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Adapting teaching and learning with existing generative AI by higher education Students: Comparative study of Zayed University and King Abdulaziz University

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ABSTRACT

This study examines the role of higher education students' perceptions in adapting Generative AI (GenAI) tools for teaching and learning, with a particular focus on the factors that influence student satisfaction and engagement. A comparative approach is adopted, exploring student experiences at Zayed University (ZU) in the UAE and King Abdulaziz University (KAU) in Saudi Arabia. The principal variables of interest, including Expected Benefits (EB), University Support (US), Ethical Awareness (EA), and Technology Self-Efficacy (TSE), are examined, with particular attention to their direct and mediated influences through Behavioral Intention (BI) on student satisfaction (SS). Data were collected through surveys and analyzed using SmartPLS-4. The findings reveal notable similarities and differences between the two universities. At both ZU and KAU, BI demonstrated the strongest direct influence on SS, confirming its central role. EB and TSE significantly impacted SS both directly and indirectly through BI in both contexts, although their effects were stronger at KAU. Conversely, US and EA showed no significant direct or mediated effects on SS at either institution. R^2 values indicated substantial explanatory power of the model, and Q^2 values confirmed strong predictive relevance. These results suggest that while the core drivers (BI, EB, TSE) are consistent across contexts, institutional and cultural factors shape their relative impact. The findings highlight the importance of integrating GenAI tools into teaching practices and emphasize the role of student motivation, confidence, and institutional support in fostering effective adoption and enhancing learning experiences. Institutions should prioritize enhancing students' perceived benefits and technological self-efficacy by providing practical training and demonstrating the value of GenAI tools. These factors significantly influence student satisfaction and engagement, particularly in culturally distinct settings.

1. Introduction

In contemporary years, the realm of higher education has experienced profound metamorphoses propelled by technological innovations, especially in the domain of artificial intelligence (AI), along with its multifaceted applications within the educational sector (Yusuf & Tambuwal, 2018). The incorporation of generative artificial intelligence (GenAI) tools into pedagogical methodologies has emerged as a fundamental element of contemporary educational paradigms (Zhang et al., 2023). Tools such as ChatGPT provide unprecedented opportunities to enhance pedagogical approaches and deepen student engagement with academic content (Nguyen et al., 2024).

The expanding corpus of scholarly inquiry into generative artificial intelligence (GenAI) underscores its significant contribution to the realm of higher education, facilitating sophisticated tutoring mechanisms and pioneering educational ecosystems (Ivanov et al., 2024; Zhou, 2024). However, studies reveal that students' ability to adapt and benefit from GenAI tools varies due to multiple factors. Key benefits such as increased engagement and personalized learning, which enhance student satisfaction and learning effectiveness, are widely recognized (Sahu, 2024; Borah et al., 2024, January). However, these benefits are contingent upon the level of university support, including necessary infrastructure, training, and clear guidelines (Shailendra et al., 2024). Without a structured framework, the integration of GenAI into university systems remains limited (Chiu et al., 2024), and over-reliance on technology could negatively affect students' critical thinking and independence

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(Chan & Lee, 2023). A balanced approach is essential to optimize GenAI's potential while preserving academic quality. Research also emphasizes the importance of ethical awareness, including transparency and fairness, for the responsible use of GenAI tools (Wahid, 2024; Williams, 2024). Higher technological self-efficacy is crucial for boosting students' confidence in using these tools (Wang et al., 2024).

These factors impact student satisfaction and behavioral intention, which in turn influences their continued use of GenAI tools (Chai et al., 2021). Understanding the interaction between these variables is vital for maximizing the effectiveness of GenAI tools in higher education.

Despite growing recognition of GenAI's benefits, there is still a gap in understanding how these benefits are perceived across different educational contexts and student groups, especially in Gulf universities. Studies also highlight risks such as passive learning and diminished social interaction, which could undermine critical thinking and problem-solving skills (Rasul et al., 2023). Institutional support, including access to GenAI tools, is crucial but remains underexplored in terms of its impact on adoption and effectiveness (Johnson, 2023; Kishore et al., 2023). Additionally, while ethical considerations are increasingly emphasized, research on their influence on students' trust, satisfaction, and engagement with GenAI tools in various educational contexts is scarce. There is also a gap in understanding how students' and instructors' confidence in using GenAI tools varies based on prior experiences, competencies, and technological skills. Moreover, the relationship between students' satisfaction with GenAI tools and their long-term academic outcomes, including performance and behavioral intentions, remains insufficiently explored.

This study aims to address the existing gaps by exploring the factors that influence the adaptation of teaching and learning with existing GenAI tools and their influence on the satisfaction levels of students as well as their prospective intentions to persist in utilizing these tools within the Gulf region, particularly at Zayed University (ZU) in the United Arab Emirates (UAE) and King Abdulaziz University (KAU) in the Kingdom of Saudi Arabia (KSA). Both universities represent leading models of higher education with progressive strategies for integrating technology into their educational frameworks. ZU focuses on fostering digital innovation by heavily investing in technological infrastructure and implementing educational initiatives utilizing advanced tools. On the other hand, KAU is dedicated to a holistic digital transformation, improving curriculum development and leveraging AI to enhance educational quality. Despite their shared objectives, the institutional and cultural contexts at ZU and KAU differ, providing a valuable opportunity to compare how students engage with GenAI technology. Comparative studies examining the technical, social, ethical, and educational factors that influence the adoption of GenAI tools across varied contexts are crucial to optimizing the adaptation of teaching and learning in higher education, especially in the Gulf region. Literature reviews reveal a lack of studies that compare how different cultural and institutional contexts impact the adoption and use of these tools, particularly in the Gulf region. Moreover, there is limited focus on the human and social aspects of using GenAI, hindering the ability to provide comprehensive recommendations for universities. The study addresses the following research questions.

RQ1: What are the similarities and differences in students' perceptions regarding the actual use of GenAI tools in learning at ZU and KAU?
RQ2: How do the impacts of adapting teaching and learning with GenAI tools—such as expected benefits (EB), university support (US), ethical awareness (EA), and technology self-efficacy (TSE)—affect student satisfaction with the learning experience at ZU and KAU?
RQ3: Does the mediating effect of behavioral intention (BI) on the relationship between adapting teaching and learning with GenAI tools (EB, US, EA, TSE) and student satisfaction differ between ZU and KAU students?

2. Literature review and theoretical framework

2.1. Conceptual understanding of GenAI

Generative Artificial Intelligence (GenAI) is an advanced evolution of artificial intelligence (AI), extending traditional AI capabilities by focusing on creating human-like content in various formats, including text, images, audio, and video (Strzelecki & ElArabawy, 2024). Unlike rule-based AI systems, GenAI uses deep learning, neural networks, and probabilistic models to replicate human creativity (Tlili et al., 2023). Its impact on higher education is particularly significant, as it transforms learning environments and academic practices, generating novel, coherent outputs from extensive data sets, enhancing educational tools and resources by offering personalized learning and fostering creativity and engagement among students (Helm et al., 2020).

2.2. Adapting teaching and learning with GenAI tools

The integration of GenAI has revolutionized education, making teaching, learning, and research more accessible (Chan, 2023; Grassini, 2023). Tools like ChatGPT and other AI technologies are essential for tasks such as essay drafting, problem-solving, and providing real-time feedback, enhancing academic performance and student satisfaction (Kishore et al., 2023). These tools foster dynamic, personalized learning, critical thinking, and adaptive learning processes that help students overcome challenges (Yusuf et al., 2024). GenAI's role in education is evident in tools like ChatGPT for personalized learning, Gemini for content creation, and Jasper AI and Copy. ai for marketing content. Grammarly and QuillBot improve writing, while Zotero and EndNote assist with citation management. Scribe aids in creating detailed transcripts and summaries (Chen et al., 2020; Helm et al., 2020). Studies show that students are drawn to GenAI after learning about its capabilities in the media and recognizing its potential for practical projects and innovation (Kishore et al., 2023). They are motivated by a desire to enhance technical and creative skills and improve research and assignment outcomes (Wecks et al., 2024). This interest also stems from the tools' ability to streamline routine tasks and explore new technologies (Zouhaier, 2023). Students primarily use GenAI for writing essays, solving assignments, creating presentations, and preparing for exams (Chambers & Owen, 2024). These tools also support collaboration and communication tasks, such as group projects and writing emails (Bates et al., 2020). These activities highlight the broad applicability of GenAI in enhancing individual and collaborative learning. As the potential of GenAI to reshape education is recognized, its integration into teaching practices is crucial for improving academic performance and student satisfaction. However, successful integration requires key factors to support the adaptation of educational practices.

2.3. Conceptualization and research hypothesis

2.3.1. Students' satisfaction (SS) on learning experience with GenAI

Student satisfaction is regarded as a dependent variable due to its susceptibility to various factors associated with the students' engagement with Generative AI tools. In this context, satisfaction is conceptualized as a psychological condition that arises when students believe their needs and expectations have been sufficiently addressed. Within the educational paradigm, contentment with Generative AI tools is essential for promoting academic involvement and motivating the sustained utilization of these technologies (Alshammari & Babu, 2025). Empirical research demonstrates that the dependability of content produced by these tools significantly influences student satisfaction, resulting in an augmented frequency of usage (Almufarreh, 2024). When Generative AI tools correspond with students' academic requirements, they are regarded as more advantageous, thereby enhancing student satisfaction and encouraging ongoing engagement (Wang et al., 2025). Moreover, the psychological predisposition of students during their engagement with these tools significantly impacts their levels of satisfaction. When students experience a sense of comfort and involvement with the tools, they are more predisposed to persist in utilizing them, which ultimately leads to improved academic performance (Arpaci & Kusci, 2025). Empirical research indicates that satisfaction is a pivotal factor in influencing students' intentions to maintain their use of Generative AI tools. When students recognize that their academic requirements are satisfactorily met through these tools, they demonstrate a heightened propensity for sustained usage, consequently resulting in superior academic achievements. Satisfaction not only augments student engagement but also fosters self-directed learning, which is crucial for developing the competencies demanded in the labor market (Bouzar et al., 2025). Frequent usage of generative AI tools is positively correlated with student happiness, according to research by Fakhri et al. (2024). Regular users of these resources often improve their abilities and accomplish their learning objectives more successfully. Furthermore, according to Khlaif et al. (2024), the strategies used by educational institutions to include AI tools into assessments have a beneficial impact on student satisfaction, which increases the tools' efficacy in evaluative situations. Almulla (2024) further confirmed that the employment of generative AI technologies improves student happiness by streamlining academic activities and enhancing the effectiveness and interactivity of the learning process.

2.3.2. Key factors influencing student satisfaction

The integration of GenAI is swiftly becoming a key component in education, offering innovative solutions to enhance teaching and learning for both students and educators. To fully leverage its potential, it is essential to understand the factors that influence student satisfaction with these tools in their educational experiences (Almufarreh, 2024). The effectiveness of these tools varies across institutions, shaped by numerous factors.

