Students' Use of Generative Artificial Intelligence in Higher Education

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Abstract

Generative artificial intelligence (GenAI) is omnipresent these days. One of the key uses of GenAI in higher education (HE) is for enhancing students' learning experience through its ability to respond to user prompt to generate output. Text-to-text generators provide writing assistance to students. GenAI tools are useful research aids for generating ideas, synthesizing information, and summarizing an immense amount of information (Chan & Hu, 2023). Nonetheless, gaps in the literature for future research regarding an understanding of the possibilities provided through GenAI in HE has been identified, e.g. by Crompton and Burke (2023). Such gaps include studies conducted in disciplines like general business management and studies focusing on detecting unexplored possibilities on GenAI in HE. The goal of this paper is to contribute to the ongoing research activities in the field of GenAI in HE in two ways. Firstly, by summarizing the existing literature on GenAI in HE, focusing on its impact on students' learning processes. And secondly, by the empirical results from a qualitative survey conducted in general management course classes in the Business Information Technology Bachelor's degree program (BIT) at the University of Applied Sciences and Arts Northwestern Switzerland (FHNW) in autumn 2025. The survey results provide insight into the extent to which students use GenAI, as well as which GenAI tools are used for which activities in HE.

Keywords: artificial intelligence, generative artificial intelligence, generative pretrained transformers, gioia methodology, higher education, large language model, more knowledgeable other, unified theory of acceptance and use of technology

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Introduction

The evolution of the computer and the field of artificial intelligence (AI) have been a gradual process that has spanned several decades and involved numerous steps (Grzybowski et al., 2024). Alan Mathison Turing (1912–1954) was a British mathematician, computer scientist and military officer. He is widely regarded as a seminal figure in the fields of computer science and AI. The term “AI” was first coined by John McCarthy in name the Darthmouth College Summer Artificial Intelligence Conference, which was held at Dartmouth College (Hannover, New Hampshire, USA) in 1956 (Grzybowski et al., 2024).

AI is defined as “computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and the use of data for complex processing tasks” (Almassaad et al., 2024).

In November 2022, OpenAI released ChatGPT, a conversational artificial intelligence interface that uses natural language processing (NLP) to interact in a realistic way. It even answers follow-up questions, admits its mistakes, challenges incorrect premises and rejects inappropriate requests (OpenAI, 2022). Within the broad domain of AI, GenAI signifies a particularly auspicious technological development, but it also hallucinates, which is an inherent problem of all large language model (LLM).

GenAI can be used to create new content, including audio, code, images, text, simulations and videos (Kohnke et al., 2023). In contrast to conventional data processing and analysis, GenAI employs these advanced methods to create content directly (Almassaad et al., 2024). Subsequently, a range of other GenAI tools, including Gemini, Notebook LM, Perplexity, Claude etc., were released into the market.

Several studies highlighted the lack of empirical research and the need for further investigation into the benefits and challenges of using GenAI in HE (Almassaad et al., 2024). A gap regarding the understanding of the collective affordances provided using AI in HE has been noted (Crompton & Burke, 2023). Future analysis is needed to address variations in results based on different prompts or words used with ChatGPT (Andrade-Girón et al., 2024).

Literature Review

This section reviews part of the literature on GenAI tools in HE, identifying some contributions, challenges and opportunities.

Several research papers that focus on the opportunities and challenges of GenAI in HE has been identified by the authors. For example, Ruiz-Rojas et al. (2024) identifies that integration of GenAI tools in HE has a positive impact on the development of student’s critical thinking.

Nikolopoulou (2024) summarizes that ChatGPT can generate new content and human-like responses. She mentions various positive aspects such as personalized/adaptive learning experience, editing, abstracting, language translation, research aid, as well as grading and assessment. According to Nikolopoulou’s research, the challenges include cheating in assignments, overreliance on the AI tools, ethical and privacy concerns, as well as uncertainty/anxiety among students about their future careers (Nikolopoulou, 2024).

Investigations have been undertaken that focus on the systematic review of the topic. Andrade-Girón et al. (2024) investigates the acceptance, validity, usefulness, and time optimization of ChatGPT in HE by a systematic literature review covering publications between 2022 to 2024. The researchers reveal diverse global contributions predominantly from Asia and identify prevalent quantitative research among the studies. Also, Crompton and Burke (2023) performed a systematic review of AI in HE covers the years 2016 to 2022. According to their work 72% of the studies under examination focus on students' intended use of AI. AI in HE was used for assessment/evaluation, predicting, AI assistant, intelligent tutoring system, and managing student learning.

