Harnessing generative AI for next-gen education: a cognitive load and knowledge-based view approach to fuel innovation

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Abstract

Purpose – *This study aims to examine how students' generative artificial intelligence (GenAI) knowledge acquisition and knowledge application are associated with their innovation ability and information literacy (IL) skills. It further explores how these factors are associated with their level of motivation and behavioral intentions (BI).*

Design/methodology/approach – *The study collected responses from 250 students using GenAI for their educational purposes. Based on the knowledge-based view (KBV) and cognitive load theories (CLT), the study developed an empirical model assessed using the partial least squares structural equation modeling (PLS-SEM) method.*

Findings – *The findings reveal that GenAI knowledge acquisition significantly enhances students' innovation ability, while GenAI knowledge application exhibits a negative but significant relationship with IL. Students' innovation abilities, backed by GenAI, positively influence their level of motivation and BI. However, IL negatively impacts students' level of motivation and shows no significant effect on their BI.*

Originality/value – *The study results support KBV and CLT theories that effective utilization of knowledge resources fosters students' innovation ability, while excessive cognitive load can hinder their learning processes. Current research contributes to both theory and practice and offers insights for educators and policymakers.*

Keywords *GenAI knowledge acquisition, GenAI knowledge application, Innovation ability, Information literacy, Motivation, Knowledge-based view, Cognitive load theory*

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1. Introduction

Generative artificial intelligence (GenAI) is an advanced version of AI that has the capacity to create and develop new forms of content based on existing available data (Feuerriegel *et al.*, 2024). Previous AI tools can provide their output based on certain inputs or directions given to them (Lv, 2023). But GenAI is better in its ability to produce human-like content from written text to artwork, to develop music or coding on its own (Kanbach *et al.*, 2024). GenAI is based on deep learning and artificial neural network systems, where machines are trained to act like human brains (Nah *et al.*, 2023). Nowadays, GenAI is used in different industries for different purposes, like customer support, product design, content crafting and more (Holmström and Carroll, 2024; Kumar, 2025). In academia, GenAI is used for personalized learning assistance, analyzing data, summarizing reports and effective writing

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(Almogren *et al.*, 2024). The students used GenAI to acquire and apply advanced knowledge to generate the latest information, which enhances their learning abilities (Al-Emran *et al.*, 2025).

GenAI increases students' knowledge acquisition abilities by providing them customized and interactive learning experiences that adapt to their educational needs (Chan and Zhou, 2023). It also fosters students' curiosity through real-time feedback and enables a deeper understanding of complex problems and concepts (Chan and Hu, 2023). The application of GenAI in professional courses intensifies students' exploration and critical thinking by simulating real-world scenarios (Chan and Lee, 2023). This strengthens their capacity to apply knowledge, which further empowers their innovation abilities (Duong and Nguyen, 2024). The students' application of GenAI in academia develops their critical thinking skills (Jose *et al.*, 2024) to assess the credibility, relevance and accuracy of documentation sources, whether digital or print (Changalima *et al.*, 2024). The synergy between GenAI and education thus transforms learners into active problem-solvers, equipping them with the skills necessary for innovation in an increasingly AI-driven world (Crompton and Burke, 2023; Huang *et al.*, 2025b).

GenAI's ability to acquire advanced knowledge equips students with the skills and experience needed to work effectively with AI tools (Kumar *et al.*, 2025; Lee *et al.*, 2024). The combination of students' GenAI knowledge and GenAI mindset reflects their openness and confidence in using AI that empowers their innovation abilities and informational needs (Al-Hattami, 2025). A strong GenAI mindset enhances students' knowledge-gathering capacity, which sharpens their innovative and digital content evaluation skills (Mirhabibi *et al.*, 2025). The innovation ability and IL generated through GenAI boost students' motivation to use GenAI-integrated learning tools (Jose *et al.*, 2024). Motivated students are more focused on completing the challenging tasks, embracing continuous learning and engaging with AI-integrated coursework (Gupta *et al.*, 2024). Students' strong motivation toward GenAI significantly enhances their behavioral intentions (BI), particularly their willingness to adopt and use GenAI in academia (Chan and Lee, 2023).

Although existing research on GenAI in higher education has examined ethical considerations, student perceptions and the broad benefits and challenges of GenAI adoption (Chan and Hu, 2023; Huy *et al.*, 2024), several gaps remain. Prior studies have explored GenAI's role in entrepreneurial education, sustainability and teaching–learning processes (Al-Emran *et al.*, 2025; Bell and Bell, 2023), but limited attention has been given to education, where innovation ability and IL are central to students' professional development (Changalima *et al.*, 2024). The existing literature showcases that GenAI works as a knowledge amplifier for students (Chen *et al.*, 2023), but at the same time, its over-reliance reduces their critical thinking (Jose *et al.*, 2025). This study provides an understanding of the mechanism by which GenAI-based knowledge management factors transform students' innovation abilities and information literacy (IL), which are further associated with their motivation and behavioral intention. In particular, the roles of innovation ability and IL have been overlooked, leaving unclear how GenAI fosters competencies (e.g. new ideation, current and up-to-date information) essential for students. To address these gaps, the proposed model establishes links between GenAI knowledge acquisition and application, innovation ability and IL and further demonstrates how these competencies shape students' motivation and BI. To address the above gaps, the study used the knowledge-based view (KBV) and cognitive load theory (CLT) to examine how GenAI knowledge acquisition and application in academia reduce students' cognitive load and motivate them to achieve their learning objectives (Caputo *et al.*, 2019; Jose *et al.*, 2024). The study also investigates how much GenAI as a resource is valuable for students to acquire IL that enhances their innovation abilities and motivates them to attain their goals. To investigate the relationships, research questions are developed:

RQ1. How are GenAI knowledge acquisition and knowledge application associated with students' innovation ability and information literacy?

RQ2. How are students' innovation ability and IL associated with their motivation and BI?

Grounded in KBV and CLT theories, the study develops a structural model to examine how GenAI knowledge acquisition and application influence students' innovation ability and IL, thereby motivating them to influence their BI. The study assessed the roles of innovation ability and IL in shaping students' motivation and BI toward the use of GenAI. The theoretical frameworks used elucidate students' behavior toward the use of GenAI based on their anticipated likelihood of success and the perceived value of the resulting outcomes.

2. Literature review

2.1 Theoretical framework

The KBV focuses on knowledge as a strategic resource (Grant, 1996; Stoian *et al.*, 2024). The theory depicts that an individual's knowledge significantly contributes to gaining a competitive advantage (Martin and Javalgi, 2019; Yang *et al.*, 2025). The practical application of intellectual knowledge enhances individuals' innovation and operational efficiencies, which boosts their level of motivation and influences their BI (Pereira and Bamel, 2021; Sun *et al.*, 2025). The KBV highlights how students' use of GenAI amplifies their knowledge, which in turn influences their adoption of GenAI tools (Ferreira *et al.*, 2020). GenAI's role in providing customized knowledge (i.e. access to blended information, creative solutions to complex problems and simple communication) and inspiring exploration motivates students to engage thoroughly with their academic content (Jose *et al.*, 2024). This empowerment uplifts their proactive learning mindset that strengthens their behavioral intention to adopt AI tools as valuable extensions of their personal knowledge systems in both academic and professional environments (Kuo-Wei, 2025; Marvi *et al.*, 2025).

