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Does the use of Generative AI contribute to university students' engagement or disengagement in their studies? Examining the antecedents of fear of missing out, perceived ease of use, and perceived usefulness.

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Abstract
While GenAI has demonstrated numerous advantageous effects in education, there are still some concerns regarding the benefits of GenAI on student engagement. This research addresses this gap by thoroughly examining the distinctive impact of novel GenAI on both student engagement and disengagement in the classroom. The study focuses on first-year and second-year students from the European University of Lefke, with a total of 250 usable responses collected, representing an 81.7% response rate out of 306 questionnaires distributed to registered students. Utilizing SmartPLS software version 4.32, the data analysis employed the partial least squares structural equation modelling (PLS-SEM) technique to scrutinize the proposed hypothesized model. The results of the analysis shed light on the research questions, revealing that students can simultaneously experience both engagement and disengagement in classroom activities due to the improper use of GenAI. This study enhances our understanding of the complex relationship between GenAI adoption, student engagement, and educational outcomes, offering valuable insights for educators and policymakers alike.

Keywords
GenAI, Fear-of-Missing-Out, Student Engagement, Classroom Disengagement, Perceived Usefulness, Perceived Ease-of-Use, Student Satisfaction.

1. Introduction

The significance of student engagement in promoting learning and academic performance in higher education is commonly acknowledged, leading to extensive study and theoretical exploration in this area (Bond et al., 2020; Ferrer et al., 2022). Student engagement pertains to the level of optimism, attention, interest, curiosity, and motivation that learners manifest regarding their studies (Khaleel et al., 2020). This is not limited to superficial learning, such as memorizing content and meeting minimum requirements to pass a course. Instead, it involves deep thinking activities like analyzing, understanding materials, applying them to solve problems, and deriving meaning. Additionally, it requires social interaction between learners and teachers, where they exchange experiences, perspectives, and encouragement. Regardless of the content or the teaching methods, effective teaching and learning depend on students' engagement (Lee et al., 2019). Academics support the idea that engaged students are more likely to enhance their academic performance, including their grades and critical thinking abilities. Furthermore, they can utilize the knowledge they acquire in real-world situations (Lee et al., 2019).

There is a proliferation of studies dedicated to the utilization of digital technologies, especially generative AI (GenAI) chatbots, to improve learners' engagement and learning outcomes in higher education. An AI chatbot is software that makes use of natural language processing (NLP) and semantic analysis to communicate with users through text or voice, assimilate their requests, and provide immediate responses based on its training data and algorithms (Adamopoulou & Moussiades, 2020). Li and Xing (2021) suggested that using chatbots in education can have advantages, including offering students a platform for continuous study and asynchronous conversation. This characteristic has been proven to positively impact student engagement, as it promotes a learner-centered studying environment by enabling students to ask questions and participate in friendly conversations without any constraint of time or geographical position (Cotton et al., 2023). Chang et al. (2021) proposed that chatbot-powered learning has a significant likelihood of increasing students' engagement as learners tend to be more open to studying in a learner-centered environment. Several academics have suggested that teachers typically lack the time necessary to satisfy each student's unique demands (Collinson & Cook, 2001; Hao, 2019). Additionally, students have limited chances to speak with teachers in class and even less so after class when they need assistance, which can lead to disengagement. Therefore, finding a tool that enables students to complete learning assignments independently is essential (Chang et al., 2021). Chatbots are such potential tools for supporting adaptable studying, personal studying success, and self-confidence (Chen et al., 2023). Lee et al. (2022) investigated how an AI-based chatbot can be used to help students with their after-class review process for consolidating knowledge and understanding the subject content. They have proven that the use of chatbots in the review process facilitates learning engagement by helping students feel recognized and establishing a relaxing and friendly interaction, thereby improving their academic performance. Okonkwo and Ade-Ibijola (2021) argued that these days, students prefer learning through online platforms and using their smart devices to access information rather than traditional textbooks or course materials. Chatbots create a comfortable and enjoyable atmosphere for studying. They also noted that learning with a conversational tool is more convenient and interesting for students, and the use of chatbots in education can lead to increased student engagement. Hamam (2021) also highlighted numerous advantages of incorporating chatbots into higher education, including enhancing and personalizing the educational experience, particularly in classes with a large number of students.