Stojanov (2023) highlights that ChatGPT acts as a more knowledgeable other (MKO). She highlighted some red flags, e.g. that information provided by ChatGPT is not always consistent or logical, in some cases even contradicting. Sometimes ChatGPT provide opposite answers for the exact same questions. Tlili et al. (2023) also mentions honesty and truthfulness beside cheating, privacy misleading, and manipulation. Yusuf et al. (2024) highlight ChatGPT's prominence due to its adaptability for tasks such as content generation and questions answering.

Zhu et al. (2025) conclude that the ability of GenAI to generate and automate processes significantly contributes to students learning experiences. The research paper synthesized findings from 26 empirical research studies to evaluate the influence of GenAI on students learning outcomes. Almassaad et al. (2024) list personalized and immediate learning support, provision of automated personalized assistance and feedback, virtual teaching assistance, time savings, enabling access to information, offering quality explanations and clarification, promoting critical thinking skills, research aid for brainstorming and generating writing ideas and analyzing data and group work and collaboration as beneficial.

The authors summarize that most research articles discovered many opportunities and challenges of GenAI, with major focus on the prominent GenAI tool ChatGPT, based on various research methods, some of them using the theoretical framework of the unified theory of acceptance and use of technology (UTAUT), or any predecessor models of UTAUT e.g. TAM (Meakin, 2024; Shahzad et al., 2025) and extensions/variations of UTAUT. Only limited number of contributions provide deeper insight into the relationship between behavioral intention and use behavior, two major elements of UTAUT, as illustrated in figure 1 below.

Aldreabi et al. (2025) refer to multiple research that showcased the great potential of GenAI in education using UTAUT2. In comparison to UTAUT, UTAUT2 includes more elements. The researchers hypothesize, besides other hypothesis, that the behavioral intention has a positive linear impact on HE student's use of GenAI tool. Zhao et al. (2024) also see it the same.

The lack of understanding of the relationship between behavioral intention and use behavior, two elements in the UTAUT, drive the research question of this paper: "Why, how, and in what way do students use GenAI tools in class? Also, which specific GenAI tools do they use?"

Methodology

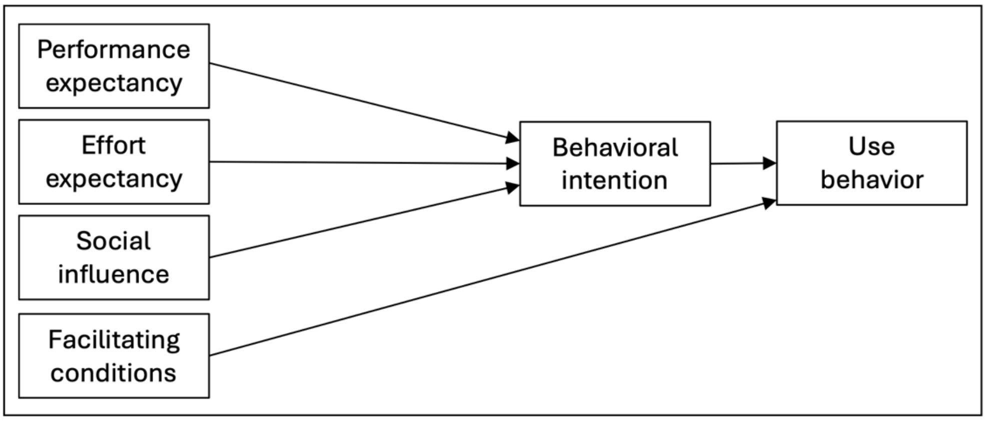
The theoretical framework for the research question as mentioned above and derived by the researchers through the literature review is the Unified theory of acceptance and use of technology (UTAUT). UTAUT was developed as a comprehensive synthesis of eight prior technology acceptance models by Venkatesh et al. (2003). UTAUT has four key constructs, which are performance expectancy, effort expectancy, social influence, and facilitation conditions. Those four influence behavioral intention to use a specific technology.

Performance expectancy is defined as the degree to which using technology is expected to provide benefits to consumers in performing certain activities. Effort expectancy is the degree of ease associated with consumers' use of technology. Social influence stands to the extend wo which consumers perceive important others (e.g. fellow students, friends) believe they should use a certain technology. Facilitating conditions refer to consumers' perceptions of the resources and support available to perform a behavior.