CLT is an essential framework in educational psychology that explains how humans' cognitive abilities impact their learning behavior (De Jong, 2010; Jose *et al.*, 2025). According to CLT, humans have limited capacity in their working memory to store information (Sweller, 1988, 2011). Learning helps to transfer information from working memory to long-term memory by forming mental structures known as schemas (Paas and Van Merriënboer, 2020). The theory identifies three types of cognitive load: intrinsic load contains complex information; extraneous load refers to the way information is presented; and germane load depicts the cognitive effort put into learning and schema construction (Gkintoni *et al.*, 2025). Effective learning requires managing intrinsic load, minimizing extraneous load and fostering germane load (Patac and Patac, 2025).

By using both theories in the model, the study examines how students' knowledge-based capabilities (knowledge acquisition and application) help them manage intrinsic load, reduce extraneous load and enhance germane load using GenAI-assisted learning. For example, the acquisition and application of knowledge using GenAI help students reduce their intrinsic and extraneous load by providing simple results for intricate issues and generating structured content from complex data (Dong *et al.*, 2025; Gkintoni *et al.*, 2025). This kind of result develops higher-order thinking skills in students that improve their learning abilities (Gkintoni *et al.*, 2025). To conclude, KBV improves students' structural foundation of knowledge (acquisition of knowledge and its application), while CLT deals with the process mechanism (allocation of learning resources to improve cognitive abilities). The optimum use of cognitive resources delights students, which leads to increased motivation and a stronger intention to adopt GenAI tools in their educational pursuits (Koć-Januchta *et al.*, 2022).

2.2 The use of generative artificial intelligence in education

In academia, the use of GenAI is increasingly prevalent among students to collect updated knowledge regarding their educational content (Jose *et al.*, 2024). Tools like ChatGPT help students to find relevant information and it is used in academia (Changalima *et al.*, 2024). Providing extensive information in a synthesized form opens students' minds to multiple ideas, broadening their comprehension of complex problems and keeping them ready to meet the educational objectives (Mohamed *et al.*, 2025). The application of GenAI provides knowledge and widens students' cognitive abilities, strengthening their objective evaluation and reasoning skills (Jose *et al.*, 2025). This fosters students' mindset with experimentation and adaptive thinking, a key component of innovation (Al-Hattami, 2025). Furthermore, knowledge acquired through GenAI reduces students' habit of rote learning and promotes inquiry-based exploration, enabling them to ask complex questions and receive coherent, contextually rich answers (McDonald *et al.*, 2025). The studies prove that the use of GenAI facilitates students' innovation abilities by expanding their informational horizons and idea-generation capabilities (Hao *et al.*, 2024). Duong and Nguyen (2024) found a crucial role for GenAI (ChatGPT) in enhancing business students' entrepreneurial knowledge. The knowledge of current opportunities motivates students to pursue their entrepreneurial intentions. Similarly, Jose *et al.* (2024) found that students with technological efficiency attain their IL goals by using the GenAI tools. Updated information strengthens students' academic or professional knowledge, which opens new opportunities for them. Although studies also examine that overconsumption of GenAI, information bias, privacy and data security are some issues attached to GenAI that directly influence students' cognitive thinking and adoption of technology in academia (Gkintoni *et al.*, 2025; Jose *et al.*, 2025).

3. Hypotheses development

3.1 Generative artificial intelligence knowledge acquisition association with innovation ability and information literacy

Knowledge acquisition is defined as acquiring new knowledge and forming a basic understanding based on new insights (Al-Emran and Teo, 2020; Gong *et al.*, 2025). GenAI knowledge acquisition means the use of GenAI to gather information from vast amounts of data or sources (Al-Emran *et al.*, 2025). *Further*, innovation ability is the students' ability to use acquired knowledge or information to identify, modify and develop novel ideas or solutions (Li *et al.*, 2022*;* Zastempowski, 2022). The acquisition of information is an enabler of creative innovation, supporting learners in solving complex problems and developing innovative solutions (Wang and Fan, 2025).

The thoughtful integration of GenAI in the learning process empowers students to become more knowledgeable and agile thinkers, thereby strengthening their innovation abilities to confront complex educational and business environments (Clegg and Sarkar, 2024). The advanced information acquired through GenAI significantly influenced students' academic and innovative endeavors (Al-Emran *et al.*, 2025). Al-Hattami's (2025) study found that digital learning skills enhanced students' innovation capacity when they were more prone to technological self-efficacy. Wang and Fan (2025) examined the constructive effect of ChatGPT (GenAI) on students' learning and cognitive outcomes, which positively influences their innovative and higher-order thinking. Similarly, Kirchner *et al.* (2025) examined the positive association between GenAI and knowledge management factors that further influence software developers' innovation abilities. Within the KBV, knowledge acquisition is a critical intangible resource that strengthens students' GenAI adoption (Al-Emran *et al.*, 2025). In other words, when GenAI-acquired knowledge is embedded in learning, it fosters students' innovative ability and long-term value creation (Chen *et al.*, 2023). Based on the facts, the study constructed its first hypothesis:

H1a. GenAI knowledge acquisition is positively associated with students' innovation ability.

Barton (2018) defined IL as "a set of abilities that require individuals to recognize when information is needed and have the ability to locate, evaluate and use effectively the needed information." IL improves students' cognitive and procedural abilities, enabling them to understand digital learning environments, check data credibility and apply information to achieve desired academic outcomes (Jose *et al.*, 2024). Students benefit from IL in many ways, helping them to grow academically and professionally (Hicks *et al.*, 2023). KBV posits that knowledge is the most valuable strategic resource, enabling individuals and organizations to effectively interpret, integrate and use information. IL fosters students' analytical ability by enhancing their cognitive knowledge (Chen *et al.*, 2023). The current and updated information motivates students to enhance their learning process with the use of advanced technological tools (Changalima *et al.*, 2024). The use of GenAI in higher education has significantly impacted students' knowledge acquisition, thereby influencing their IL (Chen *et al.*, 2023). GenAI assists students in collecting accurate and correct information for their academic pursuits and helps them achieve their educational objectives (Jose *et al.*, 2024). The use of GenAI's knowledge acquisition ability fosters students' personalized learning experiences, allowing them to simulate managerial scenarios, generate strategic ideas and receive instant feedback, all of which contribute to a more profound understanding of academic environments (Kuo-Wei, 2025). Consistent with KBV, the use of GenAI for knowledge acquisition serves as a catalyst for students' IL, fostering their cognitive thinking and adaptive learning in a data-driven world (Patac and Patac, 2025). GenAI knowledge acquisition equips individuals with cognitive and analytical capacities that significantly advance IL as a core competence. For this, the underline hypothesis is designed:

H1b. GenAI knowledge acquisition is positively associated with students' information literacy.