There are several GenAI tools available to students today. These include Microsoft's Bing Chat (now integrated as Microsoft Copilot), launched in February 2023; Alphabet's Bard, rebranded as Google Gemini in February 2024; Baidu's Ernie Bot, introduced in March 2023; Claude by Anthropic, released in March 2023; Perplexity AI, launched in August 2022; You.com launched in November 2021, DeepSeek-V2, released in May 2024; and OpenAI's ChatGPT, debuted in November 2022. ChatGPT, short for Conversational Generative Pretrained Transformer, stands out as one of the most remarkable among them. ChatGPT uses deep learning algorithms to generate human-like responses to text-based prompts, making it capable of holding natural language conversations with humans. ChatGPT by OpenAI has been trained on a massive database, including books, articles, and websites, and has the ability to learn and generate responses on a wide range of topics in multiple languages. ChatGPT has garnered a lot of attention and has achieved a record-breaking milestone by becoming the fastest-growing consumer internet application in history, reaching 100 million monthly active users as of January 2023, just two months after its release (Hu, 2023).

Despite the numerous proven advantageous effects of chatbots in education, there seems to be disagreement regarding the inherent advantages and subsequent benefits of GenAI chatbots with regard to students' engagement. The new generation's sophistication and open access have triggered both skepticism and excitement. To start, unlike other AI chatbots that repeat responses to generic questions, New GenAIs can understand context and are generative, which means they can produce "original" human-like content based on a variety of inputs (Miller et al., 2022). For example, ChatGPT has 175 billion parameters; with this level of complexity, the chatbot defies formulaic, scripted responses (Graham, 2022). Lastly, most of these new GenAI's have a free plan, removing the financial blockage that restricts students' access to other AI tools. Their usage may then be difficult to control and can result in significant practical and ethical issues, as highlighted by Basic et al. (2023). Some educators contend that by relying too heavily on these technologies, students risk losing the ability to think critically and solve problems effectively, both of which are essential for success in their future professional lives (Lo, 2023; Bai et al., 2023; Sallam et al., 2023a; Tlili et al., 2023). Others contend that by offering tailored learning experiences and encouraging autonomous study, GenAI's can actually increase student engagement (Guo & Lee., 2023; Kostka & Toncelli, 2023; Rudolph et al., 2023a).

In light of the limited attention given to students' perspectives in existing studies, this research endeavors to fill a crucial gap by thoroughly examining the peculiar impact of novel GenAI on student engagement, classroom disengagement, learning performance and satisfaction. An in-depth exploration of students' perceived ease of use and perceived usefulness is essential to gaining a comprehensive understanding of its implications. Given the influential role that students play in shaping educational outcomes through their engagement, their viewpoints become paramount. With regards to the research questions posed, it prompts an exploration into the potential scenario wherein students may concurrently experience both engagement and disengagement during classroom activities. Therefore, this study seeks to provide valuable insights into the distinctive effects of GenAI on students' engagement, acknowledging the potential implications for learning outcomes and overall satisfaction. The hypotheses outlined further underscore the critical need to delve into these unexplored dimensions, aiming to contribute significantly to the existing body of knowledge in the field of educational technology.

2. Literature Review

Exploring the Influence of Perceived Ease of Use and Perceived Usefulness on the Actual Use of GenAI.

The utilization of generative AI (GenAI) in education has emerged as a noteworthy subject of interest due to its potential to shape the dispensation and acquisition of knowledge (Lo, 2023). The perception of technology as easy to use plays a substantial role in its acceptance (Sugandini et al., 2018). The factor of ease of use contributes to individuals' perceptions of self-efficacy, thereby increasing the likelihood of embracing the technology. Furthermore, the perceived ease of use influences the effectiveness of responses, as people are more inclined to utilize technology that they find easy to use (Vaportzis et al., 2017).