2.3.2.1. Expected benefits (EB). This variable pertains to the students' cognitive evaluations and dispositions regarding the significance of integrating GenAI tools within their educational experiences. The students' assessments of these advantages have a direct correlation with their propensity to embrace, utilize, and integrate technology into their academic practices (Venkatesh et al., 2012). Kishore et al., 2023 found that students who recognize the potential benefits of GenAI tools, such as personalized learning, increased engagement, enhanced efficiency, and innovation are more likely to adopt them. This is supported by Vroom's Expectancy Theory (Vroom, 1964), which suggests that individuals are motivated to engage in behaviors based on expected outcomes. If students believe that using GenAI will improve their learning outcomes and academic experience, they are more likely to adopt these tools. Tian et al. (2024) found that graduate students in Chinese universities, who recognized the expected benefits of AI chatbots in education and research, showed increased adoption and satisfaction with the tools. Similarly, Lee and Moore (2024) conducted a systematic review on the integration of GenAI into learning environments, highlighting that student satisfaction was closely linked to engaging with personalized educational content and receiving real-time automated feedback. However, studies such as Marshall (2023) from Liberty University have reported mixed results, with some students expressing dissatisfaction due to limited technological experience and unrealistic expectations of AI tool capabilities. Similarly, Brill et al. (2022) found that users with little knowledge of AI tools (e.g., Siri, Alexa) and few prior experiences were less satisfied with these applications. These findings suggest that the relationship between expected benefits and student satisfaction is context-dependent and influenced by factors such as cultural and educational settings. Based on these insights, the current study proposes the following hypothesis.

H1. EB have a significant positive impact on SS.

2.3.2.2. University support (US). This factor highlights the essential role of universities in providing resources, policies, training, and infrastructure to promote the effective use of GenAI tools in education (Wang et al., 2021). Research emphasizes the importance of institutional support in facilitating the adoption and successful integration of these tools. Chen et al. (2020) found that continuous training and access to resources for faculty are crucial for higher adoption rates and increased student satisfaction. Zouhaier (2023) also noted that investments in infrastructure and faculty development create favorable conditions for AI integration, which aligns with Wecks et al. (2024) who highlighted the importance of institutional support in enhancing the academic benefits of GenAI. Cohen and Wills' Social Support Theory (Cohen and Wills, 1985) further suggests that institutional support is key in enabling students to navigate technological advancements. Faculty involvement is critical to enhancing student engagement with GenAI tools. Research by Chen et al. (2020) and Kishore et al. (2023) emphasizes the positive impact of faculty participation on student interaction with these tools. Chiu et al. (2024) highlighted that teacher support is equally critical for the effective implementation of institutional policies, as it plays a key role in enhancing academic interaction and motivating students to engage with AI-based chatbots. Subhi (2020) and Koller et al. (2006, pp. 1–13) also highlight the role of well-trained instructors in aligning GenAI with curriculum objectives to improve learning outcomes. Institutional policies are crucial in addressing issues such as plagiarism and AI bias, ensuring a smooth integration of GenAI tools (Wecks et al., 2024; Zouhaier, 2023). While studies from countries with advanced technological infrastructures, such as the U.S., China, and Japan, confirm the positive impact of institutional support on student satisfaction, challenges exist in under-resourced regions. In India (Gomathi, 2024) and Afghanistan (Khan et al., 2024), limited infrastructure and poor integration of GenAI tools can hinder student satisfaction despite institutional efforts. Khan et al. (2024) found that in Afghanistan, the involvement of parents and teachers played a significant role in fostering positive outcomes, alongside institutional support. This suggests that while university support is essential, its effectiveness is influenced by contextual factors such as infrastructure, culture, and faculty readiness. Based on these insights, the study proposes the following hypothesis.

H2. US has a significant positive impact on SS.

2.3.2.3. Ethical awareness (EA). In the context of GenAI tools, EA refers to students' understanding of key issues such as privacy, transparency, safety, fairness, academic integrity, and responsible AI use (Wahid, 2024). This awareness fosters trust and encourages responsible behavior, enhancing students' learning experiences and satisfaction (Williams, 2024). Previous research underscores the importance of ethical guidelines for AI use. Yusuf et al. (2024) found that such focus promotes responsible student behavior, helping them recognize risks like academic dishonesty and bias. MacIntyre's Theory of Ethical Responsibility (MacIntyre, 1984) supports this, emphasizing that ethical education promotes responsible decision-making. Studies by Gomathi (2024) demonstrated that students with a greater understanding of ethical considerations report higher levels of satisfaction with their educational experience. Similarly, Kishore et al. (2023) emphasized that ethical awareness builds trust in AI tools, essential for students to fully adopt and integrate these technologies into their learning. Similarly, Bates et al. (2020) noted that incorporating ethical guidelines into curricula helps students make informed, responsible decisions. Wecks et al. (2024) found that students with strong ethical awareness are less likely to engage in academic dishonesty, improving academic outcomes. Transparency, fairness, and safety are also crucial for AI adoption. Schwartz and Rane (2022) revealed that students are more likely to adopt GenAI tools when they trust that these systems operate under transparent policies. However, Gomathi (2024) pointed out that ethical training alone does not guarantee successful GenAI integration, which may impact student satisfaction. The study recommends incorporating ethical issues into curricula for responsible AI use. These findings suggest that while ethical awareness alone may not fully determine satisfaction, its role in ensuring responsible use and academic integrity is crucial. Based on this, the current study proposes the following hypothesis.

H3. EA has a significant positive impact on SS.

2.3.2.4. Technology self-efficacy (TSE). TSE, a measure of confidence in using technology, aligns with Ajzen's (2002) perceived behavioral control (PBC) and Bandura's self-efficacy theory (Bandura, 1983). Ajzen noted that self-efficacy predicts behavioral intention (BI), with studies (e.g., Chai et al., 2021) showing its role in adopting new technologies, including GenAI tools. Gomathi (2024) found that higher TSE levels correlate with better GenAI tool usage, improved learning outcomes, and increased satisfaction. Studies by Black (2024), Bouteraa et al. (2024), and Du and Lv (2024) also highlighted that students with higher TSE engage more actively with GenAI tools, leading to enhanced academic performance. This supports Bandura's theory that individuals confident in their abilities apply their skills effectively. Kishore et al. (2023) further emphasized that strong TSE leads to greater academic engagement and better performance with AI tools. Bates et al. (2020) found that targeted training programs enhance TSE, enriching academic experiences. Wecks et al. (2024) confirmed that fostering TSE encourages greater engagement with new technologies. Hoang and Dang (2021) stressed that TSE, combined with self-motivation, maximizes satisfaction in learning, especially with technology. Yildiz (2018) showed that TSE positively influences students' readiness for flipped learning models, further shaping their attitudes toward AI adoption. Zhang et al. (2019) linked TSE to behavioral intention in the Theory of Planned Behavior (TPB), highlighting its role in AI tool adoption. Based on these insights, this study proposes that TSE is a critical determinant of student satisfaction with GenAI tools. Therefore, the following hypothesis is proposed.

H4. TSE has a significant positive impact on SS.

2.3.2.5. Mediating effects in behavioral intention (BI). Ajzen's (1991) Theory of Planned Behavior (TPB) posits that Behavioral Intention (BI) functions as an intermediary between external determinants such as Expected Benefits (EB), University Support (US), Ethical Awareness (EA), and Technology Self-Efficacy (TSE) and the construct of student satisfaction (SS). Research supports this idea, with Dhaha and Ali (2014) showing that BI mediates the relationship between benefit predictions and service satisfaction. Similarly, Wecks et al. (2024) indicate that institutional support and knowledge dissemination shape students' BI, further mediating the relationship between US and SS. Ethical awareness also plays a significant role in shaping BI, as noted by Wong et al. (2024), who argue that ethical considerations influence trust in AI technologies and, subsequently, BI and satisfaction. However, Gomathi (2024) suggests that ethical awareness could have a direct impact on satisfaction, bypassing BI. These contrasting views highlight the complexity of BI's role in the process. Furthermore, TSE is another key predictor of BI, as students with high self-efficacy are more likely to adopt GenAI tools, improving their satisfaction (Zhang et al., 2019). Budu et al. (2018) also found that BI mediates the relationship between TSE and satisfaction, supporting the idea that students with favorable attitudes toward technology are more likely to be satisfied with their learning experience. Contrary to this, Hoang and Dang (2021) argue that BI alone may not fully mediate the relationship between US, EA, and satisfaction. Their findings suggest that external factors such as institutional and motivational support can directly influence satisfaction, without needing to pass through BI. This indicates that BI's role may vary across contexts. The literature presents both supporting and conflicting views on the role of BI as a mediator in the relationship between various factors and satisfaction. The following hypotheses are proposed based on these insights.

H5. BI mediates the relationship between EB & SS.

H6. BI mediates the relationship between US & SS.

H7. BI mediates the relationship between EA & SS.

H8. BI mediates the relationship between TSE & SS.

H9. BI to use GenAI has a significant positive impact on SS.

Based on the theoretical framework, Fig. 1 illustrates the relationships among the discussed constructs, serving as the basis for the development of the proposed hypotheses.

3. Methods

3.1. Research design

This investigation employed a descriptive and correlational research methodology. This quantitative approach identifies the strength and direction of the relationship between independent (exogenous) and dependent (endogenous) variables without manipulating them (Nardi, 2018), providing valuable insights into the factors associated with adapting teaching and learning with existing GenAI by higher education students, making it well-suited for investigating the research questions.

3.2. Data collection tools (measurement)

Data pertinent to this research were amassed through a cross-sectional survey administered across two universities situated in distinct countries: Zayed University (ZU) in the United Arab Emirates (UAE) and King Abdulaziz University (KAU) in the Kingdom of Saudi Arabia (KSA). The first section of the questionnaire included demographic questions such as gender, university, and academic level. In the second section, six questions measured the actual use of generative AI tools, designed to allow multiple responses. The third section measured the influence of various constructs outlined in the conceptual model (see Fig. 1), comprising a total of 38 items adapted from previous literature (Almufarreh, 2024; Black, 2024; Bouteraa et al., 2024; Chan & Hu, 2023; Du & Lv, 2024; Elshaer et al., 2024; Ivanov et al., 2024; Kim & Ko, 2022; Ko & Leem, 2021; Ur Rehman et al., 2024; Zhao, Cox, & Cai, 2024) and validated through a pilot study.

Each question was scored on a 5-point Likert scale, where 1 represented severe disagreement and 5 represented strong agreement. Ethical Awareness (EA, 7 items), Technology Self-efficacy (TSE, 5 items), Expected Benefits (EB, 8 items), University Support (US, 6 items), Student Satisfaction with Learning Experience with GenAI (SS, 6 items), and Behavioural Intention to Use GenAI (BI, 6 items) were among the constructs assessed.

All items were carefully modified and adapted from previously validated scales to ensure relevance and reliability. The questionnaire was distributed in English at ZU (where English is the language of instruction). At KAU, the questionnaire was translated into Arabic by a language expert and further validated for content by a senior professor in the field of e-learning and educational technology to ensure clarity, relevance, and comprehensive coverage of the constructs.

In designing the survey instrument, particular attention was given to ensuring a balanced focus on both learning and teaching adaptation to the use of generative AI tools in higher education. While a significant portion of the survey explores students' engagement with AI in their academic activities, the University Support (US) construct explicitly addresses the role of faculty and institutional efforts in AI integration. Several survey items assess the extent to which faculty members incorporate generative AI into their teaching strategies, provide guidance on its appropriate use, and support students in utilizing these tools for academic purposes. Additionally, institutional efforts—such as the provision of training sessions, workshops, and AI-enhanced learning

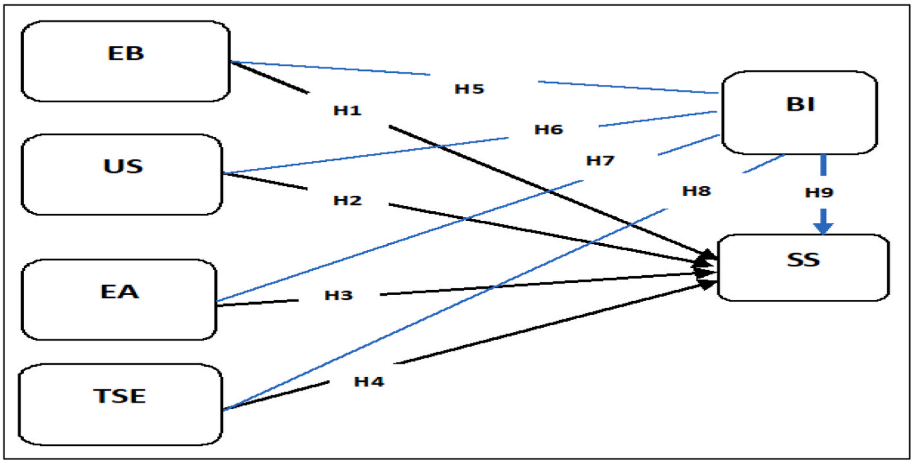

Fig. 1. Research conceptual framework.

resources—are included to examine their role in fostering AI-driven teaching methodologies. Thus, the study does not merely investigate students' experiences with AI in learning but also offers valuable insights into how faculty members and universities facilitate AI adoption in teaching practices. This holistic approach ensures that the study contributes to a deeper understanding of both student learning experiences and faculty-driven AI integration in teaching.