3.2 Generative artificial intelligence knowledge application association with innovation ability and information literacy

Knowledge application is the process of applying the acquired knowledge gathered through diverse sources efficiently and effectively for the creation of new knowledge (Arpaci *et al.*, 2020). The KBV highlights knowledge utilization as a strategic source of sustained advantage (Pereira and Bamel, 2021). While knowledge acquisition provides the foundation, its true value emerges when applied to solve problems, generate insights and design novel solutions. The existing studies depicted that GenAI knowledge application strengthens students' innovation abilities (Al-Hattami, 2025). Arpaci (2017) stated that effective application of cloud computing in education remarkably influences students' knowledge creation and innovation ability. Further, GenAI knowledge application is also significantly associated with university students' utilitarian benefits (Jo, 2023). The studies show that digital transformation is a bridge between knowledge and innovation, empowering students to become agile thinkers and future-ready leaders (Magistretti *et al.*, 2021). GenAI mindset acts as a pivotal link that transforms knowledge into actionable innovation, making it an essential variable in the educational and professional development of students in the AI era (Chen *et al.*, 2023). Due to the certain risk (i.e. misinformation, incorrect or vague information) associated with GenAI, it is essential to know how students acquire and apply the knowledge for their academic outcomes, ensure the academic integrity and improve their innovative learning (Chan and Hu, 2023; Cotton *et al.*, 2023). The next hypothesis is:

H2a. GenAI knowledge application is positively associated with students' innovation ability.

Knowledge application of GenAI reflects a strong association with IL, as both these factors develop critical evaluation, ethical use and effective communication of information among students (Al-Emran *et al.*, 2025). KBV asserts that competitive advantage arises not only from possessing knowledge but also from effectively applying it to create value. In higher education, students progressively use GenAI to enhance their learning skills, analyze trends and generate reports (Tang *et al.*, 2025). Here, students' knowledge application to assess GenAI-generated information credibility and relevance becomes an important predictor that improves their IL (Jose *et al.*, 2024). The results are consistent with KBV, where GenAI knowledge application strengthens IL by converting abstract knowledge into actionable competence. The application of advanced information and knowledge helps students to solve complex problems and provides them with innovative solutions to perform the same task more effectively (Hasanein and Sobaih, 2023). The integration of GenAI not only fosters students' IL but also develops a technological mindset that empowers them to responsibly use complex information in the competitive academic landscape (Clegg and Sarkar, 2024). Further, adoption of GenAI significantly improved the germane load and reduced the intrinsic and extraneous load among students (Gkintoni *et al.*, 2025). The next hypothesis is:

H2b. GenAI knowledge application is positively associated with students' information literacy.

3.3 Innovation ability association with student motivation and behavioral intentions

The use of GenAI is a crucial factor influencing students' innovation abilities, which in turn enhances their overall motivation and engagement in academic learning (Jose *et al.*, 2024). From the perspective of CLT, innovation ability can significantly enhance student motivation by optimizing the way learners process and manage information (De Jong, 2010). In other words, innovation ability fuels student motivation through effective cognitive management (Evans *et al.*, 2024). GenAI provides quick access to different ideas, creative prompts and effective feedback that strengthen students' innovation ability (Al-Hattami, 2025). This kind of ability motivates students to explore new perspectives and identify novel solutions to complex academic problems (Corvello, 2024). The AI-based learning provides students with self-direction and autonomy, enhancing their critical thinking and motivation (Mohamed *et al.*, 2025). The studies examined that students' use of GenAI helps them to develop new skills, analyze existing academic literature and create effective strategies that motivate them to master new advanced technologies and uplift their learning competence (Jose *et al.*, 2025). This creative empowerment presents students with a sense of control and ownership over their learning, which is a key driver of intrinsic motivation (Jose *et al.*, 2024). Furthermore, the interactive and personalized nature of GenAI creates a dynamic learning environment that adapts to individual interests and strengths, making the educational experience more relevant and engaging (Chan and Lee, 2023). This synergy between innovation and motivation fosters a cycle of continuous learning, where students are inspired not just to complete tasks but to excel and explore beyond expectations (Lee *et al.*, 2024). In this way, GenAI becomes more than a technological tool. It becomes a partner in cultivating motivated, innovative thinkers prepared for future challenges (Hao *et al.*, 2024). In consideration of the above information, the study designed the following hypothesis:

H3a. Students' innovation ability is positively associated with their level of motivation.

The literature shows that knowledge acquired through the use of GenAI significantly influences students' BI (Changalima *et al.*, 2024). The students use GenAI to identify innovative ideas, solve problems and conduct deep academic analysis, which enhances their creative capacity and helps them generate novel solutions (Chan and Zhou, 2023). The continuous exposure to GenAI fosters students' innovation ability, characterized by an openness to experimentation and adaptability in dynamic learning environments (Chan and Hu, 2023). The studies found that the use of digital tools enhanced the innovation ability of students, which directly influenced their BI. Specifically, the studies focus on students' willingness to adopt innovative technologies, pursue academic activities or make decisions in complex educational scenarios (Al-Hattami, 2025; Changalima *et al.*, 2024). Based on CLT, Patac and Patac (2025) found GenAI to be a cognitive supporting tool and learning facilitator for students to assess innovative ideas in virtual environments. The immediate feedback strengthens students' confidence in applying innovative approaches in academia as well as in their professional life. Gado *et al.* (2021) investigated that students with innovative mindsets exhibit proactive behaviors that aim to implement change and challenge conventional thinking in academic and managerial contexts. The synergistic relationship between GenAI and students' innovation ability is a critical driver of their behavioral intention (Crompton and Burke, 2023). To examine this relationship, the study constructed the next hypothesis:

H3b. Students' innovation ability is positively associated with their behavioral intentions.

3.4 Information literacy association with student motivation and behavioral intentions

The students' use of GenAI for educational purposes is linked to the development of their IL, which significantly increased their motivation in academic learning (Jose *et al.*, 2024). Strong IL reduces extraneous cognitive load by filtering irrelevant content and enhances germane load by promoting more profound engagement with meaningful knowledge (Patac and Patac, 2025). As students gain confidence in handling information effectively, they experience a sense of competence and autonomy, which strengthens their intrinsic motivation (Jose *et al.*, 2025). The studies found that GenAI helps the students to search, evaluate, analyze and interpret large amounts of information (Chan and Lee, 2023; Corvello, 2024). IL empowers students to fulfill complex educational and professional tasks with greater confidence and autonomy (Kelley *et al.*, 2023). The effective use of information enhances the intrinsic motivation of students as they perceive their learning to be more meaningful, satisfactory and academically goal-oriented (Wang *et al.*, 2023). Based on CLT, Jose *et al.* (2024) argued that the use of GenAI by students not only improves their IL but also fosters their cognitive skills, a key psychological factor that drives motivation. The study further highlighted that embedding GenAI in education helps the students to nurture themselves both cognitively and motivationally. Thus, the study proposes an underline hypothesis:

H4a. Information literacy is positively associated with students' level of motivation.

