tools. However, the intersection of how students' SRL approaches relate to their perceptions and use of AI-based tools, such as ChatGPT, has not yet been interrogated, motivating the aim of this study. Hence, our study examined the relationship between students' SRL strategies, TAM constructs and students' use of GenAI tools in the first year of their proliferation in higher education through the following research questions:

(1) How are university students' SRL skills associated with their technology acceptance of GenAI for supporting their learning?
(2) How do students' SRL skills and technology acceptance of GenAI differ between students who use GenAI for different purposes (academic vs. non-academic)?

Methods

To answer the above research questions, a survey was administered to students enrolled at two mid-size universities, one in Australia and one in Canada, in 2023. Data collection occurred in two rounds with separate cohorts of students, the first round between May and June 2023 (*n* = 258) and the second between October and November 2023 (*n* = 177) at both universities. The initial data collection phase did not yield an adequate sample size for robust analysis. Consequently, a second round of data collection was undertaken in the same year, aligning with semester dates. Data from the two sites was combined to allow for a greater sample size for statistical analysis (*n* = 435). Human ethics approval was obtained from both institutions before data collection, and all data was collected using the Australian university's Qualtrics survey platform. Participants were students enrolled in on-campus or online study and were studying either in a pre-bachelor enabling pathway programme (total *n* = 204; round one *n* = 146; round two *n* = 56) at the Australian university or were pre-service teachers in education programmes at the Australian university (total *n* = 73; round one *n* = 28; round two *n* = 43) and the Canadian university (total *n* = 164; round one *n* = 84; round two *n* = 78). Recruitment occurred during class, where a link to the participant information sheet and online survey was presented to on-campus students with an option to complete in class. Online students were recruited through a link to the study information on their learning management platform. Both on-campus and online students received a follow-up reminder about the study opportunity through class email announcement. Data was combined to allow for an international perspective of how students perceive GenAI tools regardless of country of residence and discipline of study rather than a comparative study. Future studies will expand to other disciplines and universities to allow for a more comprehensive investigation. The survey findings, however, provide early insight into the factors that influence students' adoption of GenAI tools.

Survey design

The survey used six validated subscales of the SRL-O questionnaire (Broadbent et al., 2022) and an extended validated TAM instrument for AI tools (Al Shamsi et al., 2022) and with questions asking students if they used AI tools, including ChatGPT or Grammarly, for university learning or for non-academic purposes (e.g., personal use or for work). The survey was administered towards the end of the semester following key assessment deadlines where students may have chosen to use GenAI tools to support their mastery of the curriculum. A 5-point Likert scale was used for the questions pertaining to TAM following the validated instrument used by Al Shamsi et al., replacing "voice assistant technology" with "AI tools". This decision was deliberately made as Shamsi et al.'s AI study concerned students' perceptions and attitudes towards the use of AI-based voice assistants, which is a technology similar to GenAI tools. A 7-point Likert scale was also used to ascertain students' SRL approaches towards their learning using subscales of the validated SRL-O instrument (Broadbent et al, 2022). The specific subscales on intrinsic and extrinsic motivation, self-efficacy, planning and organisation, effort regulation and social support were used to keep the survey instrument short yet allow the discovery of the interplay between key SRL and TAM constructs and students' use of GenAI tools. The SRL-related questions were about students' SRL approaches towards their learning in general and were not specific to the use of GenAI tools. Table 1 shows the TAM and SRL survey items.