Sallam et al. (2023b) extensively examined the concept of perceived ease of use in relation to ChatGPT. They conducted a survey including the four TAME-ChatGPT usage sub-scales, one of which was the perceived ease of use sub-scale. In terms of the perceived ease of use sub-scale, participants were asked to rate their perception of ChatGPT's ease of use on a scale ranging from 2 to 10, where higher scores indicated a greater perceived ease. The study sample reported a high level of user-friendliness for ChatGPT. Importantly, there were no statistically significant differences observed among various factors, including age, gender, nationality, university, and educational level. This indicates that individuals across different demographics had a consistent perception of ChatGPT's ease of use.

It is worth emphasizing that perceived ease of use and perceived usefulness are closely interconnected. These two factors work together to influence the adoption of technology. When individuals perceive technology as both easy to use and beneficial, it strengthens their motivation to adopt and effectively utilize the technology (Granić 2022). The survey conducted by Sallam et al. (2023b) included the perceived usefulness as one of the four sub-scales. Participants were asked to rate their perception of ChatGPT's usefulness on a scale ranging from 6 to 30, with higher scores indicating greater perceived usefulness. A score of 18 represented a neutral attitude. The average score for perceived usefulness was 24.2 ± 4.9, indicating that participants who had prior experience with ChatGPT highly perceived it as useful. Notably, there were no statistically significant differences observed based on the control variables.

Chan and Hu (2023) had similar results with a survey conducted among 399 undergraduate and postgraduate students from various academic disciplines in Hong Kong. The findings indicate a generally positive attitude towards ChatGPT's role in teaching and learning. Students acknowledge its potential for personalized learning support, assistance with writing and brainstorming, as well as research and analysis capabilities. In particular, students place a significant emphasis on the perceived usefulness of ChatGPT in terms of offering valuable insights. MacNeil et al. (2022) recently utilized GPT-3 to generate explanations for code. Although there are still unanswered research and pedagogical questions that require further investigation, this work successfully demonstrated the potential of GPT-3 in supporting learning by providing explanations for code snippets. Therefore, we hypothesized that:

H1 : Perceived Ease of Use positively influence Actual Use of GenAI.

H2 : Perceived Usefulness positively influence Actual Use of GenAI.

Fear-of-Missing-Out and Actual Use of GenAI.

The fear of missing out (FoMO) can be described as a persistent concern that others are having better or more valuable experiences, leading to a constant urge to stay connected with people. Initial investigations into the occurrence of FoMO revealed that approximately seventy five percent of young adults acknowledged experiencing this phenomenon (Anastasya et al., 2022). Przybylski et al. (2013) exploration of the phenomenon, they draw upon the Self-Determination Theory (SDT) developed by Deci and Ryan (2001). According to this theory, FoMO is an indication of poor self-regulation resulting from prolonged unmet psychological needs. Furthermore, the SDT theory explains how fulfilling three basic psychological needs – competence, autonomy, and connectedness – can significantly impact self-regulation and psychological well-being. Essentially, the concept of FoMO, when viewed through the lens of SDT, highlights the prolonged deprivation of these essential psychological needs, influencing one's ability to self-regulate and maintain psychological health over time.

Given the aptness of GenAI's to provide personalized assistance in education, the Fear of Missing Out (FoMO) experienced by students is a relevant factor to consider, especially in relation to the first basic psychological need of competence. FoMO can arise when students perceive that their peers or classmates are utilizing ChatGPT or similar tools to access information, receive instant feedback, or enhance their learning experiences. Students may fear that by not using these tools themselves, they may miss out on valuable resources, opportunities for personalized learning, or academic advantages that their peers may gain (Qutishat and Abu Sharour, 2019). To date, there is a gap in the literature concerning students' FoMO and how it can affect students' adoption of GenAI's in higher education. Therefore, the authors hypothesized that:

H3 : Fear-of-Missing-Out positively influence Actual Use of GenAI.

The effect of GenAI Usage on Student Engagement.