3.3. Reliability and validity checks

The internal consistency of the questionnaire was evaluated using Cronbach's alpha in order to guarantee its validity and reliability. In a pilot test with 40 students, results ranged from 0.83 to 0.90, which is significantly higher than the generally recognized cutoff of 0.70 and indicates outstanding dependability (Creswell, 2014). The reliability and trustworthiness of the data gathered for the study are guaranteed by these high internal consistency scores, which highlight how well the questionnaire questions measure the target components. To guarantee the survey's content validity, eight specialists in the domains of information science, educational technology, and e-learning were contacted. This methodical approach guaranteed that the items and variables accurately reflected the intended constructs (Lawshe, 1975). Furthermore, following Polit and Beck (2006), the perspectives of subject matter experts were incorporated to refine the questions, ensuring their clarity, relevance, and alignment with the study's objectives.

3.4. Ethical considerations

Ethical approval for the study was obtained from the management of both universities before data collection commenced. This process ensured that the research adhered to ethical principles. Measures were implemented to ensure confidentiality and privacy, and informed consent was acquired from all participants, elucidating the study's objectives, methodologies, potential risks and benefits, as well as participants' entitlement to withdraw at any juncture. Participation was entirely voluntary and anonymous, with no identifying information collected from respondents in the survey. All data were securely stored and accessible only to authorised researchers.

3.5. Study population and sample

This study specifically targeted students at Zayed University (ZU) in the UAE (approximately 9473 students) and King Abdulaziz University (KAU) in Saudi Arabia (approximately 101,933 students). Both institutions are distinguished entities within the Gulf Cooperation Council (GCC), which emphasizes the incorporation of AI into educational frameworks. The variances in cultural and educational policies between the two nations offered a distinctive opportunity for comparative scrutiny.

Given the constraints of resources and time, the study adopted a non-probability voluntary sampling strategy. Following several reminders, a total of 495 completed surveys were amassed, comprising 203 from ZU and 292 from KAU. To ensure the integrity of the sample, two preliminary measures were undertaken: (1) an assessment for missing values, whereby 11 questionnaires that exhibited over 25 % missing responses were excluded from the analysis; and (2) data cleaning through the removal of outliers, revealing no significant issues, thereby affirming the accuracy and reliability of the dataset.

During this evaluation process, a discrepancy was recognized in the responses pertaining to the utilization of generative AI tools. Specifically, while no students at KAU answered "No" to the question "Have you ever used generative AI tools in your studies (learning)?", 13 students indicated "Never" when responding to the question regarding the frequency of use of generative AI for learning and academic activities. To maintain data integrity and address this contradiction, the responses of these 13 students were excluded from the final dataset before conducting further analyses. This step ensures that the analysis accurately reflects the experiences and behaviours of students who have interacted with generative AI tools. This process resulted in a final sample size of 471 valid student respondents, with a response rate of 95.1 %, with 203 from ZU and 268 from KAU.

The sample size was deemed sufficient for testing the proposed structural model and hypotheses. According to Krejcie & Morgan (1970), for a population of 111,406 students, a sample size of 399 is required for a 95 % confidence level. Furthermore, in PLS-SEM, a widely accepted rule states that the sample size should be at least ten times the number of arrows pointing to a variable (Hair et al., 2017). Given that this study's conceptual model includes 9 arrows, the minimum required sample size is 90. As demonstrated, the final sample size of 471 surveys exceeded these thresholds for both universities, ensuring robust statistical analysis.

3.6. Data collection procedures

Data collection was conducted between August 2024 and December 2024 using an online survey distributed to undergraduate students at both universities. The survey was disseminated through multiple university communication channels, including official student email lists, student platforms, the university's learning management system (LMS), and faculty announcements. To maximize response rates, participants received an initial invitation, followed by two reminder emails. The survey instrument was meticulously crafted to require an estimated duration of 10–15 min for completion.

To ensure that the results reflect the true experiences of the students objectively, deliberate steps were taken to minimize the potential bias arising from prior interest in AI or varying levels of familiarity with modern technologies. Clear instructions were provided to the students regarding how to complete the questionnaire and its subject matter, which helped them understand the purpose of the study at the beginning of the survey, ensuring transparency and voluntary participation. Participants were also reminded to provide honest and accurate responses, maintaining the integrity of the collected data in a non-directive study.

The questionnaire was structured to enable respondents from diverse academic disciplines to articulate their perspectives grounded in their overall experiences with generative AI tools within the realm of their educational pursuits, regardless of their prior knowledge, interest, or experience with AI technologies, whether they had studied AI in courses or not. The survey included demographic questions asking whether participants had used generative AI tools in any courses and which tools they had used. This approach ensured that the study did not rely on a limited sample of students with a specific interest or prior knowledge of AI, and the survey was not exclusively targeted at students enrolled in AI courses. As a result, the data obtained from the study were balanced and reflective of the general academic reality of students at both institutions, enhancing the reliability and transparency of the findings. This approach also helped minimize bias by ensuring a diverse sample representing various academic disciplines, while reducing the impact of differing levels of AI knowledge among the participants. Furthermore, participants were assured that their responses would remain confidential, and their participation was entirely voluntary, without any form of incentive. Given the exploratory nature of this research, this methodology was deemed suitable for understanding the general trends in the use of generative AI tools among university students. Regarding the potential influence of prior knowledge on participants' responses, the survey included questions related to participants' understanding and prior experience with AI. This helped categorize the data and separate the effects of prior interest or experience in the field. Additionally, the data were carefully processed after collection to ensure that no bias arose from these factors.

Given the exploratory nature of this study, a voluntary sampling approach was deemed appropriate for capturing general trends in GenAI usage among university students. The study's methodological approach ensures meaningful insights into students' engagement with AI technologies in higher education.

3.7. Data analysis process

The survey data underwent a two-stage analysis process to ensure comprehensive examination. First, descriptive statistical analyses (including frequencies and percentages) were conducted to encapsulate the demographic attributes of the participants. Thereafter, partial least squares structural equation modeling (PLS-SEM) utilizing SmartPLS V.4.1.1.2 was applied for the correlational examination of the study variables. SmartPLS-4 was chosen for its ability to handle complex relationships between multiple constructs and its flexibility in managing non-normal data. This tool is particularly suitable for the study's sample size and research design, enabling effective exploration of relationships and testing of hypotheses. It also allows for the simultaneous validation of both measurement and structural models, making it an ideal choice for analyzing the cause-effect relationships between latent and observed variables in this study, particularly in the context of complex models, small sample sizes, and formative constructs (Hair et al., 2019).

3.8. Demographic details of respondents

Tables 1 and 2 elucidate the demographic characteristics of the student participants engaged in this research, offering a comparative examination of the demographic profiles of respondents from Zayed University (ZU) and King Abdulaziz University (KAU). KAU has a larger overall population, which contributes to its larger representation in the study (56.9 %) compared to ZU (43.1 %).

Table 1
Gender distribution of the respondents.

Gender	ZU (N)	ZU (%)	KAU (N)	KAU (%)	Total (N)	Total (%)
Male	51	10.8 %	112	23.8 %	163	34.6 %
Female	152	32.3 %	156	33.1 %	308	65.4 %
Total	203	43.1 %	268	56.9 %	471	100 %

Table 2
Academic level distribution of the respondents.

Academic Level	ZU (N)	ZU (%)	KAU (N)	KAU (%)	Total (N)	Total (%)
Undergraduate	199	42.3 %	147	31.2 %	346	73.5 %
Postgraduate	4	0.8 %	121	25.7 %	125	26.5 %
Total	203	43.1 %	268	56.9 %	471	100.0 %

In terms of gender distribution, Table 1 indicates that females represent the predominant demographic at both institutions, with KAU exhibiting a marginally higher percentage of females (33.1 %) in comparison to ZU (32.3 %). Conversely, male representation is notably greater at KAU (23.8 %) than at ZU (10.8 %).

With respect to academic classification, Table 2 reveals that the predominant category of respondents consists of undergraduate students, with ZU contributing a more substantial proportion (42.3 %) relative to KAU (31.2 %). Nonetheless, KAU demonstrates a markedly higher percentage of postgraduate students (25.7 %) in contrast to ZU (0.8 %).

3.9. Actual usage of generative AI tools

The survey's six open-ended questions were analyzed using the multiple-response technique to capture ZU and KAU students' perceptions of GenAI tool usage in learning, as shown in Table 3.

Table 3 provides a comparative analysis of the perceptions held by students from ZU and KAU regarding their actual utilization of GenAI tools, based on a sample comprising 471 students. When comparing the overall use of GenAI tools, a striking 56.9 % of KAU students report using generative AI tools in their studies, compared to 42.5 % at ZU. Interestingly, while a small fraction (0.6 %) of ZU students have never used these tools, there are no non-users at KAU, signalling a near-universal adoption. Additionally, the table shows that ChatGPT reigns supreme as the most widely used AI tool across both universities. However, at KAU (50.3 %), its usage surpasses that of ZU (42.5 %), reflecting a higher reliance on AI-driven content generation. Grammarly, Canva, and Gemini also enjoy significant popularity, but KAU students tend to explore a broader spectrum of AI tools. Notably, Jasper AI, Copy. ai, and QuillBot show much higher usage in KAU than in ZU.

When it comes to how students first encountered AI, self-discovery plays a major role at KAU (29.7 %), compared to only 13.6 % at ZU. Meanwhile, peers and friends are the primary sources of AI awareness at ZU (22.9 %); faculty influence, however, remains limited at both universities, hinting at an opportunity for educators to actively integrate AI into teaching methodologies. While some students experiment with AI tools occasionally, others integrate them into their daily academic habits. The data suggests that KAU students are more frequent users, with 32.0 % using AI frequently or very frequently, compared to only 23.4 % at ZU.

The motivations behind AI adoption further illuminate key differences between the two student populations. In KAU, students primarily turn to AI to enhance academic performance (52.4 %), develop technical and creative skills (42.0 %), and improve their studies (42.5 %). On the other hand, ZU students seem more driven by curiosity and external

Table 3
Students' actual usage of GenAI tools in learning at ZU and KAU.