According to UTAUT, performance expectancy, effort expectancy, and social influence are theorized to influence behavioral intention to use technology, while behavioral intention and facilitating conditions determine technology use.

The original UTAUT was subsequently extended several times. The extensions have not been done with careful theoretical considerations (Venkatesh et al., 2012). In addition, UTAUT already explains as much as 70% of the variance in intention (Venkatesh et al., 2003). The two arguments, 1) extension without careful theoretical consideration, and 2) UTAUT already explains 70% of the variance in intention are strengthen authors' decision to stick to the UTAUT model, rather than rely on extended version of the UTAUT model.

Figure 1
UTAUT



Source: Venkatesh et al. (2003)

The empirical part of this research paper is grounded on the Gioia methodology (GM) (Gioia et al., 2013). Gioia et al. (2013) argued that "researchers need to consider data and existing theory in tandem - as a combination of 'knowing' and 'not knowing' – and as fine balancing act that allows for discovery without reinventing the wheel." First, GM is about taking a higher-level perspective to develop the 1st-order concepts by building on students' words. Second, the analytical process enabling the development of 2nd-order themes and aggregate dimensions consists of interweaving induction and abduction, the latter promoting the creative process of theoretical development which ideally is knowledge enriching (Magnani

& Gioia, 2023). The GM results can affirm, extend or generate the theoretical framework (Magnani & Gioia, 2023).

The empirical research was designed as a qualitative study (Braun et al., 2021; Jansen, 2010). The authors conducted an online survey using Google Forms. The introduction to the survey was done face-to-face in class end of November/beginning of December 2025. The students had time to answer the questions online, anonymously, and as free-writing text. 106 students (N), divided into three classes of the exact same course, received the link to the online questionnaire on Google forms. Of the 106 students, 54 students (n) filled out the questionnaire (51%).

The questionnaire was kept rather short with seven questions, to motivate participants to participate. The questions are disclosed below.

Figure 2
Online Survey Questionnaire

Q1: What is your age, gender and nationality?

Q2: Describe the most common case, activity, question, exercise etc. for which you use generative artificial intelligence (GenAI) in the PoM course.

Q3: Which GenAI tool are you using for the most common case, activity, question, exercises etc. the PoM course?

Q4: Explain in detail how you use GenAI, distinguish in as much detail as possible for each step in the process of use for the case, activity question, exercise etc.

Q5: Why did you use GenAI for this case, activity, question, exercise etc.?

Q6: What is your major challenge when using the GenAI tool?

Q7: What is your level of knowledge about the GenAI tool used?

Note. PoM is the abbreviation for Principles of Management

The data received from students answers to the questionnaire is structured based on GM. The core of this qualitative approach is theory-building, in this research paper theory-supporting and theory-extension, from empirical data (Jiménez-Partearroyo et al., 2024).

GM enables transitioning from concrete data to abstract theoretical insight, enriching qualitative research. Key steps of GM as used in this paper are:

1. Data collection: The primary data collection method of a qualitative questionnaire was used. The questions are designed along the UTAUT theory.
2. Data analysis: It involved a detailed examination of the answer text to discover underlying patterns (1-st order concepts), themes (2-nd order themes), and dimensions (aggregate dimensions) (Gehman et al., 2018).
3. Conceptual framework: Instead of developing a conceptual framework, we decided to use the UTAUT model.
4. Theory alignment: By interpreting the data within its conceptual framework UTAUT, we aimed to assign, reject, or extend the UTAUT and therefore deepen the understanding of the subject matter (Olbrich & Mueller, 2013; Tucker, 2016).

For step 2 "data analysis" the authors analyzed students' responses using GM for inductive qualitative research (Gioia et al., 2013). In the first step, we conducted open coding to identify 1st-order concepts that closely reflected students' own terms and expressions regarding their use of GenAI in a general management course. This resulted in a diverse set of informant-centric concepts capturing purposes of use, interaction practices, tool choices, and perceived risks.