According to CLT, IL significantly influences students' BI by shaping how they process and apply knowledge in academia (Gkintoni *et al.*, 2025). CLT highlights that learning is optimized when extraneous load is minimized and germane load is enhanced (Patac and Patac, 2025). The advancement in IL empowers students to make deliberate decisions, a core competency in modern education (Jose *et al.*, 2024). The students' efficiency in handling and controlling information inclined them to engage in proactive behaviors, such as adopting innovative technologies to take data-driven decision-making in their academic and professional endeavors (Vecchiarini and Somià, 2023). The use of GenAI in academia serves as a learning assistant and an exploratory platform for students to assess their knowledge and skills effectively and efficiently (Rasul *et al.*, 2024). The perceived ability to manage information influences students' BI toward adoption of advanced technology (Chan and Lee, 2023). Strzelecki (2023) stated that higher education students' habit and expectancy to improve their educational performance with the use of GenAI (ChatGPT) were the main predictors that influenced their BI. The literature findings show that when students feel competent in navigating information-rich environments with the aid of GenAI, they feel academically accomplished and confident (Chan and Lee, 2023). The use of updated information significantly improves students' effort and performance expectancy and their intention to adopt GenAI in academia (Huy *et al.*, 2024). Thus, the study proposes:

H4b. Information literacy is positively associated with students' behavioral intentions.

Figure 1 maps out eight hypothesized paths linking two GenAI knowledge processes, acquisition and application, to two mediator constructs (innovation ability and innovation literacy) and, ultimately, to two key outcomes (motivation and BI).

4. Methods

4.1 Sampling

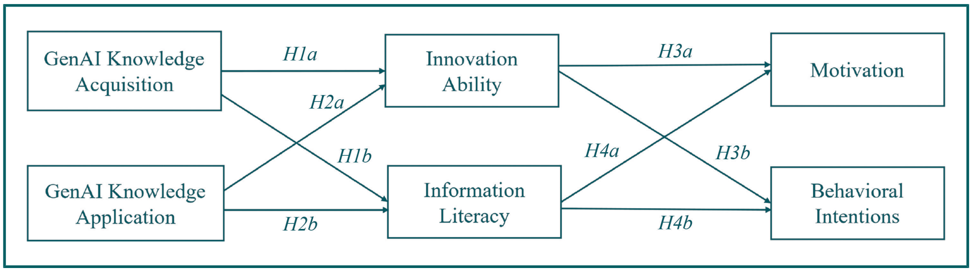
This study adopted a cross-sectional, quantitative survey design to examine the relationship between management students' GenAI knowledge acquisition and application with their BI (Wang and Cheng, 2020). The cross-sectional approach was selected for its efficacy in capturing data at a single point, allowing for the analysis of patterns and associations among variables without the need for longitudinal tracking. Data were collected using a structured online questionnaire, a method chosen for its ability to efficiently gather standardized information from a large and geographically dispersed sample (Wang & Chang, 2020). Participants from the US and the UK were recruited through Prolific, an online platform renowned for its diverse and prescreened participant pool, which is particularly advantageous for behavioral research (Douglas *et al.*, 2023). Prolific advanced filtering capabilities allowed for the precise targeting of students actively engaged with GenAI applications. This recruitment strategy made sure the sample matched the study's focus and improved the findings' generalizability within the targeted population.

4.2 Data collection

The survey commenced with a clear definition and examples of GenAI to ensure a collective understanding among respondents. Participation was voluntary and confidentiality was assured to uphold ethical research standards. Out of the responses received, 250 were deemed valid and complete, meeting the criteria for inclusion in the analysis. This sample size is considered adequate for the application of partial least squares structural equation modeling (PLS-SEM), the analytical technique used to evaluate the hypothesized relationships within the conceptual model.

The US and UK were chosen as the study context due to their rapidly evolving technological landscape and diverse socio-cultural fabric, which influence technology adoption behaviors (Singh and Ngai, 2024). The country's multifaceted environment provides a rich backdrop for examining how GenAI knowledge acquisition and application influence management

Figure 1 Overview of the conceptual framework



students' levels of motivation and BI for using GenAI for academic purposes. By focusing on this demographic, the study aims to contribute insights relevant to educational institutions and policymakers seeking to foster advanced technology in educational contexts. The demographic profile of the respondents is listed in Table 1.

4.3 Measures

The study used standardized constructions to prepare the questionnaire. The GenAI knowledge acquisition scale and GenAI knowledge application scale were derived from the Al-Emran *et al.* (2025) study. Innovation ability and IL scales were adapted from Al-Hattami (2025) and Jose *et al.* (2024) studies. To measure students' level of motivation toward GenAI, the scale was adapted from the Jose *et al.* (2024) study. The behavioral intention scale was adapted from the Changalima *et al.* (2024) study. Issues with model fit or cross-loading led to the removal of certain items from the constructs. A 5-point Likert scale was used to evaluate each item.

4.4 Common method bias

To guard against common method bias (CMB), which can inflate observed relationships when all data are collected from only one source at one point in time, the study implemented both procedural and statistical remedies (Podsakoff *et al.*, 2012). First, the survey was carefully designed to reduce respondents' ability to infer causal relationships among constructs by ensuring anonymity and confidentiality, thereby minimizing social desirability and evaluation apprehension. Varying item ordering so that measures of predictors, mediators and outcomes were interspersed rather than presented in contiguous blocks. Using established scales with slightly different Likert-point anchors (for example, some constructs on a 5-point scale, others on a 7-point scale) can disrupt common response patterns. Two complementary statistical checks were conducted. Using Harman's one-factor test, an exploratory factor analysis was performed on all measurement items without rotation. The first (unrotated) factor did not account for a majority of the variance (it explained less than 40%), indicating that no single latent factor dominated the covariance matrix. The study examined variant inflation factors (VIFs) for all latent constructs within the PLS-SEM measurement model. As shown in Table 2, all VIF values fell well below the conservative threshold of 3.3, confirming that multicollinearity and, by extension, potential method bias were not problematic. The variance remained low because no single factor dominated it. Therefore, the study concludes that CMB is unlikely to have materially influenced our findings. Consequently, the relationships assessed in the

Table 1 Demographic profile

Demographic characteristic (n = 250)	*Frequency*	*%*
Gender		
Female	134	53.60
Male	115	46.00
Prefer not to say	1	0.40
Educational qualification		
Under-graduate	145	58
Post-graduate	100	40
Professional degree	5	2
Age (years)		
17–21	56	22.40
22–26	122	48.80
27–31	71	28.40
32–36	1	0.40

Table 2 Variance inflation factors for latent constructs

Construct	*VIF range*
Behavioral intentions (BI)	2.14–2.90
Knowledge acquisition (KA)	1.81–2.01
Knowledge application (KAP)	1.61–1.83
Innovation ability (IA)	1.79–2.48
Information literacy (IL)	1.27–1.54
Student motivation (SM)	1.59–2.18

structural model can be interpreted with confidence that it reflects substantive associations rather than measurement artifacts (Podsakoff *et al.*, 2012).