Table 1
Administered survey items and their associated constructs

Constructs	Survey items
Perceived Usefulness (TAM)	I think AI tools can improve my productivity. I think AI tools can increase my performance. I think AI tools can encourage me to finish my tasks quickly. Overall, using AI tools is useful.
Perceived Ease of Use (TAM)	Learning how to use AI tools is easy to me. My interaction with AI tools is clear and understandable. I find AI tools to be easy to use.
Behavioural Intentions (TAM)	I intend to use AI tools in the future. I will recommend AI tools to my friends and family. I will keep myself updated with the latest AI tools.
Subjective Norm (TAM)	People who are close to me recommend that I use AI tools. People around me use AI tools. People who are close to me would guide me to use AI tools.
Enjoyment (TAM)	I enjoy interacting with AI tools. The conversations with AI tools are interesting. My creativity can be stimulated when using AI tools.
Facilitating Conditions (TAM)	I have the knowledge to use AI tools. I have the required skills to use AI tools. I can get assistance from others when I get trouble using an AI tool.
Trust (TAM)	AI tools are trustworthy. I think AI tools are reliable. I believe that AI tools are honest.
Security (TAM)	I am concerned about AI tools leaking my personal information without my authorisation. Using AI tools might threaten my personal privacy. I am afraid that AI tools might collect my personal information without my acknowledgement.
Self-Efficacy (SRL)	I am confident that I will be able to master the content and assignments in my class. I am confident in my ability to successfully persist in my class, even if I find the content difficult. I am confident I can put in the effort required to get a high grade in my class. I am confident that I can accurately work out what the task is requiring me to do.
Intrinsic Motivation (SRL)	I always find aspects of the content that arouse my curiosity. I love learning new things in my class. I find studying enjoyable. I find it very satisfying when I learn new material. I get a sense of achievement when I learn new skills or information
Extrinsic Motivation (SRL)	I want to do well so I can show off to my friends and family. I want to do well because of others real or perceived expectations of me. I want to get a better grade than others in class.
Effort Regulation (SRL)	I work hard in my study, even when there are more interesting things to do. When my study gets difficult, I remain committed to reaching my study goals. When my mind begins to wander during a learning session, I make a special effort to keep concentrating. No matter how I am feeling, I persevere with my study.
Planning & Time Management (SRL)	I set short-term (daily or weekly) goals. I set realistic deadlines for learning. I break larger goals into smaller actionable goals. I make a list of detailed actions that I need to complete. I plan out my schedule each week so I have the appropriate amount of time available for online study.

Constructs	Survey items
Social Support (SRL)	I try to help other students when they ask a question online, I can answer. I ask for help from knowledgeable others through online channels when I am not sure what to do in my class. I ask the teacher and/or my peers to clarify information in my course. When I have difficulties with my class, I seek assistance from others through online means (discussion boards, social media, email, instant messaging, etc.). I use email, discussion boards, social media, etc., to connect with the teacher and other students when I need help.

Data analysis

We first implemented factor analysis, a method used to explore the relationships among variables by uncovering the underlying constructs that may not be directly observed in the data set (Field et al., 2012). More specifically, we used two exploratory factor analyses (EFA) to identify the dimensions related to TAM-related and SRL-related constructs. Next, we employed structural equation modelling (SEM), a methodology well-suited for identifying latent variables and examining their correlational relationships in educational psychology (Gabriel et al., 2020). This approach integrates measurement and structural models, allowing us to test the linear causal relationships among variables and evaluate the hypothetical model using both observed and latent variables (Field et al., 2012). Although the measurement model was implemented using confirmatory factor analysis (CFA) to confirm the factor structure identified by EFA, the structural model component of the SEM was used to conduct a regression-like path analysis and to examine the directional and non-directional nature of relationships between the observed and latent variables (Gabriel et al., 2020). We further employed a multigroup SEM analysis to investigate group differences (Finch & French, 2015) between students who used GenAI for university learning (n = 153) and those who used it for non-academic purposes (n = 179). We checked the model fit for the individual CFA and SEM using comparative fit index (CFI), root mean square error of approximation (RMSEA) and standardised root mean square residual (SRMR), in line with Gabriel et al. (2020).