The University	ZU		KAU	
	N	%	N	%
1. Have you ever used generative AI tools in your studies (learning)?				
Yes	200	42.5 %	268	56.9 %
No	3	0.6 %	0	0 %
2. If you use generative AI tools, which of the following do you use? Select all that apply.				
ChatGPT (OpenAI)	200	42.5 %	237	50.3 %
Gemini	57	12.1 %	142	30.1 %
Jasper AI	6	1.3 %	65	13.8 %
Grammarly	132	28.0 %	157	33.3 %
Copy.ai	7	1.5 %	109	23.1 %
Scribe	10	2.1 %	80	17.0 %
QuillBot	1	0.2 %	108	22.9 %
Zotero	5	1.1 %	85	18.0 %
EndNote	3	0.6 %	1	0.2 %
AI Dungeon	1	0.2 %	56	11.9 %
Canva	148	31.4 %	137	29.1 %
3. How did you first start using generative AI tools in your learning process?				
I was introduced to it by my faculty members	31	6.6 %	26	5.5 %
I learned about it through peers & friends	108	22.9 %	102	21.7 %
I discovered it on my own through research & media	64	13.6 %	140	29.7 %
4. Frequency of Use: Please indicate how frequently you use generative AI to support your learning and academic activities.				
Never	3	0.6 %	0	0.0 %
Rarely	24	5.1 %	37	7.9 %
Occasionally	66	14.0 %	80	17.0 %
Frequently	65	13.8 %	82	17.4 %
Very Frequently	45	9.6 %	69	14.6 %
5. Motivations for Use: What motivated you to use generative AI? Select all that apply.				
Interested after hearing about it in the media.	88	18.7 %	81	17.2 %
To develop practical projects and innovative solutions.	83	17.6 %	139	29.5 %
To enhance and develop my technical and creative skills.	134	28.5 %	198	42.0 %
To use it effectively in my studies.	114	24.2 %	200	42.5 %
To learn how to use AI better.	77	16.3 %	170	36.1 %
To enjoy exploring new technologies.	67	14.2 %	130	27.6 %
To achieve better results in research and assignments.	122	25.9 %	247	52.4 %
To streamline daily routine tasks.	38	8.1 %	130	27.6 %
6. Types of Activities of Use: For which types of academic activities do you primarily use generative AI? Select all that apply.				
Writing essays, reports, and research.	154	32.7 %	173	36.7 %
Solving assignments or exercises	117	24.8 %	182	38.6 %
Creating presentations	110	23.4 %	184	39.1 %
Preparing for exams	97	20.6 %	161	34.2 %
Collaborating on group projects	93	19.7 %	159	33.8 %
Communication (e.g., writing emails)	87	18.5 %	112	23.8 %

influence, such as hearing about AI from the media (18.7 %) or wanting to explore new technologies (14.2 %). While both universities utilize AI for academic support, KAU students demonstrate a broader and more strategic application of these tools. Writing essays and research papers remains the most common use case at both universities, but KAU students employ AI more extensively for solving assignments (38.6 %), creating presentations (39.1 %), preparing for exams (34.2 %), and collaborating on group projects (33.8 %).

4. Results

The analysis involved two stages: assessing the measurement model for reliability and validity, followed by evaluating the structural model to test hypotheses and examine relationships. Smart PLS-SEM V.4.1.1.2 software was used, providing valuable insights into how effectively the model explained the target constructs.

Step 1: Common method bias: The Harman's Single Factor Test was employed to evaluate common method bias through Principal Component Analysis. The findings indicated that the initial component accounted for a mere 29.48 % of the total variance, which is significantly below the 50 % threshold. This suggests that common method bias does not pose a substantial concern within this study, thereby reinforcing the validity of the data.

Step 2: Measurement model assessment (Outer Model): The measurement model underwent rigorous evaluation for reliability and validity, employing a variety of criteria: Variance Inflation Factor (VIF), reliability (Outer Loading, Cronbach's Alpha, Composite Reliability), convergent validity (Average Variance Extracted [AVE]), and discriminant validity (Fornell-Larcker and HTMT). The results are encapsulated in Tables 4–6 and are further illustrated through the outer loadings of the items depicted in Figs. 2–4.

Table 4 presents the results of the measurement model in this study, which demonstrates a high level of reliability and validity across all statistical indicators. For each university, ZU and KAU, as well as the overall sample, the key metrics (VIF, α, CR, and AVE) were carefully analyzed and compared.

Starting with the Variance Inflation Factor (VIF), values for ZU ranged between 1.554 and 2.612, indicating a low level of multicollinearity among variables. For KAU, values ranged from 1.276 to 3.176, also well below the accepted threshold of 5, though slightly higher than ZU on some items such as EB2, EB3, and US6. The overall sample reflected a balanced distribution, with VIF values ranging from 1.357 to 2.766, further confirming the absence of harmful collinearity

Table 4
Reliability and validity of the measurement model.

Variables	Items		Zayed University (ZU)				King Abdulaziz University (KAU)				Overall Sample			
			VIF	α	CR	AVE	VIF	α	CR	AVE	VIF	α	CR	AVE
Expected Benefits	**EB1**	GenAI tools have improved my academic writing skills (e.g., grammar, paraphrasing, formatting, information retrieval, gathering citations, facilitating literature searching & summarising readings).	1.724	0.891	0.913	0.569	1.293	0.844	0.880	0.501	1.418	0.863	0.893	0.512
	EB2	Using GenAI tools enables me to accomplish my academic assignments more quickly.	1.864				3.052				2.272			
	EB3	Using GenAI makes it easier to do my academic assignments.	2.280				3.176				2.490			
	EB4	Using GenAI tools improves the quality of my academic research outputs.	2.178				1.665				1.726			
	EB5	GenAI tools assist me more effectively in managing my study time.	2.087				1.841				1.897			
	EB6	GenAI tools have positively enhanced my overall learning experience through personalized and immediate feedback and suggestions for my assignments.	2.261				1.479				1.661			
	EB7	GenAI technologies such as ChatGPT improved my digital competence.	2.274				1.858				1.928			
	EB8	GenAI tools promote the development of communication skills (e.g., presentation skills).	1.894				1.559				1.656			
University Support	**US1**	The university library provides access to advanced GenAI tools and technologies as part of its educational resources.	1.554	0.855	0.892	0.580	1.971	0.884	0.909	0.628	1.816	0.878	0.908	0.624
	US2	The university offers workshops and training sessions on the effective use of GenAI tools.	1.852				1.460				1.354			
	US3	The university's online platform (such as Blackboard & Moodle) supports using GenAI tools for various academic activities.	2.119				2.230				2.167			
	US4	Faculty members effectively integrate GenAI tools into their teaching strategies.	2.450				2.649				2.766			
	US5	Faculty members show a supportive attitude towards the use of GenAI tools for solving assignments and academic projects.	1.870				2.416				2.242			
	US6	Faculty members provide clear guidance on how to use GenAI tools for academic assignments.	1.710				2.988				2.499			
Ethical Awareness	**EA1**	I recognize the responsibility to avoid unethical practices when using GenAI tools in my academic assignments.	2.094	0.886	0.911	0.596	1.692	0.855	0.889	0.536	1.864	0.882	0.908	0.586
	EA2	I verify the credibility of the content generated by GenAI tools.	1.645				1.769				1.658			
	EA3	I recognize that cultural differences should be taken into account when using GenAI tools.	1.673				1.812				1.777			
	EA4	I adhere to the highest ethical standards when using GenAI tools to complete academic tasks.	2.204				1.908				2.033			
	EA5	I recognize the importance of having clear guidelines on the ethical use of GenAI tools.	2.612				2.408				2.514			
	EA6	I recognize that leakage or privacy violations may occur when using GenAI tools.	1.819				1.732				1.753			

(*continued on next page*)

Table 4 (*continued*)

Variables	Items		Zayed University (ZU)				King Abdulaziz University (KAU)				Overall Sample			
			VIF	α	CR	AVE	VIF	α	CR	AVE	VIF	α	CR	AVE
	EA7	I understand that personal information should be protected when using GenAI tools.	2.204				1.878				2.043			
Technology self-efficacy	**TSE1**	I find GenAI tools easy to use.	1.884	0.849	0.893	0.625	1.835	0.806	0.865	0.564	1.840	0.823	0.876	0.587
	TSE2	Learning how to use GenAI in my study routine is easy for me.	2.195				2.043				2.075			
	TSE3	I update GenAI tools regularly.	1.603				1.400				1.450			
	TSE4	I have the ability to handle technical problems that may arise when using generative AI tools.	1.909				2.139				1.994			
	TSE5	I have access to the necessary technical resources to use GenAI tools effectively.	1.975				2.259				2.120			
Student Satisfaction	**SS1**	Having used GenAI tools, I am quite pleased with my academic performance.	1.705	0.854	0.891	0.577	2.140	0.831	0.878	0.548	1.873	0.836	0.880	0.552
	SS2	Having used GenAI tools, I am in the mood to study.	2.220				2.588				2.162			
	SS3	Having used GenAI tools, I tend to overindulge when studying.	1.922				1.276				1.357			
	SS4	Having used GenAI tools, I can handle the pressure of studying.	1.854				2.224				1.970			
	SS5	I feel that GenAI technologies are valuable instructional tools for my educational resources and information.	1.919				1.677				1.669			
	SS6	I am satisfied with the speed and efficiency of the GenAI tools available to me.	1.790				1.460				1.570			
Behavioural Intention	**BI1**	I intend to employ GenAI tools regularly in the future as an integral tool for my academic endeavours.	1.861	0.884	0.912	0.632	2.656	0.890	0.916	0.646	2.214	0.886	0.914	0.639
	BI2	I plan to explore newer GenAI tools.	2.047				1.968				1.977			
	BI3	I intend to recommend using GenAI tools for other students to help complete learning tasks.	2.430				2.154				2.262			
	BI4	I plan to continue to use GenAI going forward in my personal life frequently.	1.919				2.023				1.955			
	BI5	I am determined to increase my usage of GenAI tools in my studies.	2.196				2.713				2.396			
	BI6	I intend to renew my subscription to GenAI tools in the future.	1.894				1.625				1.699			

across the model.

Regarding Cronbach's alpha (α) values, ZU exhibited exceptional internal consistency, with values oscillating between 0.849 and 0.891 across all dimensions. The Alpha values for KAU ranged from 0.806 to 0.890, which similarly denotes robust internal consistency. The overall sample demonstrated similarly high reliability, with alpha values ranging from 0.823 to 0.886. These consistent results across both universities confirm that each sub-construct reliably measures its intended concept.

Looking at Composite Reliability (CR), ZU's values ranged between 0.891 and 0.913, comfortably above the acceptable minimum of 0.70. KAU showed a similar pattern, with CR values ranging from 0.865 to 0.916, indicating that the constructs are well-represented by their respective items. The overall sample maintained a comparable level of reliability, with CR values ranging from 0.876 to 0.914, reinforcing the consistency and structural soundness of the measurement model.

Finally, the Average Variance Extracted (AVE) values across all groups substantiate satisfactory convergent validity. At ZU, AVE values ranged from 0.569 to 0.632, while KAU reported AVE values between 0.501 and 0.646. Similarly, the overall sample showed AVE values ranging from 0.512 to 0.639. In all cases, the values exceeded the recommended threshold of 0.50, indicating that the latent constructs capture a substantial portion of variance from their indicators. This supports the notion of good convergent validity, where more than 50 % of the variance in each construct is explained by its associated indicators (Ramayah et al., 2018), thereby demonstrating a robust and reliable measurement model across both universities and the overall sample.

Tables 5 and 6 provide insights into discriminant validity based on the Furnell-Larker criterion and the Heterotrait-Monotrait (HTMT) ratio, respectively, for ZU, KAU, and the overall sample. Table 5 presents the Fornell-Larcker criterion values, where the square root of the Average Variance Extracted (AVE) for each construct (shown on the diagonal) should be greater than its correlations with other constructs (off-diagonal values), confirming discriminant validity (Hair et al., 2017). The results indicate satisfactory discriminant validity across both universities and the overall sample. For ZU, the square roots of the AVE values are as follows: BI (0.795), EA (0.772), EB (0.754), SS (0.759), TSE (0.790), and US (0.762). These diagonal values exceed their respective

Table 5
Discriminant validity (furnell larker criterion).