Table 4 reports R^2 values for each endogenous construct, both before and after including a method-bias marker variable (Lindell and Whitney, 2001; Sharma *et al.*, 2021). The study finds behavioral intention and innovation ability exhibit substantial explanatory power, whereas IL (0.04) and student motivation (0.16) are less well explained, an expected result given the complexity of motivational and literacy processes. Cohen's f^2 values were zero for all constructs except for student motivation ($f = 0.012$), which thus can be considered very small. The near-identical R^2 values with and without the marker variable suggest that common-method bias has a negligible effect on structural estimates (see Table 4).

4.5 Analysis and findings

Table 3 presents a detailed measurement-model evaluation for each latent construct, showing Cronbach's alpha (CA), composite reliability (CR), average variance extracted (AVE), factor loadings (FL) and VIF for all observed indicators (Hair *et al.*, 2019). Together, these statistics speak to indicator reliability and the absence of problematic multicollinearity in the study's PLS-SEM analysis (Streukens and Leroi-Werelds, 2023). All three behavioral-intention items load very strongly on their underlying construct, demonstrating excellent convergent validity. Their VIFs remain comfortably below 3.3, indicating that these indicators do not suffer from multicollinearity. Each innovation-ability item exceeds the common 0.70 threshold for FL, confirming that they reliably measure the same underlying dimension. VIF values clustered around two further reassure us that collinearity among these measures is minimal. For IL, two items are also above the threshold. Although the third item (0.67) is slightly under the ideal threshold, the study retained it here because it contributes unique content coverage and its VIF poses no collinearity concerns. All knowledge-acquisition indicators load strongly and exhibit VIFs around 2, confirming reliable measurement with no inflation due to intercorrelations. The knowledge-application construct shows very high loadings and low VIFs, demonstrating that each item consistently reflects the underlying application dimension without redundancy. Motivation items exhibit solid loadings and modest VIFs, indicating they form a coherent construct and are free from problematic multicollinearity (Streukens and Leroi-Werelds, 2023) (see Table 3).

4.6 Reliability and validity

Tables 2, 3 and 4 provide a comprehensive assessment of the measurement model's reliability, convergent validity, discriminant validity and overall fit, as well as the explanatory power of the structural model both with and without a marker-variable adjustment (Hair *et al.*, 2019). The study reports two complementary reliability statistics for each construct: CA and CR. The CA for all constructs exceeds the conventional threshold of 0.70, except for IL, which is marginally lower at 0.69, indicating acceptable internal consistency. The CR values span 0.82 (IL) to 0.92 (BI), comfortably above the recommended 0.70 benchmark and the often-cited 0.80 standard for rigorous applications. Together, these results confirm that each set of

Table 3 Summary of measurement model results

Construct	*Measurement item*	*Factor loading*	*VIF*
GenAI knowledge acquisition (KA)	– Gen AI tools facilitate the process of acquiring knowledge from diverse sources	0.83	1.97
C-Alpha = 0.85 CR = 0.90 AVE = 0.69	– Gen AI tools enhance the process of acquiring knowledge through interactive and engaging discussions	0.84	2.01
	– Gen AI tools enable me to generate new knowledge based on my existing understanding	0.81	1.81
	– Gen AI tools assist in acquiring knowledge tailored to my specific needs	0.85	2.01
GenAI knowledge application (KAP)	– Gen AI tools provide instant access to various types of knowledge, aiding learning and research	0.85	1.81
C-Alpha = 0.80 CR = 0.88 AVE = 0.72	– Gen AI tools enable me to apply the acquired knowledge in practical scenarios, including learning activities and assignments	0.83	1.61
	– Gen tools facilitate the integration of different types of knowledge in problem-solving	0.86	1.83
Innovation ability (IA)	– I often use gen AI tools in new and creative ways to solve my academic problems	0.82	1.91
C-Alpha = 0.86 CR = 0.90 AVE = 0.70	– The use of gen AI tools enables me to develop innovative academic solutions	0.88	2.48
	– Experimenting with new gen AI tools improves my academic work	0.82	1.79
	– Using gen AI tools enhances my ability to innovate in my field	0.83	2.03
Information literacy (IL)	– I find it challenging to decide what keywords to use for online searches	0.79	1.27
C-Alpha = 0.69 CR = 0.82 AVE = 0.61	– I am not sure whether the information I find online is reliable or not	0.87	1.54
	– I am always skeptical of the information I encounter	0.67	1.37
Student motivation (SM) C-Alpha = 0.86 CR = 0.90 AVE = 0.59	– I always motivated to learn new things	0.80	2.18
	– I have a strong desire to succeed academically	0.77	1.89
	– I believe that learning is important for my future	0.78	1.95
	– I always eager to explore and expand new knowledge	0.77	1.93
	– I am curious and actively seeking out new information and experience	0.74	1.67
	– I believe that learning helps me to develop new skills and abilities	0.73	1.59
GenAI behavioral intention (BI)	– I intend to continue using gen AI in the future	0.87	2.14
C-Alpha = 0.87 CR = 0.92 AVE = 0.80	– I will always try to use gen AI in my studies	0.88	2.28
	– I plan to continue to use gen AI frequently	0.92	2.90

Note(s): Cronbach's alpha (C-alpha), average variance extract (AVE), composite reliability (CR)

items coherently captures its intended latent variable. Convergent validity was evaluated via the AVE for each construct. An AVE value of 0.50 or higher indicates that, on average, a construct explains more than half of the variance in its indicators. All constructs surpass the 0.50 threshold, demonstrating that each latent variable accounts for a substantial proportion of its measurement items' variance (Hair *et al.*, 2019). Discriminant validity ensures constructs are empirically distinct. Here, the study compares the square root of each construct's AVE (diagonal entries) against its correlations with other constructs (off-diagonal entries). For every construct, the diagonal AVE-square-root exceeds its highest correlation with any other construct (Fornell and Larcker, 1981). This pattern holds across all six constructs, confirming that each latent variable shares more variance with its own indicators than with any other construct in the model (see Table 4).