Results

EFA

We explored the factor structure of the questions loading on the different TAM constructs. We fitted an exploratory factor model with eight factors. The results highlight that Q7_1, Q7_2, Q9_1, Q10_1 and Q10_2 were loading onto two factors (see Table A1 in the Appendix). This suggests that they were not a good fit and were removed from the subsequent analysis. Additionally, because a minimum of three items (questions) per factor is required (Field et al., 2012), all questions from Q7_9 (regarding behavioural intentions), Q9 (regarding enjoyment) and Q10 (regarding facilitating conditions) were excluded from the analysis. We investigated the revised factor structure of the TAM constructs using another EFA. The results in Table A2 (Appendix) show that all the questions were loaded onto their respective factors, indicating a good fit. These five TAM constructs are perceived usefulness, ease of use, subjective norm, trust and security.

Similarly, using EFA, we investigated the factor structure of the questions loading on the different SRL constructs. The results (see Table A3 in the Appendix) suggest that the questions were loaded onto their respective factors and indicate a good fit. Therefore, the six constructs used in our study are self-efficacy, intrinsic motivation, extrinsic motivation, effort regulation, planning time management, and social support.

SEM

To answer Research question 1, first, we used a measurement model (CFA) to estimate the latent constructs and check how well they fit the expected structure. We also calculated the correlation between each pair of these identified latent constructs (Table 2). Analysing the correlations, ease of use had a strong positive correlation with perceived usefulness. Similarly, self-efficacy had a strong positive correlation with intrinsic motivation and extrinsic motivation. Analysing the measurement model (CFA) results, as outlined in Table A4 in the Appendix, we found that all the standardised loadings of the TAM and SRL-related questions were statistically significant. Overall, the model indicates a good fit (CFI = 0.939 > 0.9; RMSEA = 0.051 < 0.08; SRMR = 0.058 < 0.08), suggesting that the identified factor structure is supported well by the data.

Table 2
Correlation between latent constructs

Construct	Ease of Use	Perceived Usefulness	Self-Efficacy	Intrinsic Motivation	Extrinsic Motivation	Effort Regulation	Social Support
Ease of Use	1.000						
Perceived Usefulness	**0.626**	1.000					
Self-Efficacy	0.164	0.167	1.000				
Intrinsic Motivation	0.068	0.194	**0.627**	1.000			
Extrinsic Motivation	0.080	0.108	0.287	0.265	1.000		
Effort Regulation	-0.009	0.013	**0.527**	0.608	0.260	1.000	
Social Support	0.174	0.149	0.323	0.346	0.360	0.272	1.000

Note. The numbers in bold indicate a strong relationship.

Second, we fitted the following structural model (Figure 1) to examine relationships between the latent constructs. In this model, we used self-efficacy, intrinsic motivation, extrinsic motivation, effort regulation, and social support to predict perceived usefulness and ease of use.