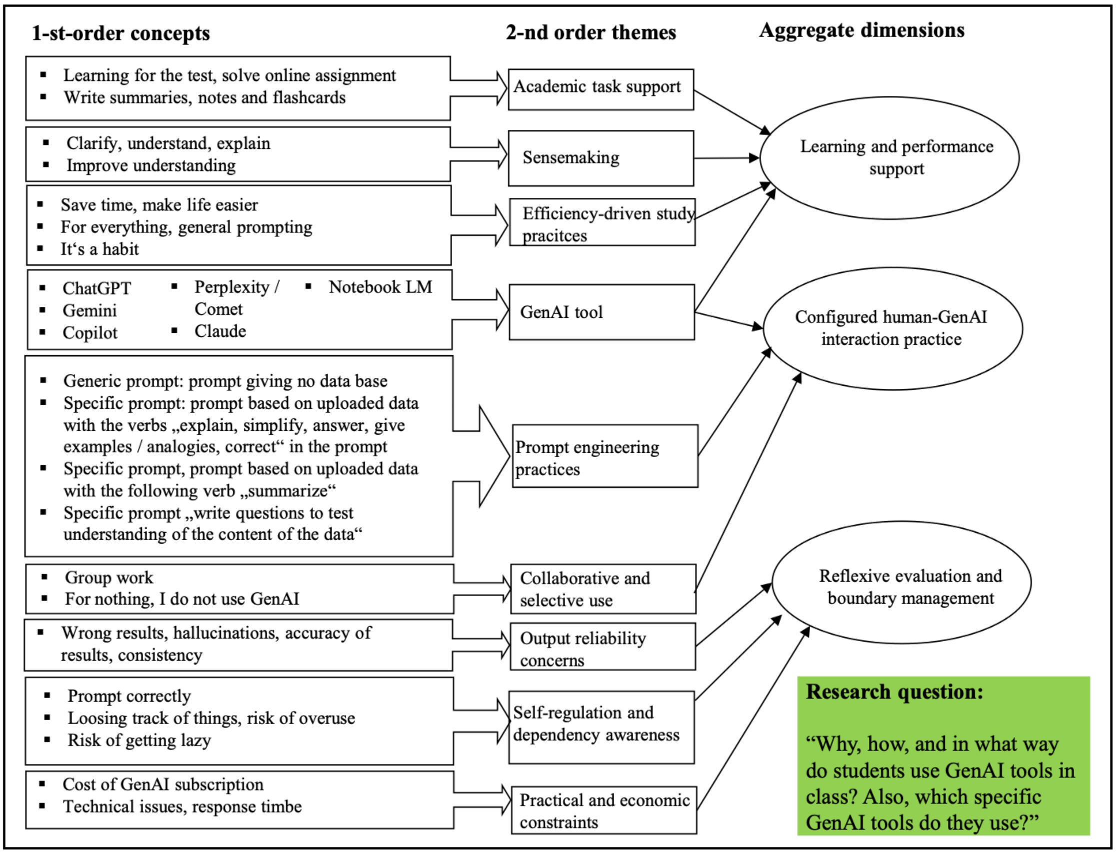
In a second step, we engaged in axial coding (Simmons, 2018) to group these 1st-order concepts into 2nd-order themes that reflected emerging patterns and similarities across responses, while moving toward more abstract, researcher-centric interpretations. These themes captured distinct but related aspects of instrumental learning support, modes of human-GenAI interaction, and reflexive evaluations of GenAI use.

Finally, we aggregated the 2nd-order themes into three overarching aggregate dimensions that theoretically explain "Why, how, and in what way do students use GenAI tools in class? Also, which specific GenAI tools do they use?" Throughout the analysis, we iterated between data and theory to ensure that emerging interpretations remained grounded in student accounts while contributing to a more generalizable understanding of GenAI use HE.

Results

Figure 2 below shows the data structure as the result of the application of the GM to the collected data and the data analysis thereon.