The advancement of generative artificial intelligence prompts a reevaluation of the teaching-learning process, given its influence on the trajectory of adaptive education. Incorporating generative artificial intelligence tools to boost student engagement signifies a novel and promising strategy for meeting the changing demands of contemporary education (Ruiz-Rojas et. al., 2023). These tools harness extensive datasets and machine learning algorithms to customize students' learning experiences, tailoring instruction to their unique needs and preferences (Rudolph et al., 2023b). Through the analysis of a student's strengths, weaknesses, and performance patterns, GenAI can offer personalized feedback and recommend specific study materials or exercises. Moreover, the integration of GenAI techniques into the educational landscape not only enhances the assessment of students' progress but also plays a crucial role in fostering heightened student engagement. Salinas-Navarro et al. (2024) delve into the nuanced challenges associated with the utilization of ChatGPT, exploring the viewpoints of both educators and students. Their study sheds light on a spectrum of concerns ranging from academic integrity and the credibility of ChatGPT-generated content to digital safety, biases inherent in AI systems, and the potential impact on traditional and online assessment methods. Moreover, the authors stated the potential ramifications for critical thinking skills. They advocate for the responsible integration of AI technologies into educational frameworks, emphasizing the need for strategic recommendations to ensure that technological advancements uphold educational standards and cultivate a secure learning environment. GenAI tools serve as invaluable resources for unpacking pedagogical theories, offering an abundance of precise definitions, in-depth explanations, and practical applications from various angles. These insights hold great potential for educators and learners alike, enabling them to enhance the quality of student-centered learning experiences (Salinas-Navarro et al., 2024). It's worth noting that each GenAI tool brings its own unique perspectives, depth of understanding, and strengths to the forefront. While ChatGPT 3.5 shines in delivering comprehensive explanations spanning definitions, principles, and practical advice, Google Bard emphasizes the application of theories in real-world scenarios. New Bing focuses on clarifying theories and concepts with precision, while Anthropic Claude emphasizes the elucidation of goals and principles. Based on the insights from the literature, we have formulated this hypothesis:

H4 : Actual Use of GenAI positively influence Student Engagement.

The effect of GenAI Usage on Classroom Disengagement.

While AI has the potential to enhance learning efficiency, it also introduces a more transactional aspect to education. With the rise of GenAI and technological advancements, the path of strategic disengagement becomes even more accessible to students. GenAI becomes a perfect toolkit for students whose primary goal is to attain a degree with minimal investment. AI-driven tools streamline the learning process, potentially reducing it to a series of optimized steps designed to achieve a degree with minimal effort. This ease of achieving results might tempt students to disengage, prioritizing other values and activities over academic immersion. Tools promising enhanced learning may, in some instances, deepen the divide between education as a transformative journey and education as a mere transaction. Some studies have investigated the extent to which GenAI tools can complete university assignments. According to Katz et al. (2023), GPT-3 successfully passed the United States Bar Exam, a rigorous assessment typically completed after seven years of post-secondary education. A more recent study reported that GPT-4 performs notably better than human test-takers, showing a substantial 26% improvement compared to GPT-3 and outperforming humans in five out of seven subject areas. Kung et al. (2023) conducted a study to evaluate the performance of ChatGPT on the United States Medical Licensing Exam. The evaluation results showed that ChatGPT performed at or above the passing threshold on the exam without any domain-specific fine-tuning. However, concerns have emerged regarding the unintended consequences of GenAI usage on classroom disengagement among students. One argument posits that the overreliance on AI-generated content may diminish students' intrinsic motivation and critical thinking skills, leading to passive consumption rather than active engagement in the learning process (Washington, 2023; Michel-Villarreal et al., 2023). As students become accustomed to receiving pre-generated responses and content from AI-driven tools, they may exhibit reduced interest and enthusiasm for classroom activities, contributing to disengagement and disconnection from the learning experience. Therefore, the authors hypothesized that:

H5 : Actual Use of GenAI negatively influence Classroom Disengagement.

The effect of Student Engagement on Student Learning Performance and Student Satisfaction.