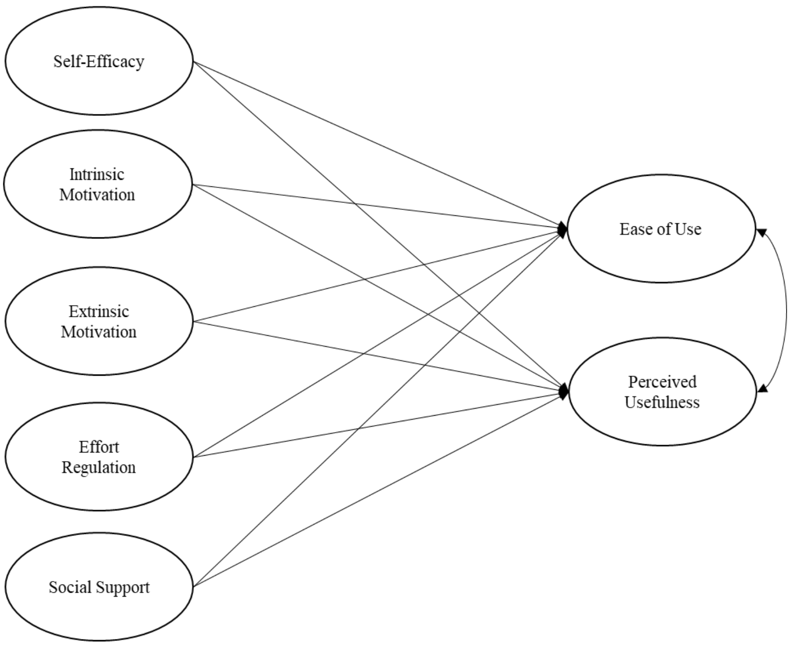

Figure 1. Hypothesised structural model

The structural model also indicates an overall good fit to the data (CFI = 0.94 > 0.90; RMSEA = 0.055 < 0.080; SRMR = 0.059 < 0.080). Assessing the regression-like path analysis of the structural model (Table 3), self-efficacy and social support significantly predicted ease of use, while intrinsic motivation and effort regulation significantly predicted perceived usefulness.

Table 3
Path analysis of SEM

Construct	Estimate	SE	*z* value	*P* value	Std.lv	Std.all
Ease of Use ~						
Self-Efficacy	0.212	0.084	2.527	**0.012**	0.205	0.205
Intrinsic Motivation	-0.030	0.096	-0.314	0.753	-0.029	-0.029
Extrinsic Motivation	0.012	0.077	0.157	0.875	0.012	0.012
Effort Regulation	-0.148	0.088	-1.671	0.095	-0.143	-0.143
Social Support	0.157	0.076	2.064	**0.039**	0.152	0.152
Perceived Usefulness ~						
Self-Efficacy	0.105	0.083	1.270	0.204	0.101	0.101
Intrinsic Motivation	0.223	0.097	2.304	**0.021**	0.215	0.215
Extrinsic Motivation	0.049	0.087	0.562	0.574	0.047	0.047
Effort Regulation	-0.214	0.085	-2.515	**0.012**	-0.206	-0.206
Social Support	0.085	0.081	1.053	0.293	0.082	0.082

Note. Std.lv represents the values in the standardised model parameters (the variances of the latent variables are set to unity). Std.all represents the values in the (completely) standardised model parameters (the variances of both the observed and the latent variables are set to unity).

Multigroup analysis

To answer research question 2, based on the structural model results, we revised the structure, as shown in Figure 2, to investigate the multigroup differences. The structural model indicates an overall good fit to the data (CFI = 0.914 > 0.90; RMSEA = 0.065 < 0.080; SRMR = 0.072 < 0.080) when fitting a group-wise analysis to investigate the behaviour between students who indicated they used GenAI for university learning (n = 153) compared to using GenAI for non-academic purposes only (n = 179). It is important to note that although the data was coded as students using AI for university learning or non-academic purposes, some students who used GenAI for university learning also used GenAI for non-academic purposes. The path analysis of using GenAI for university learning and for non-academic purposes is shown below. The model with students using GenAI for university learning has self-efficacy and intrinsic motivation, significantly predicting ease of use and perceived usefulness, respectively (Table 4). The model with students using GenAI for non-academic purposes has intrinsic motivation, significantly predicting the perceived usefulness of GenAI (Table 4). However, the association of intrinsic motivation and perceived usefulness is higher for students using GenAI for university learning (0.275) than for non-academic purposes (0.261).