	BI	EA	EB	SS	TSE	US
Zayed University (ZU)						
BI	0.795					
EA	0.395	0.772				
EB	0.613	0.376	0.754			
SS	0.746	0.449	0.635	0.759		
TSE	0.635	0.453	0.632	0.683	0.790	
US	0.334	0.321	0.399	0.329	0.363	0.762
King Abdulaziz University (KAU)						
	BI	EA	EB	SS	TSE	US
BI	0.804					
EA	0.115	0.732				
EB	0.578	0.185	0.694			
SS	0.688	0.220	0.687	0.740		
TSE	0.416	0.469	0.465	0.534	0.751	
US	0.130	0.188	0.204	0.180	0.074	0.793
Overall Sample						
	BI	EA	EB	SS	TSE	US
BI	0.799					
EA	0.245	0.765				
EB	0.590	0.291	0.715			
SS	0.706	0.305	0.662	0.743		
TSE	0.506	0.452	0.544	0.593	0.766	
US	0.159	0.128	0.237	0.210	0.160	0.790

Table 6
Discriminant Validity Heterotrait-Monotrait (HTMT ratio).

	BI	EA	EB	SS	TSE	US
Zayed University (ZU)						
BI	–					
EA	0.434	–				
EB	0.677	0.416	–			
SS	0.837	0.497	0.712	–		
TSE	0.726	0.527	0.724	0.785	–	
US	0.372	0.369	0.453	0.372	0.418	–
King Abdulaziz University (KAU)						
	BI	EA	EB	SS	TSE	US
BI	–					
EA	0.161	–				
EB	0.658	0.244	–			
SS	0.801	0.274	0.821	–		
TSE	0.469	0.563	0.553	0.647	–	
US	0.139	0.227	0.236	0.199	0.133	–
Overall Sample						
	BI	EA	EB	SS	TSE	US
BI	–					
EA	0.274	–				
EB	0.667	0.331	–			
SS	0.815	0.347	0.776	–		
TSE	0.582	0.537	0.639	0.707	–	
US	0.177	0.160	0.271	0.244	0.187	–

inter-construct correlations, suggesting good discriminant validity. Notably, the highest correlations appear between BI and SS (0.746), BI and EB (0.613), and TSE and SS (0.683), but in all cases, the square root of the AVE remains higher, maintaining discriminant validity.

In the case of KAU, the square roots of the AVE are BI (0.804), EA (0.732), EB (0.694), SS (0.740), TSE (0.751), and US (0.793). These values also exceed the corresponding inter-construct correlations. The strongest correlations are seen between EB and SS (0.687) and BI and SS (0.688), yet these still remain below the square root of AVE values, supporting adequate discriminant validity. Interestingly, the correlations between EA and other constructs are generally weaker in the KAU sample than in ZU, suggesting different patterns of relationships.

For the overall sample, the AVE square roots again confirm validity: BI (0.799), EA (0.765), EB (0.715), SS (0.743), TSE (0.766), and US (0.790). The highest correlations observed are between SS and BI (0.706), SS and EB (0.662), and SS and TSE (0.593). Even in these cases, the square root of AVE for each construct remains larger than any of its correlations, affirming discriminant validity across the full sample.

The Fornell-Larcker analysis confirms that each construct is distinct from others within the model across both individual universities and the aggregated sample. The results provide strong support for the discriminant validity of the measurement model and justify the continued use of

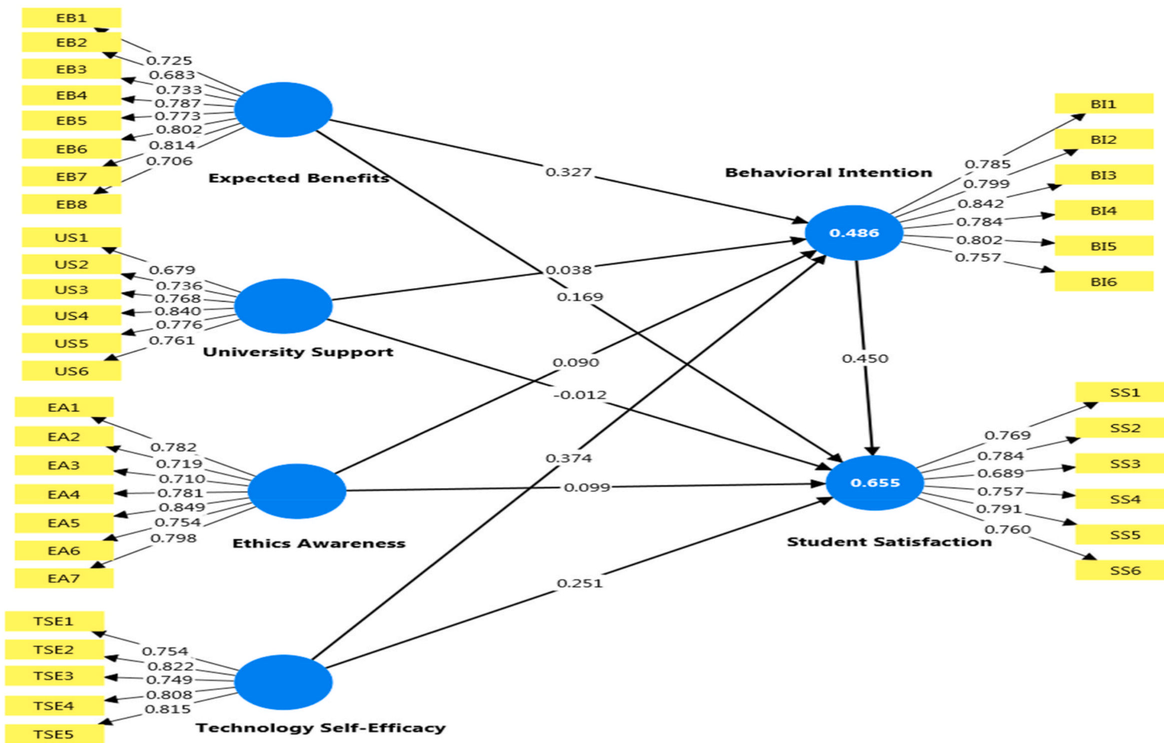

Fig. 2. Research measurement model (outer model)- ZU

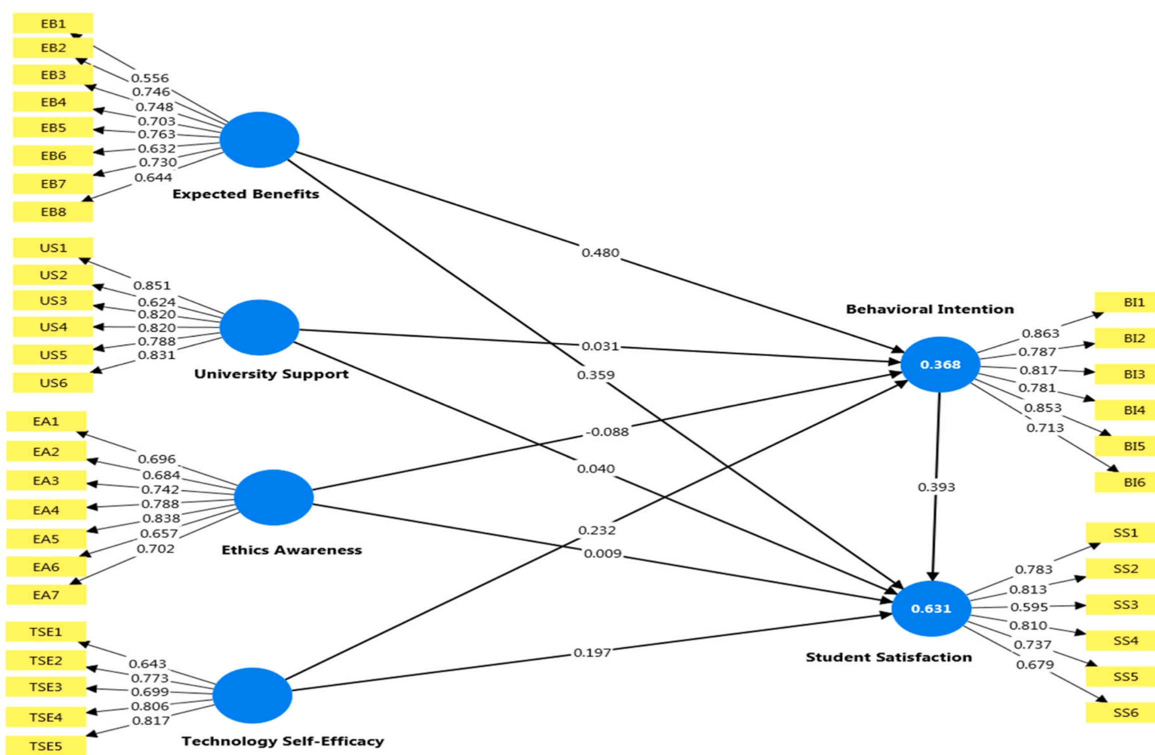

Fig. 3. Research measurement model- KAU

these constructs in subsequent structural modeling.

Table 6 (HTMT ratio) further supports the findings of discriminant validity. For ZU, the HTMT ratios for all pairs of constructs are well below the recommended threshold of 0.85 (Hair et al., 2017), confirming that the constructs are distinct from one another. The highest ratio observed is between BI and SS, which is 0.837. While this value is relatively high, it remains below the threshold of 0.85, indicating that the relationship between these two constructs is strong but does not suggest excessive overlap. This strong correlation could suggest a meaningful relationship, which could be explored further in future studies to understand how these variables interact within the academic context.

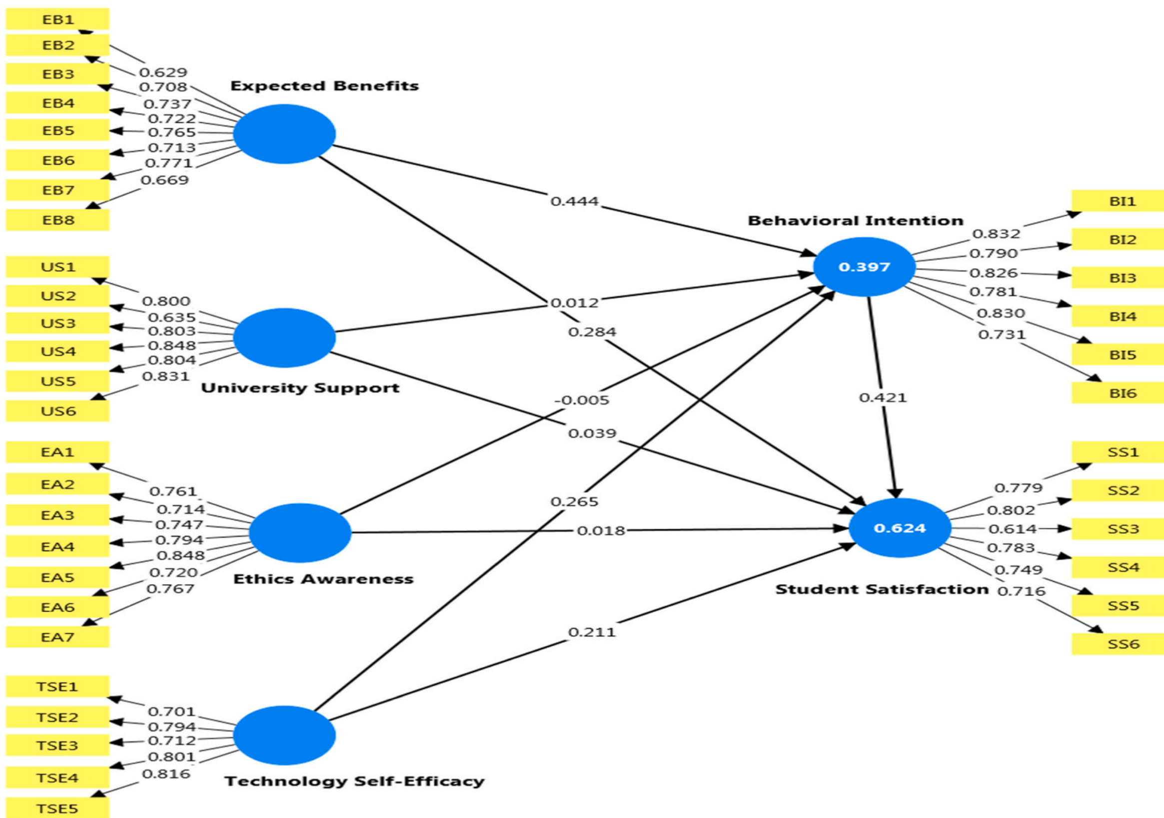

Fig. 4. Research measurement model (outer model)- overall sample.