Kasneci et al. (2023) stated that another relationship to consider is the one between student engagement and satisfaction. The active involvement of students in their educational journey significantly influences their level of satisfaction. According to Boulton et al., (2019), student participation and engagement in learning activities play a key role in student academic achievement. When students actively engage in their learning experience, they generally exhibit higher satisfaction levels with their education. Gray and Diloreto (2016) further highlight that engaged students demonstrate motivation, interest, and active participation in classroom activities both online and offline. They also cultivate a sense of belonging and contribute to creating a positive learning atmosphere (Wood and Harris, 2015). Furthermore, they benefit from personalized and interactive learning opportunities. As a result, they achieve academic success, encounter growth opportunities, and enjoy a gratifying overall educational experience (Cents-Boonstra et al., 2021). Educational institutions that prioritize student engagement have a greater likelihood of enhancing student satisfaction and improving students learning performance. Therefore, we hypothesized that:

H6 : Student Engagement positively influence Student Satisfaction.

H7 : Student Engagement positively influence Student Learning Performance.

Classroom Disengagement and Student Learning Performance

The detrimental effect of classroom disengagement on student learning is generally acknowledged in the literature (Manlove, 1998; Gini et al., 2015; Wammes et al., 2019). Disengagement in students emerges as decreased active participation, a lack of enthusiasm, and a loss of interest in the learning process. Juvonen et al. (2012) underscore the significance of peer relationships in academic achievement and suggest that disengagement may lead to poor peer interactions, further impeding learning outcomes. Disengaged students often struggle to comprehend concepts, fail to connect with the material, and experience a decline in academic performance (Lawson and Lawson, 2020). Anderman (2002) emphasizes that disengagement has negative consequences for psychological outcomes, particularly during adolescence. The prevalence of classroom disengagement denies students valuable learning opportunities and hinders their ability to achieve their full academic potential. Therefore, we hypothesize that:

H8 : Classroom Disengagement negatively influence Student Learning Performance.

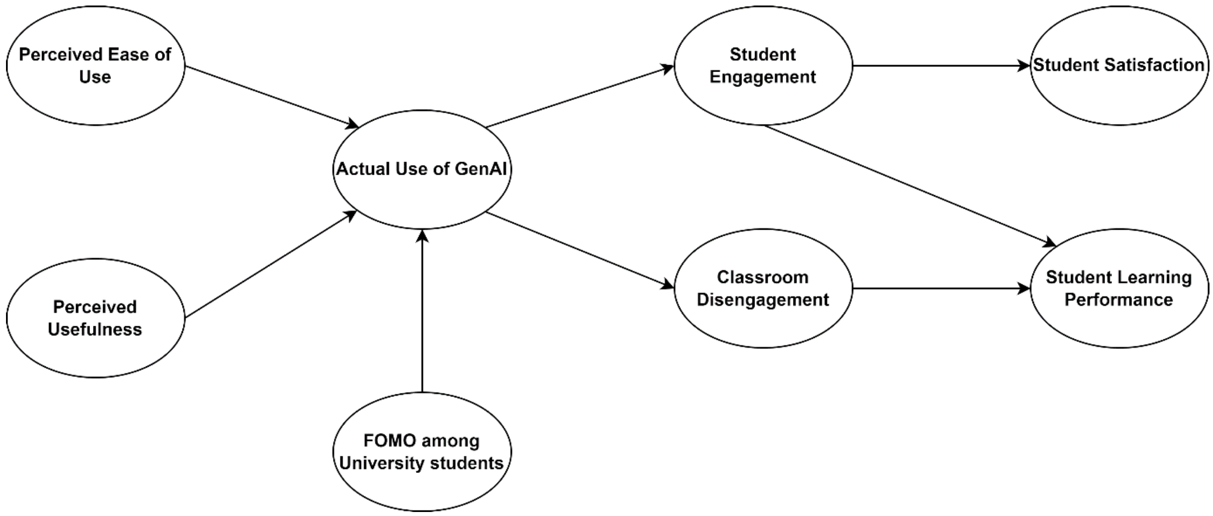

Figure 1: Hypothesized Model

3. Methodology

Sampling Recruitment

The study included first-year and second-year students from the European University of Lefke. A total of 250 usable responses were collected, indicating a response rate of 81.7% out of the 306 questionnaires distributed to registered students. Among the respondents, 53.2% (133) were male and 46.8% (117) were female, all falling within the age range of 18–25. The data collection process involved a self-administered questionnaire with explicit prior consent obtained from participants, assuring them of the confidentiality and exclusive use of their information for research purposes.