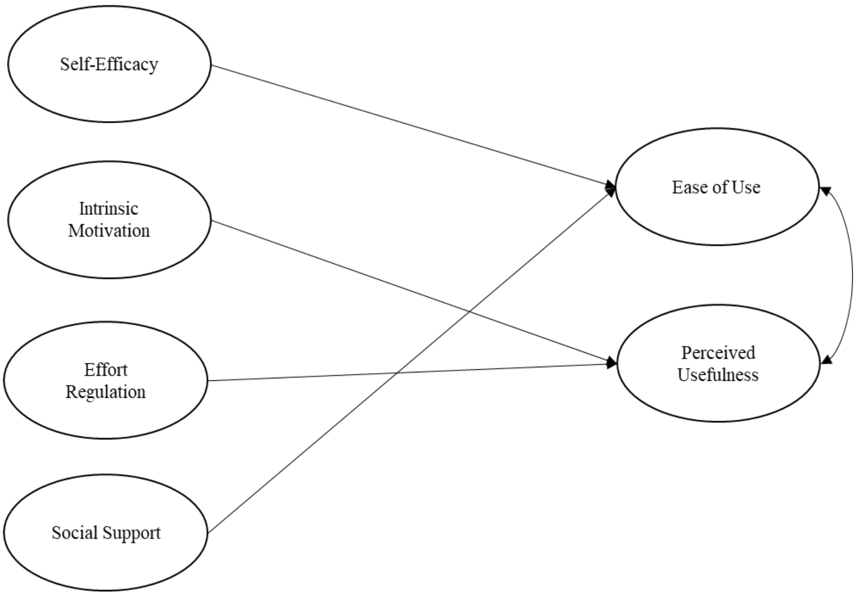

Figure 2. Revised structural model

Table 4
Path analysis of students using GenAI for university learning versus for non-academic purposes

Construct	**Estimate**	**SE**	***z* value**	***P* value**	**Std.lv**	**Std.all**
University learning						
Ease of Use ~						
Self-Efficacy	0.162	0.062	2.620	**0.009**	0.243	0.243
Social Support	0.055	0.053	1.029	0.304	0.079	0.079
Perceived Usefulness ~						
Intrinsic Motivation	0.275	0.079	3.490	**0.000**	0.451	0.451
Effort Regulation	-0.058	0.060	-0.960	0.337	-0.110	-0.110
Non-academic purposes						
Ease of Use ~						
Self-Efficacy	0.010	0.072	0.137	0.891	0.011	0.011
Social Support	0.124	0.077	1.626	0.104	0.150	0.150
Perceived Usefulness ~						
Intrinsic Motivation	0.261	0.119	2.198	**0.028**	0.250	0.250
Effort Regulation	-0.109	0.090	-1.213	0.225	-0.135	-0.135

Note. Std.lv represents the values in the standardised model parameters (the variances of the latent variables are set to unity). Std.all represents the values in the (completely) standardised model parameters (the variances of both the observed and the latent variables are set to unity).

Discussion

This study investigated the relationships between university students' SRL approaches, TAM constructs and their use of GenAI for learning support. It also explored how these factors differ based on the purpose of AI use, for academic or non-academic purposes. Our findings reveal strong interconnections between SRL approaches and TAM constructs in the context of GenAI. The strong positive correlation between ease of use and perceived usefulness aligns with the core tenets of TAM (Davis, 1989), suggesting that students who find GenAI tools easy to use are more likely to perceive them as beneficial for their learning.

The significant relationship between self-efficacy and both intrinsic and extrinsic motivation underscores the importance of students' belief in their capabilities in fostering motivation to use GenAI. This finding extends the understanding of SRL in technology-enhanced learning environments (Broadbent et al., 2022; Rosli & Saleh, 2023) to GenAI. Our results show that self-efficacy and social support predict ease of use, while intrinsic motivation and effort regulation predict perceived usefulness, providing a nuanced understanding of how SRL components interact with TAM constructs. When students feel confident in their capabilities, they are more likely to engage with and effectively use technological tools, reinforcing a positive perception of their ease of use (Rosli & Saleh, 2023). Similarly, social support provides the necessary guidance and emotional backing that helps students navigate technological tools with greater confidence and less apprehension. This network of support mitigates feelings of isolation and uncertainty, thereby making the technology feel more accessible and easier to use. Effort regulation, another critical element of SRL, involves controlling one's effort and attention in the face of distractions or uninteresting tasks (Pintrich & De Groot, 1990). Students who effectively regulate their efforts are better equipped to overcome initial difficulties with new technology, leading to a higher appreciation of its utility. This persistence ensures that students continue to engage with the technology long enough to recognise and appreciate its full potential, thereby increasing its perceived usefulness.