Table 7
Coefficient of determination (R^2 Value).

Endogenous construct	Std. Beta	R^2 Value	Relationship
Zayed University (ZU)			
BI	0.486	48.6 %	substantial
SS	0.655	65.5 %	substantial
King Abdulaziz University (KAU)			
BI	0.368	36.8 %	substantial
SS	0.631	63.1 %	substantial
Overall Sample			
BI	0.397	39.7 %	substantial
SS	0.624	62.4 %	substantial

The HTMT values for KAU also demonstrate that the constructs are sufficiently distinct, as all HTMT ratios are well below the 0.85 threshold. The highest ratio is observed between EB and SS at 0.821, which again remains within the acceptable range. This value indicates a strong relationship between these two constructs, but like the results for ZU, does not imply that they are indistinguishable from each other. When considering the overall sample, the HTMT ratios also remain below 0.85 for all pairs of constructs. These findings collectively support the discriminant validity of the constructs across all groups in the study.

Figs. 2–4 display the reliability indicators in terms of outer loadings for both universities. Consistent with the guidelines by Hair et al. (2017, 2011), all item loadings exceeded the acceptable threshold of 0.50, indicating strong indicator reliability across both contexts. This is particularly important given that the Average Variance Extracted (AVE) values also surpassed the recommended 0.50 cutoff, reinforcing the

Table 9
Predictive relevance of the model (Q^2 value).

	ZU		KAU		Overall Sample	
	Q^2	Predictive Relevance	Q^2	Predictive Relevance	Q^2	Predictive Relevance
BI	0.450	Strong	0.343	Moderate	0.382	Strong
SS	0.521	Strong	0.514	Strong	0.503	Strong

Table 8
Effect size (f^2 value).

Construct	ZU		KAU		Overall Sample	
	f^2 Value	Effect Size	f^2 Value	Effect Size	f^2 Value	Effect Size
BI - > SS	0.301	Medium	0.264	Medium	0.285	Medium
EA - > SS	0.021	Small	0.000	No Effect	0.001	No Effect
EB - > SS	0.042	Small	0.205	Medium	0.119	Small
TSE - > SS	0.086	Small	0.062	Small	0.067	Small
US - > SS	0.000	No Effect	0.004	Very Small	0.004	Very Small

model's convergent validity. According to Hulland (1999, p. 198), if any item demonstrates a loading below 0.50, it should be excluded to maintain the integrity of the measurement model. However, in this study, no such exclusions were necessary, as all items met the required standards, thereby supporting the reliability and validity of the constructs across both samples.

Step 3: Structural model assessment (inner model): Following the evaluation of the measurement model, the structural model (inner model) was assessed to test the research hypotheses and examine the relationships between constructs. This step aimed to evaluate the strength, direction, and significance of these relationships through the analysis of path coefficients, R^2 values, and statistical significance, thereby enhancing understanding of the model's dynamics (Hair et al., 2019). In line with the guidelines of Chin (2010), Hair et al. (2011, 2013), and Ramayah et al. (2018), the evaluation incorporated key criteria such as the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and path coefficients alongside bootstrapping to assess the significance of the proposed paths.

Table 7 presents R^2 values for both ZU and KAU, as well as the overall sample. For ZU, the R^2 value for BI was 0.486, indicating that 48.6 % of the variance in BI is explained by the model, which is considered substantial. Similarly, the R^2 value for SS was 0.655, also reflecting a substantial level of explained variance. In comparison, KAU showed a slightly lower R^2 value for BI at 0.368, suggesting that 36.8 % of the variance in BI is accounted for by the model, while the R^2 value for SS was 0.631, still within the substantial range. When looking at the overall sample, the R^2 for BI was 0.397 and for SS was 0.624, both indicating substantial explanatory power. These results suggest that the model explains a stronger proportion of variance in both constructs at ZU compared to KAU, with the overall sample reflecting consistent, substantial levels of explanatory power across the key constructs.

Table 8 shows that BI had the strongest effect on SS across both universities, with a medium effect size in ZU (0.301), KAU (0.264), and the overall sample (0.285). EA had a small effect in ZU (0.021) but showed no effect in KAU and the overall sample. EB had a medium effect in KAU (0.205) and a small effect in ZU and the overall sample. TSE showed a consistently small effect across all groups, while US had no notable impact. These findings highlight BI as the most influential predictor of SS compared to other variables.

Table 9 presents the Q^2 values assessing predictive relevance. For ZU, both BI and SS show strong predictive relevance, with Q^2 values of 0.450 and 0.521, respectively. In KAU, BI demonstrates moderate predictive relevance (0.343), while SS maintains strong predictive power (0.514). Similarly, the overall sample reveals strong predictive relevance for both constructs, with Q^2 values of 0.382 for BI and 0.503 for SS. These results indicate that the model has substantial predictive capability across both institutions.

As shown in Figs. 5–7, nine hypotheses were formulated based on the research framework. The evaluation results are as follows.