4.7 Structural model assessment: path analysis

The study assesses overall model fit using the standardized root-mean-square residual (SRMR = 0.075), which is below the threshold of 0.08, demonstrating a good model fit. Table 5 presents the estimated path coefficients for each hypothesized relationship, along with their standard errors, *t*-values, *p-values* and the corresponding hypothesis test outcomes. The study found a positive association across GenAI knowledge acquisition (β = 0.28, t = 3.08, p < 0.001) and GenAI knowledge application (β = 0.53, t = 6.01, p < 0.001) with innovation ability, supporting *H1a* and *H2a*. A non-significant association between GenAI knowledge acquisition and IL (β = 0.04, t = 0.30, p = 0.38) rejected *H1b*. Further, the negative but significant relationship of GenAI knowledge application with IL (β = −0.22, t = 2.15, p < 0.05) rejects *H2b*. The positive association across innovation ability, student motivation (β = 0.28, t = 4.76, p < 0.001) and their BI (β = 0.73, t = 15.72, p < 0.001) supported *H3a* and *H3b*. The significant but negative association between IL and student motivation (β = −0.24, t = 4.10, p < 0.001) rejected *H4a*. No significant direct association of IL with students' future use intentions (β = 0.03, t = 0.75, p = 0.23), rejected *H4b* (Figure 2).

5. Discussion

Based on KBV and CLT theories, the study developed an empirical model that examines how students' GenAI knowledge acquisition and application are associated with their innovation abilities and IL, further influencing their level of motivation and BI. The study addressed *RQ1* by examining the positive association between GenAI knowledge acquisition and students' innovation ability. This means that when students acquire theoretical and conceptual knowledge using GenAI, their ability to innovate improves. The result aligns with Al-Hattami's (2025) study, which examined students' technological self-efficacy and their use of digital accounting tools, enhancing their innovation abilities. Wang and Fan (2025) also investigated the related results and highlighted that GenAI enhanced personalized and adaptive learning among students, enabling them to assimilate complex concepts more effectively. This enriched understanding fosters creativity and innovation among students (McDonald *et al.*, 2025). Further, this result contradicts the findings of Cotton *et al.* (2023), who raised the concern that the reliability of outputs provided by GenAI influences the academic integrity of students.

The concern of knowledge acquisition using GenAI is also depicted in this study's results, where no association was examined between students' GenAI knowledge acquisition and IL. It means acquiring knowledge through technology alone does not enhance students'

Table 4 Correlations among the constructs

Contructs	*BI*	*IA*	*IL*	*KA*	*KAP*	*SM*
BI	*0.89*	0.83	0.12	0.76	0.80	0.26
IA	0.72	*0.84*	0.24	0.79	0.89	0.38
IL	−0.10	−0.18	*0.78*	0.18	0.25	0.35
KA	0.65	0.67	−0.13	*0.83*	0.89	0.44
KAP	0.67	0.74	−0.20	0.74	*0.85*	0.47
SM	0.23	0.33	−0.29	0.38	0.39	*0.77*

Note(s): R^2 without marker: BI: 0.52; IA: 0.58; IL: 0.04; SM: 0.16; R^2 with marker: BI: 0.52; IA: 0.58; IL: 0.04; SM: 0.17

Table 5 Path analysis

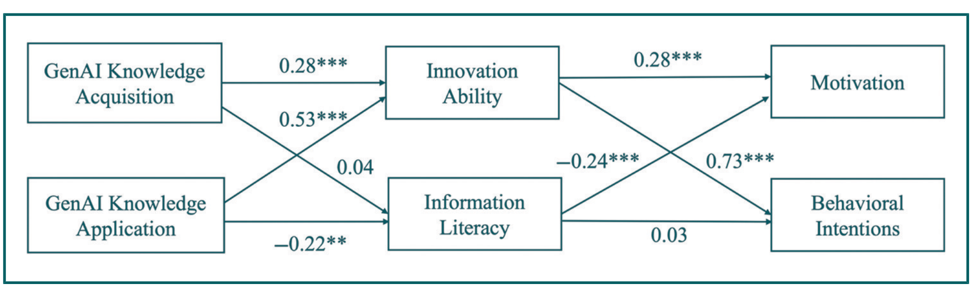
Direct	B	*SD*	t-*value*	p-*value*	*Hypo*	*Status*
Knowledge acquisition → innovation ability	0.28	0.09	3.08	0.00	*H1a*	Supported
Knowledge acquisition → information literacy	0.04	0.12	0.30	0.38	*H1b*	Not supported
Knowledge application → innovation ability	0.53	0.09	6.01	0.00	*H2a*	Supported
Knowledge application → information literacy	*−0.22*	*0.10*	*2.15*	*0.02*	*H2b*	*Not supported*
Innovation ability → student motivation	0.28	0.06	4.76	0.00	*H3a*	Supported
Innovation ability → behavioral intention	0.73	0.05	15.72	0.00	*H3b*	Supported
Information literacy → student motivation	*−0.24*	*0.06*	*4.10*	*0.00*	*H4a*	*Not supported*
Information literacy → behavioral intention	0.03	0.04	0.75	0.23	*H4b*	Not supported

information needs; academic institutions must design specific interventions (i.e. workshops, guest lecturers or hackathons) to enhance students' IL. Another reason is that passive knowledge acquisition does not involve students' practical engagement or critical reflection. The result is supported by Chan and Hu's (2023) study. They examined IL skills, requiring active inquiry, source evaluation and reflective thinking—elements that are not necessarily developed through knowledge acquisition alone. Contrary to this, some studies examined the use of GenAI in education, positively influencing students' informational goals (Changalima *et al.*, 2024; Jose *et al.*, 2024). The studies acknowledge that GenAI as an informational source not only fulfills students' information needs but also helps students to achieve their desired learning outcomes (Chan and Lee, 2023).

The study result shows *(RQ1)* that the integration of GenAI knowledge applications in educational settings is strongly and significantly associated with students' innovation ability. This result aligns with the study by Chen *et al.* (2023), which reveals that applying GenAI knowledge enhances students' creativity by providing real-time ideation support, helping them identify novel solutions to complex business problems. Empirical data from controlled experiments indicate that students exposed to GenAI-assisted learning environments produce more original and feasible entrepreneurial ideas than those relying solely on traditional pedagogical methods (Gupta *et al.*, 2024). Furthermore, Jose *et al.* (2025) argued that the right execution of the GenAI knowledge application reduces students' extraneous cognitive load by automating routine data processing and supporting idea generation, thereby freeing cognitive resources for creative problem-solving (Patac and Patac, 2025). Despite the significant potential of GenAI in educational learning, the researchers raised the issue that students' heavy dependency on GenAI produces less original work and demonstrates deficiency in their critical and innovative thinking (Cotton *et al.*, 2023).