Further, our study shows that intrinsic motivation towards learning significantly predicts perceived usefulness, with a stronger association for students who use GenAI for university learning than those who only use it for non-academic purposes. This finding reveals having an innate interest, enjoyment and curiosity for learning, including learning new skills and information (Broadbent et al., 2022), contributes to finding GenAI tools useful, especially for students who use GenAI for university learning. Since perceived usefulness is defined as the "degree in which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320), it may be expected that extrinsic motivation would be better aligned whereby students who have a tendency for striving for external recognition would use GenAI to support their performance. However, the finding suggests that students with intrinsic motivation towards their study would opt to use GenAI tools drawing on their curiosity or interest in extending their skills and knowledge, attributes of intrinsic motivation (Broadbent et al., 2022). This result may be partly due to students seeing GenAI tools aligned with their learning goals, making them feel more useful in academic settings and reinforcing intrinsic motivation. Additionally, students may receive structured support from teachers, peers, and student support services, helping them effectively use GenAI and thus increasing their engagement and perceived value of GenAI.

Comparing our findings to those in Muscanell and Robert's (2023) study, we note some interesting parallels and differences. Although their study found that 55% of students were unfamiliar with GenAI, our results suggest a higher level of engagement, possibly indicating rapid adoption of these technologies in the intervening period. Future research could explore this potential shift in awareness and use over time.

Practical implications

The relationship between SRL constructs and the use of GenAI to support university learning implies that those students who are using GenAI tools are likely to be using them as part of their repertoire of SRL strategies and hence, promoting students' SRL may lead to improved perceptions of GenAI's ease of use and usefulness. In view of the findings discussed above, we recommend that students will be likely to perceive AI tools as accessible and useful for their learning when they have belief in their ability for academic success, are disposed to seek help and collaborate with others, are intrinsically motivated to learn and are able persist with tasks even when they find it uninteresting. This suggests that pedagogical design should consider all of these aspects of SRL – self efficacy, intrinsic motivation, social support and effort regulation – as a strategy to improve SRL and the use of GenAI for purposes of learning.

GenAI tools are well placed to activate curiosity, enjoyment and interest in students, as individual learning pathways can be explored through interactions with AI. Course design and pedagogical approaches that encourage choice and inquiry will facilitate opportunities to explore content that is new and interesting for students, thus increasing intrinsic motivation. Learning how to use GenAI tools to master the content and assignments in class, and accurately work out what the task requires, is likely to improve persistence and performance, and in turn increase student confidence in their capacity to succeed. Using GenAI to assist students to regulate effort may lead to improved motivation, focus and concentration, while promoting a positive perception of GenAI tools to support learning. In order to improve effort regulation, chatbots such as ChatGPT or other tools such as scheduling assistants, can help with goal setting and be used to assist monitoring and/or evaluating progress. AI summarising tools can be used to assist when study becomes difficult by simplifying reading material or identifying key points, and AI task managers may help to redirect when the mind begins to wander. We recommend that academic institutions identify how (and which) GenAI tools can be used to set goals, monitor progress, assist with difficult tasks and regulate mind wandering, and support students to use those tools for those purposes.

As this study has demonstrated, social support significantly predicted students' perceptions of the ease of use of GenAI tools. In the university context, social support can be manifested in the course design through teacher-led intervention and in the generation of opportunities for peer-to-peer support, through which both intrinsic and extrinsic motivations, along with self-efficacy, can be promoted and activated. Demonstration, modelling and discussion of AI tools by knowledgeable teachers are needed to enable students to develop SRL strategies in tandem with tools that can assist them towards their learning. Demonstration and modelling involve teachers or lecturers showing students how the tools may be used in the context of their work or study. This might be achieved by modelling ways of using a chatbot tool to set goals, summarise lengthy articles or to alert them when they go off task. Discussion would involve peers in sharing and reflecting on how they used AI to, for instance, stay motivated, organise their time or check their progress.