Figure 3
Data Structure Using GM



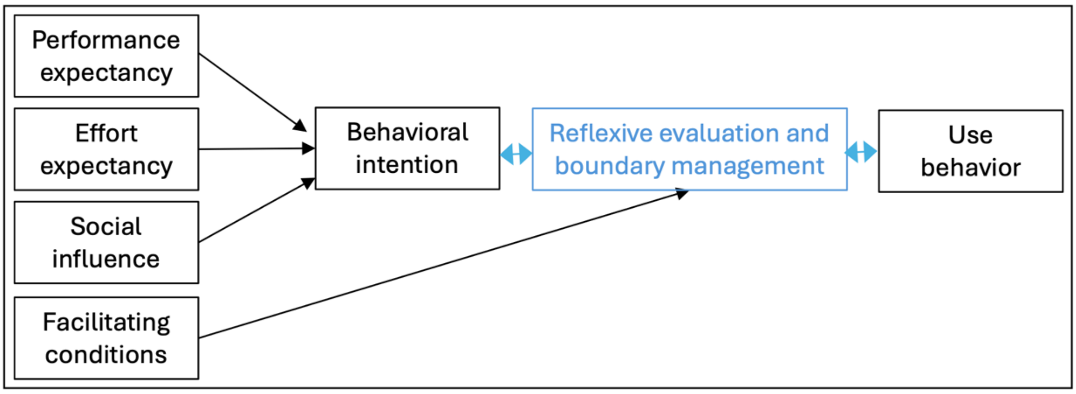
Note. Data structure using GM (Gioia et al., 2013). *Source:* Authors' compilation from questionnaire.

Findings and Discussion

Using GM, the analysis revealed a rich, practice-oriented picture of GenAI use that can be meaningfully interpreted through the UTAUT, while also pointing to important limitations of the model in its current form. In what follows, we first discuss the GM findings in relation to core UTAUT constructions. We then argue for an extension of UTAUT that incorporates reflexive evaluation and boundary management as a central explanatory mechanism in higher educational GenAI use.

To simplify readers orientation, the UTAUT model with the extension of "reflexive evaluation and boundary management" is drawn below.

Figure 4
Proposed UTAUT Extension



Source: Authors extension (in blue) of UTAUT based on data structure from GM

Consistent with UTAUT, the findings indicate that performance expectancy is a central driver of students' GenAI use (Venkatesh et al., 2013; Zhao et al., 2024). Students primarily engage with GenAI because they expect it to enhance their academic performance by supporting learning for tests, solving assignments, clarifying complex concepts, and improving understanding. These expectations are not abstract or speculative. Rather, they are grounded in concrete practices such as generating summaries, writing and structuring notes, producing flashcards, and formulating explanations and questions tailored to course content.

Importantly, performance expectancy in this context extends beyond traditional efficiency or productivity gains. Students view GenAI as a cognitive aid that supports sensemaking in a general management course characterized by conceptual complexity. This broader interpretation of performance expectancy aligns with prior UTAUT research in knowledge-intensive settings, while also highlighting that in educational contexts, perceived performance gains may be defined in terms of understanding and comprehension rather than output alone (Menon & Shilpa, 2023).

The habitual nature of the use of GenAI further reinforces performance expectancy. Once students experience GenAI as effective in supporting their learning-related goals, use becomes routinized, confirming UTAUT's proposition that positive performance beliefs strengthen continued use behavior.

The findings also strongly support the role of effort expectancy in shaping GenAI use. Students differentiate between generic prompts and more specific, data-based prompting strategies, demonstrating that perceived ease of use is not inherent to the technology but emerges through learned interaction practices. Once students develop basic prompting competencies – such as uploading materials and using directive verbs like “explain,” “simplify,” or “summarize” – interaction with GenAI becomes low-effort and efficient.

The use of multiple GenAI tools (e.g., ChatGPT, Gemini, Perplexity, Notebook LM) further illustrates how students actively configure their technological environment to minimize effort while maximizing usefulness. Over time, these configurations contribute to habitual use, reducing the perceived cognitive and operational costs of engaging with GenAI. These findings align closely with UTAUT’s emphasis on effort expectancy as a determinant of behavioral intention, while also suggesting that effort expectancy is dynamically constructed through use rather than fixed at adoption.

Social influence plays a more limited but still visible role in students’ GenAI use. The GM shows that GenAI is used in group work settings, indicating that peer context contributes to the normalization of GenAI as an acceptable academic tool. This is in line with the promotion of corporation, highlighted in research by Cordero et al. (2025). And aligns with UTAUT’s assertion that social norms can shape behavioral intentions, particularly in early stages of technology diffusion.

However, the findings also show that social influence does not lead to uniform or uncritical use. Students report selective GenAI abstinence in certain situations and activities suggesting that peer acceptance does not override individual judgments about appropriateness. This nuanced role of social influence indicates that, in HE contexts, students retain substantial autonomy in shaping their technology use, even when use is socially legitimized.

UTAUT conceptualizes facilitating conditions as “the degree to which users believe that organizational and technical infrastructure supports technology use.” The findings through GM confirm the relevance of such conditions, including subscription costs, technical issues, and response time. These factors directly affect students’ ability to access and rely on GenAI tools.