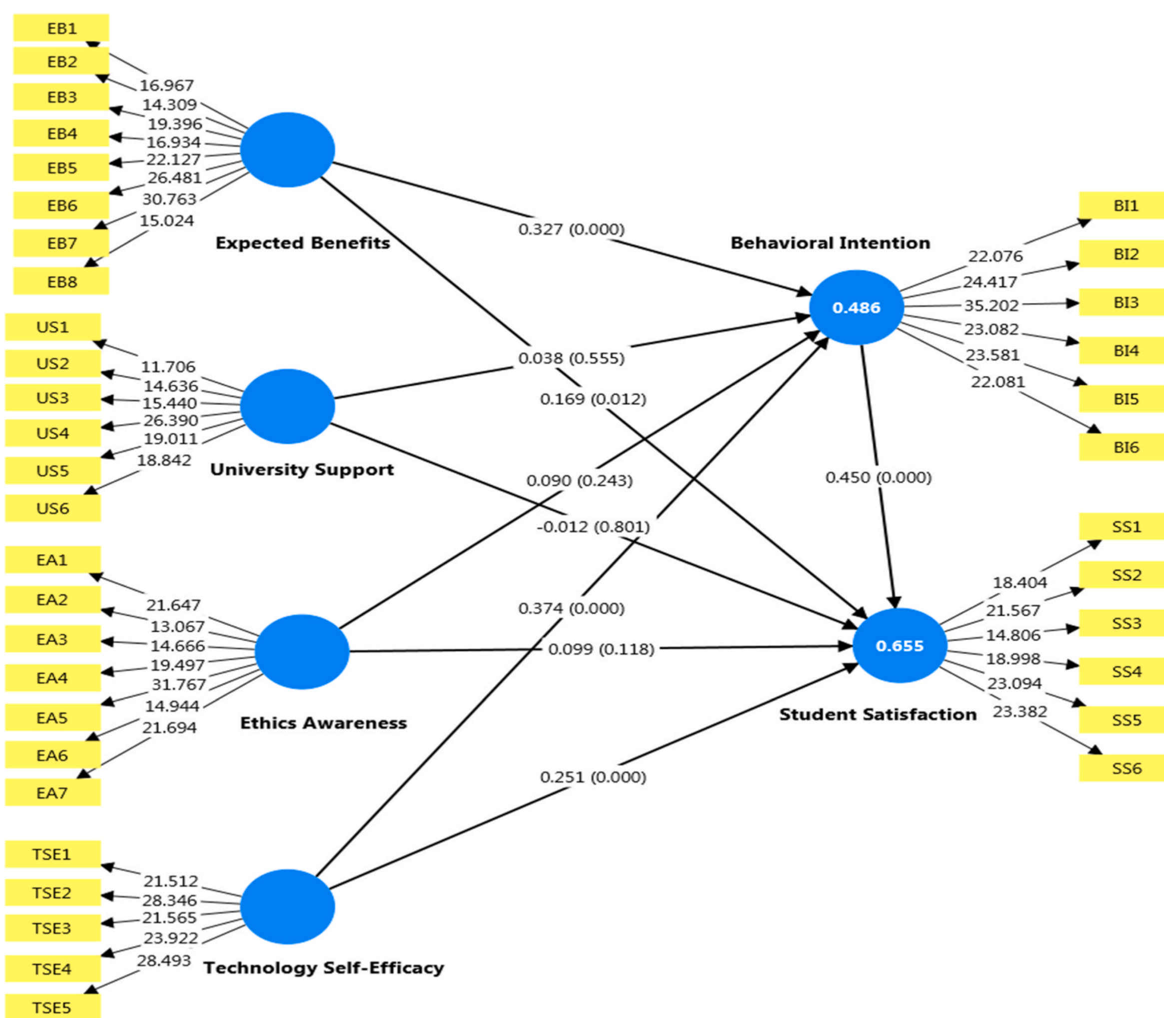

Fig. 5. Research structural model (inner model) - ZU

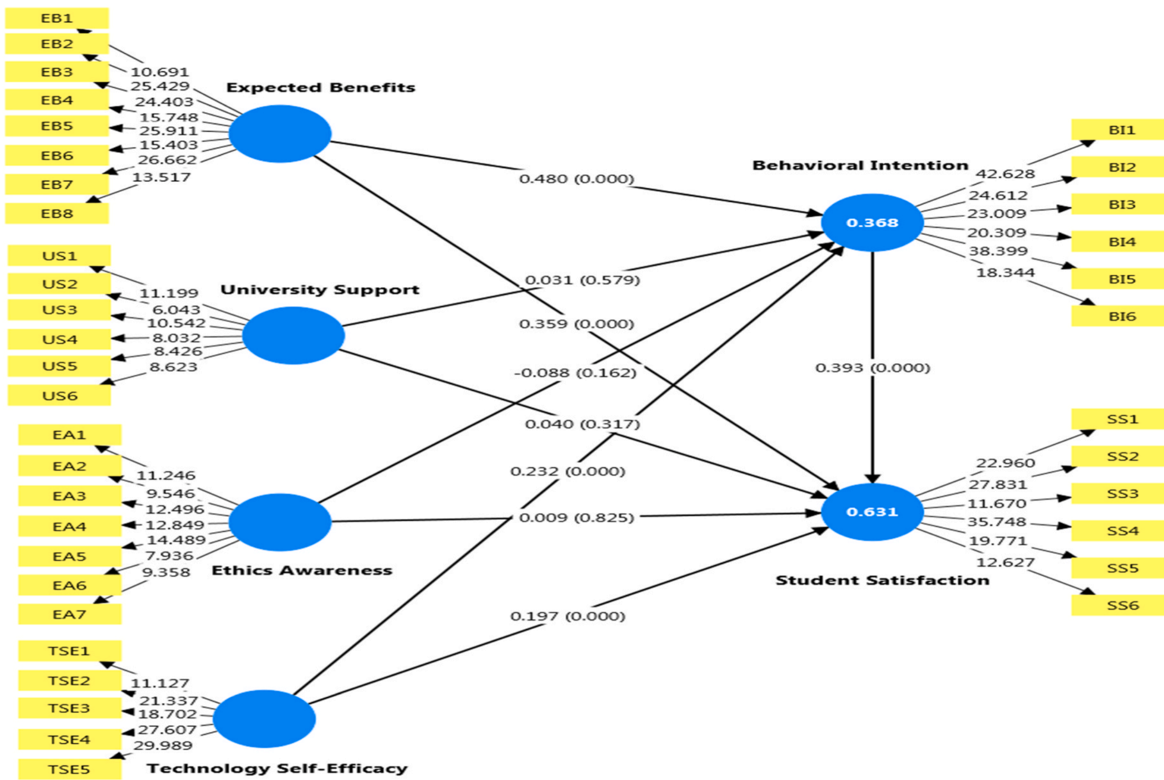

Fig. 6. Research structural model (inner model) - KAU

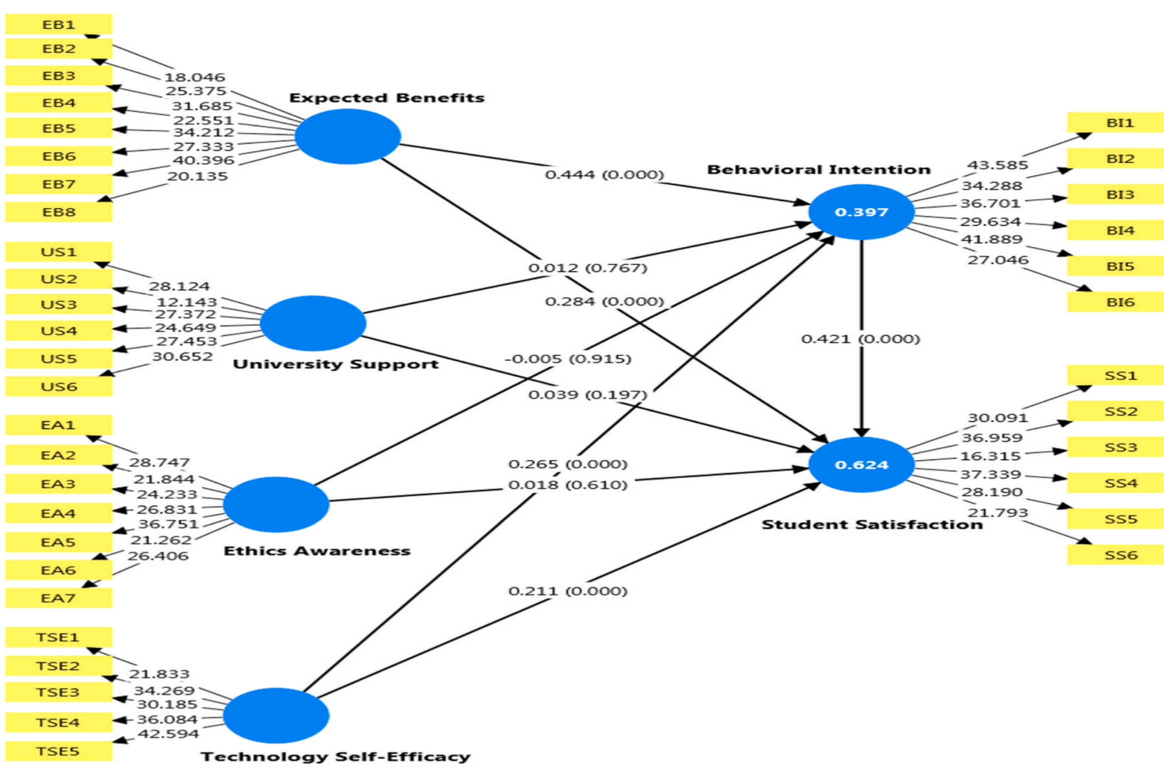

Fig. 7. Research structural model (inner model)- overall sample.

Table 10 presents the hypothesis testing outcomes, highlighting path coefficients, t-values, and p-values across both universities and the overall sample. The relationship between EB and SS is significant for both universities, with a stronger effect at KAU ($\beta = 0.359$, $p < 0.001$) compared to ZU ($\beta = 0.169$, $p = 0.012$), highlighting that KAU students are more strongly influenced by the perceived benefits of GenAI tools. The US path shows a negative effect on SS in both universities, but this effect remains statistically insignificant ($p > 0.050$), indicating no

Table 10
Hypotheses testing with path coefficients and significance levels.

Hypothesis	Path	Zayed University (ZU)			King Abdulaziz University (KAU)			Overall Sample		
		Std. Beta (β)	t	p	β	t	p	β	t	p
H1	**EB - > SS**	**0.169**	**2.518**	**0.012**	**0.359**	**6.761**	**0.000**	**0.284**	**6.494**	**0.000**
H2	**US- > SS**	**−0.012**	**0.252**	**0.801**	**0.040**	**1.002**	**0.317**	**0.039**	**1.289**	**0.197**
H3	**EA- > SS**	**0.099**	**1.565**	**0.118**	**0.009**	**0.221**	**0.825**	**0.018**	**0.510**	**0.610**
H4	**TSE- > SS**	**0.251**	**3.506**	**0.000**	**0.197**	**3.594**	**0.000**	**0.211**	**4.737**	**0.000**
H5	**EB- > BI- > SS**	**0.147**	**3.333**	**0.001**	**0.188**	**4.936**	**0.000**	**0.187**	**6.207**	**0.000**
H6	**US- > BI- > SS**	**0.017**	**0.580**	**0.562**	**0.012**	**0.540**	**0.589**	**0.005**	**0.295**	**0.768**
H7	**EA- > BI- > SS**	**0.040**	**1.108**	**0.268**	**−0.034**	**1.322**	**0.186**	**−0.002**	**0.106**	**0.916**
H8	**TSE- > BI- > SS**	**0.168**	**3.688**	**0.000**	**0.091**	**2.986**	**0.000**	**0.112**	**4.384**	**0.000**
H9	**BI- > SS**	**0.450**	**5.781**	**0.000**	**0.393**	**6.500**	**0.000**	**0.421**	**8.665**	**0.000**

substantial influence. Similarly, EA exhibits a weak and insignificant effect on SS at both institutions. However, TSE has a significant positive effect on SS, with a stronger influence at ZU ($\beta = 0.251$, $p < 0.001$) compared to KAU ($\beta = 0.197$, $p < 0.001$), suggesting that students with higher TSE are more satisfied with GenAI tools, especially at ZU. BI consistently shows a strong positive effect on SS in both universities ($p < 0.001$), with a slightly stronger effect at KAU ($\beta = 0.393$, $p < 0.001$).

Regarding mediation, BI mediates the relationship between EB and SS, as well as between TSE and SS. EB significantly positively affects BI, which in turn positively influences SS ($\beta = 0.147$ for ZU, $\beta = 0.188$ for KAU, $\beta = 0.187$ for the overall sample, $p < 0.001$). Similarly, TSE influences BI, which enhances SS ($\beta = 0.168$ for ZU, $\beta = 0.091$ for KAU, $\beta = 0.112$ for the overall sample, $p < 0.001$ for both ZU and KAU). However, BI does not mediate the effect of US or EA on SS, as their coefficients are small and their p-values exceed 0.05, indicating that these variables directly influence SS. Overall, BI plays a significant mediating role in the relationship between EB and SS, as well as TSE and SS, but its role is less prominent for US and EA.

5. Discussion and conclusions

The findings substantiate that Expected Benefits (EB) exert a substantial positive influence on Student Satisfaction (SS) at both Zayed University (ZU) and King Abdulaziz University (KAU), with a notably stronger effect observed at KAU. This supports Hypothesis 1, suggesting that while students at both institutions acknowledge the benefits of GenAI tools, the perceived value is more substantial at KAU. This discrepancy may stem from factors such as institutional support, cultural context, or the extent of GenAI integration into teaching practices. To enhance student satisfaction, it is essential for institutions, particularly ZU, to focus on increasing students' awareness of the practical benefits of GenAI tools. This can be achieved by incorporating these tools more effectively into teaching and providing tangible examples of their value. These findings highlight the critical role of institutional context in shaping students' perceptions of technology benefits. The stronger impact at KAU may reflect a deeper understanding or higher trust in GenAI tools, influenced by institutional practices or cultural factors that support technology integration. These findings align with Venkatesh et al. (2012), who assert that technology value perceptions influence adoption. Additionally, studies by Kishore et al. (2023) and Tian et al. (2024) indicate that students who perceive greater benefits from GenAI tools tend to report higher satisfaction. The relatively weaker impact at ZU might reflect limited experience or unmet expectations, as suggested by Marshall (2023) and Brill et al. (2022).

Contrary to Hypothesis 2, the US did not significantly influence SS at either ZU or KAU. This suggests that while institutional support exists, it may not be sufficiently personalized or aligned with students' actual needs when using GenAI tools. Instead, factors like perceived usefulness and ease of use may play a stronger role in shaping satisfaction. These findings contrast with prior research (e.g., Chen et al., 2020; Zouhaier, 2023), which highlights the importance of institutional infrastructure and training. However, the non-significant effect here may reflect a gap between institutional efforts and student expectations or limited engagement with GenAI tools. As seen in studies from Gomathi (2024) and Khan et al. (2024), even strong institutional intentions may fall short if infrastructure or support systems are underdeveloped. Thus, institutions should go beyond generic support by offering targeted, student-centred strategies that enhance actual usage and satisfaction.

The results do not support Hypothesis 3, as EA showed no significant direct or mediated effect on SS at either ZU or KAU. This suggests that while ethical considerations may shape students' attitudes towards the responsible use of GenAI tools, they do not directly influence their overall satisfaction with these tools in the learning context. One possible explanation is that students may prioritize functional and academic benefits of GenAI tools over ethical concerns when evaluating their satisfaction. While ethical awareness is crucial for guiding responsible behavior, its influence on satisfaction may be more indirect, perhaps affecting long-term attitudes rather than immediate experiences. This contrasts with studies like Yusuf et al. (2024), who argued that ethical training fosters responsible behavior and helps students recognize risks like academic dishonesty and bias, which could improve satisfaction. Similarly, Gomathi (2024) found that students with stronger ethical awareness were more satisfied, but also noted that ethical training alone doesn't guarantee effective GenAI integration. Other factors, such as infrastructure and hands-on experience, are also important. Williams (2024) highlighted that ethical awareness builds trust in AI systems, promoting responsible use. Furthermore, Wecks et al. (2024) found that ethical awareness leads to less academic dishonesty and better outcomes. Ultimately, the weak effect suggests that institutions should adopt a more holistic approach to integrating GenAI tools, combining ethical awareness with factors like infrastructure, institutional support, and practical exposure to fully enhance student satisfaction. Further research is needed to explore how ethical education interacts with variables like technical knowledge and prior experience to influence student outcomes in AI tool adoption.