Although this study suggests that university instructors should incorporate GenAI tools into their teaching and embed tailored instructional strategies that encourage SRL, institutional support is critical for successful implementation. University administrators should prioritise academic development by offering targeted professional development programs that equip educators with the skills to integrate GenAI effectively into the curriculum (Kurtz et al., 2024), and more specifically to foster students' SRL approaches. Additionally, student support services may play a critical role by providing students with direct guidance on the ethical and appropriate use of GenAI tools and strategies to promote their SRL skills. A combined strategy, aimed at both teachers and students, can potentially improve student GenAI use to ensure they are future ready.

Limitations and future research

Although our study provides valuable insights, it is important to acknowledge several limitations and point towards avenues for future research. The scope of our study, limited to two universities and specific disciplines, may not fully capture the diverse landscape of higher education. Different institutions and academic fields may have varying levels of exposure to and attitudes towards GenAI, as shown in the study by Kelly et al. (2023), potentially influencing the relationships we observed. This limited scope constrains the generalisability of our findings and highlights the need for more comprehensive studies across a broader range of educational contexts. The cross-sectional and correlational nature of our research presents another limitation. Our study provides a snapshot of the current state of GenAI use and its relationship with SRL and TAM constructs, but it does not allow us to draw causal inferences. The relationships we identified, while informative, should be interpreted as associations rather than cause-and-effect relationships.

The rapidly evolving nature of GenAI technology presents a unique challenge. Our study captures student perceptions and usage patterns during the early stages of GenAI adoption in higher education. Given the pace of technological advancement in this field, these findings may not reflect long-term trends or account for the impact of subsequent developments in GenAI capabilities and applications. The patterns of adoption and use may change significantly as GenAI becomes more integrated into educational practices and as both students and institutions adapt to its presence. Conducting longitudinal research would be valuable in tracking how the relationships between SRL, TAM constructs and GenAI use evolve over time. This could reveal how students' attitudes, skills, and usage patterns change as they gain more experience with GenAI tools and technology advances.

Conclusion

Based on SRL and TAM, this study investigates the factors influencing university students' adoption and use of GenAI tools during the first year of their proliferation in higher education. Although TAM primarily focuses on perceived ease of use and perceived usefulness as determinants of technology adoption (Davis, 1989), our findings suggest that these perceptions are themselves influenced by SRL strategies and motivational factors. This provides a more holistic view of technology adoption in educational settings, acknowledging the complex interplay between cognitive, motivational and social factors.

Moreover, our study offers practical implications for university teachers, administrator, and student support services. It suggests that to promote the adoption of GenAI tools, it is not enough to simply focus on the tools' features or benefits. Instead, a combined strategy is needed whereby educators are supported in integrating GenAI into the curriculum and adopting education strategies to foster students' self-efficacy, providing robust social support systems, nurturing intrinsic motivation and teaching effort regulation strategies. In tandem, university student support services should scaffold students in their responsible and effective use of GenAI to support their learning and promote SRL strategies. This multifaceted approach could lead to more effective and sustained adoption of GenAI tools in educational contexts.

Author contributions

Author 1: Conceptualisation, Investigation, Project Administration, Writing – review and editing; **Author 2:** Data curation, Writing – original draft; **Author 3:** Formal analysis, Visualisation, Writing – original draft, **Author 4:** Writing – original draft; **Author 5:** Data collection, Writing – original draft; **Author 6:** Writing – original draft; **Author 7:** Data collection, Writing – review and editing; **Author 8:** Conceptualisation, Writing – review and editing.

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Appendix

Table A1
Original factor loadings for TAM

Question #	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Q5_1	0.750							
Q5_2	0.768							
Q5_3	0.669							
Q5_4	0.718							
Q6_1		0.795						
Q6_2		0.736						
Q6_3		0.813						
Q7_1	**0.545**							**0.439**
Q7_2	**0.495**							**0.520**
Q7_3								0.413
Q8_1			0.767					
Q8_2			0.767					
Q8_3			0.764					
Q9_1	**0.441**	**0.427**						
Q9_2						0.700		
Q9_3						0.435		
Q10_1		**0.425**			**0.751**			
Q10_2		**0.450**			**0.752**			
Q10_3					0.416			
Q11_1				0.770				
Q11_2				0.757				
Q11_3				0.733				
Q11_4				0.854				
Q11_5				0.944				
Q11_6				0.843				