However, GM also reveals that facilitating conditions in GenAI use extend beyond infrastructure to include output reliability and epistemic quality. Student’s express concerns about hallucinations, inaccuracies, and inconsistent results, indicating that trust in the technology’s outputs is a critical condition for sustained use. These concerns shape not only whether GenAI is used, but how cautiously and selectively it is applied. This finding suggests that in GenAI in HE contexts, facilitating conditions must be understood as both technical and epistemic in nature.

While UTAUT provides a robust framework for explaining students’ intentions to use GenAI, the GM findings indicate that behavior intention alone does not fully explain actual use behavior in HE. Students with high performance and effort expectancy do not necessarily maximize their use of GenAI. Instead, they actively negotiate how much, when, and for what GenAI should be used. To account for this pattern, we propose “reflexive evaluation and boundary management” as a theoretically meaningful extension to UTAUT. See figure 4 above for the proposed UTAUT extension.

Reflexive evaluation and boundary management refers to users’ ongoing evaluation and regulation of their engagement with GenAI based on perceived risks, limitations, and normative concerns. In this study, students articulate boundaries related to accuracy, dependency and overuse. They express concerns about “getting lazy,” “losing track,” or relying too heavily on GenAI, even as they continue to use it regularly. This goes somehow into the same direction as the concerns about potential impact on creativity and critical thinking reported by Malik et al. (2023).

Other research also detected risk of using GenAI, which are “hindering the development of their own writing skills” (Nelson et al., 2025). Johnston et al. (2024) disclosed in their research work, “student who had higher level of confidence in their academic writing where less likely to use or consider using GenAI for academic purposes.”

Crucially, reflexive evaluation and boundary management is not equivalent to resistance or rejection. Rather, it operates as a filter between behavioral intention and actual use. Students intend to use GenAI because they perceive it as useful and easy to use, but they modulate their behavior based on reflexive judgments about appropriate use.

Proposed UTAUT Extension

Introducing reflexive evaluation and boundary management extends UTAUT in three ways.

First, it problematizes the assumption of a largely linear relationship between intention and use. In educational GenAI contexts, high intention can coexist with restrained or selective use, driven by reflective considerations rather than lack of acceptance.

Second, it reframes facilitating conditions to include epistemic trust and perceived risks. Boundary management emerges precisely because GenAI outputs are probabilistic and occasionally unreliable, requiring users to actively assess when reliance is justified.

Third, it challenges the notion that habit necessarily leads to increased or uncritical use. The findings show that habitual GenAI use can coexist with continuous evaluation and boundary-setting, suggesting that habit and reflexivity are not mutually exclusive.

Based on these findings, we propose extending UTAUT by positioning reflexive evaluation and boundary management as a moderating mechanism between behavioral intention and actual use behavior. This construct explains why students who strongly accept GenAI do not always use it extensively or indiscriminately. Instead, use behavior reflects a balance between acceptance-driven motivation and reflexive judgment. The proposed UTAUT extension is illustrated in figure 4 above.

Incorporating reflexive evaluation and boundary management into UTAUT enhances its explanatory power by accounting for the distinctive characteristics of GenAI-based systems and the reflective agency of student users.

Conclusion

In sum, the GM demonstrates that students’ GenAI use in a general management course aligns strongly with core UTAUT constructs, particularly performance expectancy and effort expectancy. At the same time, the findings reveal systematic patterns of reflexive evaluation and boundary-setting that are not fully captured by the original model. By introducing reflexive evaluation and boundary management as an extension to UTAUT, this study contributes a context-sensitive theoretical refinement that better explains GenAI use in HE.

Rather than passive adopters, students emerge as reflective users who actively shape the role of GenAI in HE.

Limitations

Due to its specific context this study has several limitations. These include potential biases in self-reported data and a narrow focus on business information technology (BIT) students in a general management course in HE.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The author declares that Deepl and ChatGPT, AI-assisted writing software, was used in proofreading and refining the language used in the manuscript. The usage was limited to correcting grammatical and spelling errors and rephrasing statements for accuracy and clarity. The author further declares that, apart from Deepl and ChatGPT no other AI or AI-assisted technologies have been used to generate content in writing the manuscript. The ideas, design, procedures, findings, analyses, and discussion are originally written and derived from careful and systematic conduct of the research.

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