The negative but significant relationship between GenAI knowledge applications and IL is indeed surprising but justified. The GenAI-based literature stated that over-reliance on AI diminishes analytical, evaluative and inferential dimensions of critical thinking and

Figure 2 Structural model



information skills (Gerlich, 2025; Qian, 2025). Sparrow *et al.* (2011) try to explain this finding through cognitive offloading, wherein users over-rely on automated systems, bypassing analytical thinking. In a recent study, MIT Media Lab found similar results, where essay writers using LLM models underperformed in neural, linguistic and behavioral measures and displayed reduced originality and engagement (Schlott, 2025). In the context of GenAI applications, Ju (2023) examined that reliance on GenAI for writing tasks led to a 25.1% reduction in accuracy and even AI-assisted reading produced a 12% drop – indicating impaired comprehension and critical engagement. This is a concern in AI-rich environments where students' frequent use of GenAI without reflective critique can lead to decreased awareness of information biases or limitations, reducing IL despite technological proficiency (Gkintoni *et al.*, 2025). The findings elucidate why knowledge application via GenAI – though beneficial for innovation – can unintentionally weaken IL by bypassing the deeper evaluative and analytical mental processes essential to competent information handling (Dolan, 2025).

The current study finding supports *RQ2* that students' innovation ability is significantly associated with their motivational level and BI, playing a critical role in shaping their academic and entrepreneurial outcomes. The result is aligned with the Jose *et al.* (2024) and Al-Hattami (2025) studies that examined students' innovation abilities (i.e. capacity to generate novel and useful ideas) and significantly enhanced their intrinsic motivation by creating an environment that promotes competence, autonomy and creative self-efficacy. Lo *et al.* (2022) also found that students with higher innovation capacity reported greater academic motivation, as the opportunity to engage in creative problem-solving increased their engagement and persistence.

Tang *et al.* (2025) supported the study findings that students' innovation ability powered by GenAI is significantly associated with their BI. The study revealed that the use of GenAI improves students' performance, correlated with their learning abilities, which fosters their intention to adopt such technologies in academic settings. Chan and Zhou (2023) argued that students' innovation ability strengthens their perceived task value, which reinforces their willingness to invest time and effort in complex and uncertain tasks (Dai *et al.,* 2023). As a result, students with strong innovation skills exhibit heightened motivation and demonstrate greater intentionality in applying their knowledge beyond the classroom (Wang *et al.*, 2023).

In *RQ2*, the study finds the inverse association between IL and students' level of motivation. It suggests that prominent levels of IL may reduce students' motivation level, potentially due to overexposure to the limitations and ethical concerns surrounding GenAI (Yeh *et al.*, 2022). Another probable reason is students' excessive efforts to validate GenAI outputs, which may cause frustration and reduce motivation. A similar kind of finding was examined by Bawden and Robinson (2009), where excessive IL may lead to information overload. In other words, the volume and complexity of information struck the students' critical thinking, which ultimately reduced their level of motivation. Sweller (2011) explained this finding with the help of CLT. The theory suggests that advanced IL may increase extraneous cognitive load where students over-analyze, filter and evaluate too much information, which drains cognitive resources and reduces motivation to persist (Patac and Patac, 2025). The result aligns with findings from Lim and Tan (2021), where higher digital literacy correlated with reduced tech enthusiasm due to perceived complexity and risks. Although the negative relationship between IL and student motivation is counterintuitive, it is still possible in the age of GenAI, which is the unique contribution of the study to the GenAI literature. In technology-driven contexts such as GenAI-enabled environments, excessive information may paradoxically heighten students' cognitive strain, which becomes the reason to decrease their motivational drive.

The study results show no direct association between students' IL and behavioral intention. It means that, despite the increasing usage of GenAI in higher education, the IL (a core benefit of GenAI) alone may not significantly influence students' BI. In other words, GenAI risks (i.e. misinformation, factual content and bias) associated with the technology become more prominent and influence students' intentions to adopt it in academia (Kökver *et al.*, 2025). Previous studies also investigated the related results (Almogren *et al.*, 2024; Sobaih *et al.*, 2024). Sobaih *et al.* (2024) examined the ease of use of GenAI and found that it did not influence students' intention to use the technology. The study discusses the importance of faculty support and structured implementation processes for boosting students' interest in GenAI. The study further indicates that factors like perceived usefulness and social influence play more substantial roles in technology adoption than IL alone. Furthermore, Almogren *et al.* (2024) also demonstrated that without recognizing the practical benefits of GenAI (i.e. ChatGPT), IL alone may not suffice to drive students' BI.

5.1 Theoretical implications

Using the KBV and CLT theories as a framework, the study presented its theoretical implications. Previous studies focused more on the use of GenAI as a technological tool in academia, but this study used KBV and CLT theories as a basis to examine how students' knowledge-based capabilities are associated with their cognitive load, thereby improving their IL and developing innovation abilities. This study not only explains how GenAI assists the students in learning but also depicts the transformation in cognitive efficiency that enhances their creative thinking.

The study emphasizes the importance of acquiring and applying GenAI knowledge for students, reinforcing KBV's notion that knowledge is the primary strategic resource in learning environments (Stoian *et al.*, 2024). The students' use of GenAI for knowledge acquisition and application is associated with KBV, suggesting that a digital mindset plays a critical role in mobilizing dormant knowledge (Al-Hattami, 2025). It acts as a catalyst that transforms acquired knowledge into innovative behavior, emphasizing the role of psychological enablers in knowledge utilization (Chen *et al.*, 2023).

The study presents innovation ability as a construct, integrating KBV's knowledge transformation process with CLT's schema development. This indicates that students who innovate based on acquired knowledge experience greater motivation and behavioral intention, linking cognitive processing with actionable outcomes (Gkintoni *et al.*, 2025). In other words, innovation ability is where knowledge turns into action and where students use their thinking skills to organize and apply information in smarter, more meaningful ways (Skulmowski and Xu, 2022).

The non-significant relationship between knowledge acquired through GenAI and IL challenges the assumption that acquiring knowledge inherently enhances IL skills. This suggests that IL development may require distinct instructional strategies beyond mere knowledge acquisition, aligning with CLT's emphasis on managing cognitive load to facilitate learning (Evans *et al.*, 2024; Gkintoni *et al.*, 2025). When learners are presented with complex information without an appropriate platform, it can lead to cognitive overload, hindering the development of IL skills (Patac and Patac, 2025). The study uplifts theoretical understanding of CLT theory by examining the importance of managing students' cognitive load to facilitate their effective learning. CLT posits that working memory has a limited capacity and when instructional materials or tasks exceed this capacity, learning can be hindered due to cognitive overload (Kuldas *et al.*, 2014; Pass & Van Merriënboer, 2020). The negative association between knowledge application and IL suggests that when students are required to apply knowledge without sufficient IL skills, they may experience increased extraneous cognitive load (De Jong, 2010; Skulmowski and Xu, 2022). This overload can impede the processing and integration of the latest information, thereby reducing the effectiveness of learning activities (Jose *et al.*, 2025).