Table A2
Revised factor loadings for TAM with five factors

Question #	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Q5_1	0.761				
Q5_2	0.786				
Q5_3	0.647				
Q5_4	0.712				
Q6_1		0.821			
Q6_2		0.800			
Q6_3		0.865			
Q8_1					0.777
Q8_2					0.740
Q8_3					0.794
Q11_1			0.772		
Q11_2			0.782		
Q11_3			0.740		
Q11_4				0.852	
Q11_5				0.942	
Q11_6				0.844	

Table A3
Original factor loadings for SRL

Question #	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Q13_1	0.778					
Q13_2	0.771					
Q13_3	0.751					
Q13_4	0.738					
Q14_1			0.529			
Q14_2			0.694			
Q14_3			0.574			
Q14_4			0.797			
Q14_5			0.768			
Q14_6						0.727
Q14_7						0.808
Q14_8						0.574
Q15_1				0.708		
Q15_2				0.723		
Q15_3				0.691		
Q15_4				0.659		
Q16_1		0.723				
Q16_2		0.663				
Q16_3		0.660				
Q16_4		0.665				
Q16_5		0.678				
Q17_1					0.564	
Q17_2					0.791	
Q17_3					0.428	
Q17_4					0.836	
Q17_5					0.695	

Table A4
CFA

	Estimate	SE	*z* value	*P* value	Std.lv	Std.all
Ease of Use ~						
Q6_1	0.915	0.046	19.738	0.000	0.915	0.872
Q6_2	0.946	0.045	20.908	0.000	0.946	0.904
Q6_3	0.942	0.044	21.521	0.000	0.942	0.920
Perceived Usefulness ~						
Q5_1	0.894	0.048	18.671	0.000	0.894	0.850
Q5_2	0.891	0.047	18.863	0.000	0.891	0.856
Q5_3	0.785	0.052	15.173	0.000	0.785	0.739
Q5_4	0.834	0.046	18.165	0.000	0.834	0.835
Self-Efficacy ~						
Q13_1	1.095	0.063	17.419	0.000	1.095	0.810
Q13_2	1.063	0.059	17.869	0.000	1.063	0.824
Q13_3	1.165	0.059	19.881	0.000	1.165	0.882
Q13_4	1.039	0.058	18.013	0.000	1.039	0.828
Intrinsic Motivation ~						
Q14_1	0.951	0.071	13.330	0.000	0.951	0.669
Q14_2	1.016	0.059	17.233	0.000	1.016	0.804
Q14_3	1.062	0.076	14.032	0.000	1.062	0.696
Q14_4	1.124	0.057	19.557	0.000	1.124	0.873
Q14_5	1.058	0.056	18.910	0.000	1.058	0.855
Extrinsic Motivation ~						
Q14_6	1.402	0.100	14.019	0.000	1.402	0.765
Q14_7	1.427	0.094	15.125	0.000	1.427	0.822
Q14_8	1.060	0.098	10.786	0.000	1.060	0.599
Effort Regulation ~						
Q15_1	1.180	0.064	18.474	0.000	1.180	0.850
Q15_2	1.175	0.059	19.952	0.000	1.175	0.894
Q15_3	0.982	0.075	13.122	0.000	0.982	0.665
Q15_4	1.085	0.076	14.375	0.000	1.085	0.712
Social Support ~						
Q17_1	1.082	0.091	11.821	0.000	1.082	0.621
Q17_2	1.506	0.087	17.222	0.000	1.506	0.823
Q17_3	0.769	0.082	9.366	0.000	0.769	0.512
Q17_4	1.519	0.087	17.409	0.000	1.519	0.830
Q17_5	1.276	0.089	14.386	0.000	1.276	0.723

Note. Std.lv represents the latent variables that are standardized while Std. all represents both latent and observed variables that are standardised.