The findings support Hypothesis 4, showing that students' TSE has a significant positive impact on their satisfaction with GenAI tools across both ZU and KAU. This suggests that students who feel more confident in their ability to use technology are more likely to engage with GenAI tools effectively and feel satisfied with their learning experience. These results align with prior research, which highlights the importance of TSE in shaping students' engagement with technology. Ajzen's (2002) concept of Perceived Behavioral Control (PBC), alongside Bandura's (1983) Self-Efficacy Theory posits that individuals exhibiting elevated self-efficacy demonstrate greater confidence in the utilization of novel tools. Chai et al. (2021) and Gomathi (2024) confirmed that higher TSE leads to better use of GenAI tools and greater satisfaction. Similarly, Black (2024), Bouteraa et al. (2024), and Du and Lv (2024) found that students with strong TSE engage more with GenAI, leading to better academic outcomes. Further, Kishore et al. (2023) and Bates et al. (2020) emphasized that higher TSE correlates with increased academic engagement and performance. Wecks et al. (2024) showed that fostering TSE enhances student participation with technology, while Yildiz (2018) demonstrated its influence on students' readiness for innovative learning models like GenAI. These findings underline the crucial role of TSE in enhancing student satisfaction with technology.

The results support H5, indicating that BI partially mediates the relationship between EB and SS. This means that students who perceive more benefits from GenAI tools are more likely to intend to use them, which in turn contributes to higher satisfaction. This supports models like the Technology Acceptance Model (TAM), emphasizing that intention is a key step between perception and satisfaction. This finding aligns with Ajzen's (1991) Theory of Planned Behavior (TPB), which positions BI as a critical mediator between external factors and behavioral outcomes. It is also consistent with Dhaha and Ali (2014), who found that perceived benefits positively influence BI, which subsequently enhances satisfaction. These results underscore the importance of not only recognizing the advantages of GenAI tools but also converting this recognition into a concrete intention to use them.

Hypothesis 6. is not supported, as BI did not significantly mediate the relationship between US and SS. This suggests that institutional support alone, even if present, does not significantly influence students' intention to use GenAI tools, nor their resulting satisfaction. The lack of effect may stem from a disconnect between the type of support provided and students' actual needs or from limited visibility or accessibility of that support. This contradicts previous research by Wecks et al. (2024), which emphasized that institutional support fosters BI, thereby improving satisfaction. However, the result aligns with Hoang and Dang (2021), who argued that in some cases, institutional or motivational support may exert a direct influence on satisfaction without being mediated by BI. This discrepancy may be due to a misalignment between the support provided by universities and the specific needs or expectations of students regarding GenAI tool usage.

Similarly, the findings do not support H7, as EA did not significantly influence SS through BI. While ethics are important in framing responsible use, they may not play a strong motivational role in students' intention to use GenAI tools. Students might value ethical awareness in theory but prioritize practical and academic outcomes when deciding whether to use such technologies. This stands in contrast to Wong et al. (2024), who found that ethical considerations shape trust and BI, ultimately enhancing satisfaction. Nevertheless, the current result is somewhat in line with Gomathi (2024), who suggested that EA may exert a more direct influence on satisfaction, bypassing BI altogether. The limited role of EA in this study may reflect students' tendency to prioritize practical utility over ethical concerns when assessing satisfaction with AI tools.

The results support H8, showing that BI significantly mediates the relationship between TSE and SS. Students with greater confidence in their tech skills were more likely to intend to use GenAI tools, leading to higher satisfaction. This finding supports the self-efficacy theory and aligns with prior research by Zhang et al. (2019) and Budu et al. (2018), who found that students with higher TSE were more likely to adopt educational technologies and experience satisfaction as a result.

H9 was strongly supported, confirming that students' BI to use GenAI tools has a significant and positive direct effect on SS. This finding is in line with TAM and UTAUT models, where BI is a central determinant of technology acceptance and satisfaction. It also supports findings by Zhang et al. (2019) and Chai et al. (2021), who emphasized the predictive power of BI in shaping students' satisfaction and learning outcomes.

6. Implications

6.1. Theoretical contributions

This study makes a significant contribution to understanding how teaching and learning adapt to the integration of GenAI tools, an area that has not been widely explored in existing literature. By analyzing the roles of TSE, BI, EB, US, and EA the study reveals how these variables interact and influence SS within the context of GenAI. An essential theoretical advancement of this study is the elaboration of Ajzen's Theory of Planned Behavior (TPB), emphasizing the mediating function of Behavioral Intention (BI). The study reveals that BI serves as a critical bridge between students' perceptions of TSE, EB, US, and EA, and their satisfaction with GenAI tools. This finding underscores the significant role of behavioral intention in shaping students' engagement with GenAI and ultimately influencing their academic satisfaction. Moreover, the study explores the role of university support, revealing that while institutional support (US) did not show a direct effect on SS, it remains an essential consideration. This finding calls for more targeted and visible support systems that are seamlessly integrated into the pedagogical process. Additionally, the study emphasizes the importance of adopting a holistic approach to student development, combining technological proficiency with motivation, self-confidence, and ethical considerations. By comparing the experiences of students at ZU and KAU, the study offers valuable insights into how institutional context, including the US and EA, shapes students' adoption of GenAI tools. These findings provide actionable guidance for educational institutions aiming to foster innovative teaching practices and create an engaging learning environment that enhances student satisfaction.

6.1.1. Integration with educational theories and pedagogies

The study's findings offer valuable insights when interpreted through key educational and behavioral theories. The significant role of EB and TSE in shaping both BI and SS aligns with Vroom's Expectancy Theory (Vroom, 1964), which posits that motivation to engage with a task is influenced by perceived value and confidence in performance. Students who perceive tangible academic benefits and believe in their ability to use GenAI tools are more likely to adopt them and experience greater satisfaction. This reinforces the importance of expectancy and instrumentality in digital learning environments. The non-significant effect of the US on SS challenges assumptions rooted in Cohen and Wills' Social Support Theory (Cohen and Wills, 1985), which emphasizes the buffering effect of support systems. This discrepancy suggests that institutional support, when not strategically designed or well-targeted, may fail to significantly enhance academic satisfaction. This highlights the need for more student-centred, proactive support structures that are integrated into the learning experience. With regard to EA, while it did not show a direct or mediated influence on SS, its theoretical relevance remains crucial. MacIntyre's Theory of Ethical Responsibility (MacIntyre, 1984) underscores the importance of ethical reflection in meaningful engagement. The weak impact of EA may reflect a gap between theoretical ethical awareness and its practical application in students' daily use of GenAI tools, suggesting that ethics education needs to move beyond theoretical knowledge to incorporate experiential, case-based learning that is directly aligned with students' academic needs. The strong influence of TSE on BI and SS validates Bandura's Self-Efficacy Theory (Bandura, 1983), emphasizing that perceived capability is a central driver of digital engagement. Students who feel confident in their ability to use GenAI tools are not only more likely to adopt them but also derive greater satisfaction. This reinforces the importance of pedagogies that foster digital confidence through hands-on learning and scaffolded experiences. Finally, the Theory of Planned Behavior (TPB) (Ajzen, 1991) remains a robust framework throughout this study. BI plays a crucial mediating role between key predictors (EB, TSE) and SS, supporting TPB's claim that intention is the immediate predictor of behavior. However, the partial or non-significant mediation observed with US and EA suggests that TPB could be complemented with additional theoretical frameworks, such as social support or ethical responsibility, to fully explain the dynamics of technology adoption in educational settings.

6.2. Managerial implications

From a managerial perspective, this study shows that the use of

GenAI tools can significantly enhance student satisfaction by improving the quality and effectiveness of education. By creating intelligent learning environments that support personalized interactions and technological skill development, educational institutions can increase student engagement and participation. Moreover, GenAI tools can serve as strategic assets in refining teaching strategies, thereby positively impacting students' academic perceptions and satisfaction. Higher education institutions ought to emphasize the incorporation of artificial intelligence technologies as an integral component of their strategic framework to enhance academic performance and student satisfaction. This focus on GenAI tools contributes to more effective educational practices, fostering student success and long-term satisfaction. Additionally, a holistic approach is essential to improve students' technical proficiency, motivation, and willingness to use these tools. To maximize the potential of AI, universities must implement training programmers for both students and faculty, including workshops, seminars, and collaborations with tech companies. This comprehensive approach ensures innovative and effective integration of GenAI tools, fostering continuous academic success and long-term satisfaction.

7. Limitations and future lines of research

This investigation presents several constraints that must be acknowledged when analyzing the findings and delineating prospective research trajectories. Firstly, the inquiry was executed within the confines of merely two academic institutions, which may restrict the applicability of the results to other educational paradigms characterized by distinct cultural and educational frameworks. To augment the validity of the outcomes, forthcoming investigations could encompass a more extensive array of universities representing diverse cultural and educational contexts, thereby facilitating a more profound comprehension of the ramifications of generative AI instruments across a variety of educational landscapes.

Secondly, although this study examined a specific set of variables, there exist a multitude of additional elements that may affect students' satisfaction and engagement with generative AI tools. Factors such as the interaction between teaching methods and technology use and the socio-economic status of students, may significantly affect the outcomes. These variables should be explored in future research to provide a more comprehensive understanding of the factors that shape student's experiences with GenAI tools. Third, the study did not delve into the interaction between GenAI tools and other technologies, such as augmented reality (AR) or machine learning. It is plausible that integrating GenAI tools with other advanced technologies may have a unique impact on educational outcomes, offering an exciting area for future exploration. Researchers could investigate how the combination of these tools' influences learning processes and student engagement. Another limitation of this study concerns the potential influence of institutional differences, including factors like curriculum design, academic specialization, school facilities, and faculty characteristics. These differences could have contributed to variations in the study's results. Although efforts were made to account for these factors, future studies should consider employing controlled sampling or case studies to better isolate the effects of institutional differences. Furthermore, the demographic and contextual differences between the two participating universities (ZU and KAU), such as gender ratios and the distribution of undergraduate and graduate students, suggest potential avenues for investigating how such factors influence the adoption of AI tools in different academic settings.

A further limitation is the potential self-selection bias in the sample. Students with a pre-existing interest in AI may have been more inclined to participate in the survey. Despite efforts to distribute the survey across various academic disciplines, the sample may not fully represent the broader student population. Future research should consider using probability sampling or stratified sampling to ensure a more balanced representation of students, particularly those with varying levels of familiarity with AI. Additionally, this study did not examine students' prior exposure to AI education in detail, such as whether they had studied AI in formal coursework, the duration of their studies, or their familiarity with AI tools. Future studies could integrate more detailed measures of prior AI exposure to assess how structured AI education influences students' perceptions and adoption of generative AI tools.

Finally, this investigation did not take into account the longitudinal consequences of the utilization of AI tools on students. A longitudinal study would be beneficial to track the impact of generative AI tools over time, examining how students' attitudes, skills, and academic performance evolve as they continue to engage with these tools. This would provide deeper insights into how AI adoption influences students' academic and professional trajectories in the long run. While this study provides valuable insights into the use of generative AI tools in higher education, future research should address the limitations mentioned above. By expanding the sample to include a more diverse range of institutions, considering additional variables, and exploring the integration of AI tools with other technologies, researchers can further enrich our understanding of how AI is shaping the educational landscape.

Statements on open data and ethics

This study was approved by an ethical committee with ID: ZU24_089_F. Informed consent was obtained from all participants, and their privacy rights were strictly observed. The data can be obtained by sending request e-mails to the corresponding author.

CRediT authorship contribution statement

Dina Tbaishat: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Ghada Amoudi:** Writing – review & editing, Resources, Investigation, Data curation. **Maha Elfadel:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis.

Availability of data and material

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT (OpenAI), scispace, Quillbot AI, and Grammarly in order to improve the clarity, grammar, and readability of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no competing interests.

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