The negative relationship between IL and student motivation indicates that higher IL may be associated with lower motivation levels. From a CLT perspective, this could be due to increased cognitive load associated with processing and evaluating information, which may overwhelm students and reduce their motivation to engage with learning tasks (Evans *et al.*, 2024). This finding underscores the importance of designing instructional materials that balance the development of IL with strategies to manage cognitive load effectively, thereby sustaining student motivation (Kuldas *et al.*, 2014). Finally, the limited influence of IL on behavioral intention suggests a threshold effect from a cognitive load perspective. It shows that additional literacy does not necessarily enhance intention when cognitive or emotional engagement is lacking (Almogren *et al.*, 2024). This implies that IL must be paired with effective and context-driven factors to be fully effective. Collectively, these implications extend the theoretical boundaries of KBV and CLT, offering a nuanced understanding of how GenAI-related knowledge and cognitive mechanisms influence innovation, motivation and technology adoption among students (Jose *et al.*, 2024).

5.2 Practical implications

Based on the study results, several practical implications emerge for educators, academic institutions and policymakers aiming to enhance students' engagement with GenAI. First, the research points to the value of developing students' GenAI mindset (knowledge acquisition and application through GenAI) and a proactive, open and adaptive attitude toward AI technologies (Al-Emran *et al.*, 2025). Therefore, it is essential for educational institutions to start programs that move beyond technical training. The inclusion of mindset-building activities, such as problem-based learning, AI-driven simulations and reflection exercises that foster curiosity, critical thinking and ethical awareness, provides beneficial exposure to students (Chan and Zhou, 2023). The use of advanced technology enhanced students' level of motivation and they became more confident in leveraging GenAI in both their academic and professional endeavors (Crompton and Burke, 2023).

Second, the study demonstrates that GenAI knowledge acquisition and application directly influence students' innovation ability. So, it becomes important for academic institutions to refine their course curriculum and integrate GenAI use cases into their coursework (Fischer *et al.*, 2024). For example, teaching students how to generate content, analyze data or solve academic or business problems using GenAI (i.e. ChatGPT or similar tools) can transform theoretical knowledge into practical, firsthand skills. Faculty should function as facilitators, guiding students on how to responsibly acquire and apply GenAI knowledge to strengthen their informational power and use it innovatively to provide creative solutions (Chan and Lee, 2023).

Third, the study found that students' innovation ability positively influences their motivation and BI to use GenAI. Here, the responsibility of higher academic institutes is enhanced so they can provide students with opportunities to engage in innovation-driven projects (i.e. hackathons, startup incubators or AI-assisted research) that significantly boost their willingness to integrate GenAI into their learning and career development. Academic institutes should have developed creative environments on campus where innovation is encouraged and supported by AI infrastructure (Huang *et al.*, 2025a).

Fourth, the negative association across students' IL and their level of motivation suggests that students may experience cognitive overload when confronted with complex information without adequate support (Evans *et al.*, 2024). To mitigate this challenge, business schools or academic institutions must encourage their students to engage in active learning strategies, such as case discussion, peer teaching, group discussions or problem-solving activities (Chen *et al.*, 2023). These strategies can help business students manage their cognitive load by breaking complex tasks into manageable segments, thereby enhancing motivation and engagement in academic activities (Patac and Patac, 2025).

Finally, the study examines that students' behavioral intention is not solely dependent on IL generated through GenAI. So, it is essential for the academicians, researchers and institutions that they should also focus on other affective factors like perceived usefulness, ease of use and social influence in the context of students' GenAI adoption (Sobaih *et al.*, 2024). Academic institutes can design GenAI workshops, peer learning sessions and mentorship programs that can increase students' trust and enthusiasm toward advanced technology (Fischer *et al.*, 2024). Additionally, academic policies should support the integration of digital literacy into educational frameworks, equipping students with the skills to navigate and evaluate information effectively in a technology-driven world (Skulmowski and Xu, 2022). To conclude, these implications accentuate the need for a holistic educational approach that integrates knowledge, mindset, skills and ethical awareness to prepare students for a future where AI plays a leading role in business and academic ecosystems.

5.3 Limitations and future research

Although the study provides valuable insights into the interplay between students' GenAI knowledge application, IL and motivation, still several limitations must be acknowledged that can be addressed in future research. The study used a sample of management students studying at UK and US universities, potentially restricting the generalizability of the findings across diverse educational and cultural contexts. Future research should include participants from varied educational backgrounds and academic institutions to ensure broader applicability. Second, the study found limited explanatory power of informational literacy and student motivation constructs. In the future, additional constructs such as educational exposure and socio-economic or institutional factors should be included to examine their association with educational productivity. Third, the quantitative method and structured model are applied in this study to examine the relationship between variables. In the future, applying mixed-method approaches, including qualitative data, could provide a more nuanced understanding of these constructs. Finally, this study has not used any control or contextual variables such as institutional support, technological infrastructure or cultural attitudes toward learning, which can significantly impact the relationships among the studied variables. In future studies, the researchers have examined the role of control variables (e.g. age, gender) to influence management students' academic endeavors.

6. Conclusion

Based on KBV and CLT theories, the results demonstrate that GenAI knowledge application plays a more dominant role than knowledge acquisition in shaping students' innovation ability (Al-Emran *et al.*, 2025). The significant relationship between GenAI knowledge application and innovation ability suggests that firsthand experience with GenAI positively enhances students' creative capacities and problem-solving abilities (Al-Hattami, 2025). In contrast, GenAI knowledge acquisition, although positively related to innovation ability, does not significantly impact IL. This indicates that passive learning or theoretical understanding of AI is not enough to develop critical evaluation skills (Yeh *et al.*, 2022).

Interestingly, GenAI knowledge application has a negative but significant effect on IL. This implies that while application of knowledge fosters innovation, it may also lead to dependency on AI tools, potentially undermining students' capacity to assess information critically (Sparrow *et al.*, 2011). This finding reflects the growing concern over cognitive offloading, where users increasingly rely on AI-generated outputs without verifying their credibility or ethical implications (Chan and Hu, 2023; Skulmowski and Xu, 2022). Furthermore, innovation ability emerges as a key variable in the model (Jose *et al.*, 2024). It strongly predicts both motivation and BI, indicating that when students feel capable of innovating through GenAI, they are internally motivated and likely to adopt these tools in their academic pursuits (Changalima *et al.*, 2024). On the other hand, IL demonstrates a significant negative impact on motivation and a non-significant effect on BI, suggesting that students' higher awareness of GenAI may reduce their enthusiasm or increase their critical caution toward AI adoption (Almogren *et al.*, 2024; Sobaih *et al.*, 2024). In a nutshell, the study's findings emphasize the crucial role of cognitive load management and knowledge application in enhancing students' educational outcomes.

Consent for human participants

All participants were informed about the objectives of the study and their voluntary consent was obtained prior to participation. Anonymity and confidentiality were maintained throughout the research process.

Ethics statement

This study was conducted in accordance with institutional ethical standards and the principles outlined in the Declaration of Helsinki.

Data availability

The data sets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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