A convenient sampling technique was employed to collect information from students who were both accessible and willing to partake in the study. The survey was implemented and distributed using the Microsoft Forms service and a paper questionnaire. Participation in the research was entirely voluntary, with no incentives provided. The e-questionnaire and paper questionnaire were administered during the 2022–23 fall and spring semesters. To prevent duplicate participation in the e-questionnaire, the "One response per person" setting available in Microsoft Forms was activated.

Measurement Items

The items utilized in this study were derived from existing studies rooted in student engagement and satisfaction literature reviews. They were adapted and refined to align with the specific objectives of this research. The set of items, including five assessing perceived usefulness and six gauging perceived ease of use, were drawn from Davis (1989). Additionally, the five items measuring the Fear of Missing Out were adopted from Przybylski et al. (2013), for the actual use of GenAI two items were adopted from Natasia et al. (2022) and another two items on problem solving category were adopted from Maillet et al. (2015), three and five items assessing Student Engagement were taken from Setiawan and Taiman (2020) and Howard et al. (2016), respectively. Furthermore, five items measuring Classroom Disengagement were incorporated from Jang et al. (2016), four items evaluating self-reported student learning performance were adapted from Carini et al. (2006), and six items gauging student satisfaction were adopted from Asosega et al. (2002). The study employed a quantitative analysis to assess the variables under consideration and the questionnaire comprising these items was pre-tested.

4. Data Analysis

The data analysis process employed SmartPLS software version 4.32, utilizing the partial least squares structural equation modeling (PLS-SEM) technique to examine the proposed hypothesized model (Ringle et al., 2015). PLS-SEM was selected due to its ability to handle non-normal distributions and its suitability for studies with limited sample sizes (Hew et al., 2015; Hair et al., 2014; Wong et al., 2015). Following the methodology outlined by Ringle et al. (2005), the analysis comprised two main steps: Firstly, assess the external measurement model, and secondly, scrutinize the internal structural model. Prior to the evaluation, common method bias (CMB) was first evaluated, employing 5000 bootstrapping sub-samples and individual sign changes for inference statistics across the 250 coded items (Hair et al., 2011).

To mitigate common method bias (CMB), we adopted a strategy where predictor measures and criterion measures were obtained from separate sources, aligning with the approach advocated by Podsakoff et al. (2012). CMB was evaluated both statistically and in line with the recommendation for bias reduction proposed by Etehadi and Karatepe (2019). Kock's (2015) method was utilized to assess the extent of common method bias. Kock proposed that collinearity statistics, particularly a variance inflation factor (VIF) exceeding 5, indicate problematic collinearity and suggest potential contamination due to common method bias. The outer VIF analyses, as displayed in Table 1, demonstrated that all constructs exhibited VIF values below 3.3, indicating that common method bias does not pose a significant concern in this study.

Measurement Model

In this section, we performed tests for both convergent validity and discriminant validity to scrutinize the internal measurement model. To assess the reliability of constructs, we examined individual item reliability, ensuring that the outer loading surpassed 0.70. Internal consistency reliability was evaluated through Cronbach's Alpha ($\alpha < 0.95$), outer loading (>0.70) Composite Reliability (CR > 0.70), convergent validity (AVE > 0.5) and rho_A of the measures associated with each construct, as suggested by Henseler et al. (2009), Hair et al. (2014), and Fornell & Larcker (1981). For discriminant validity, we followed the criteria outlined by Henseler et al. (2009) and Fornell & Larcker (1981).

Upon examining the individual item reliability for the constructs, it was observed that one item within Perceived Ease of Use (PE1), two within Student Engagement (SE7, SE8), two within Classroom Disengagement (CD1, CD5), and two within Student Satisfaction (SS1, SS2) marginally fell short of the suggested threshold of 0.7 for outer loadings, as recommended by Fornell and Larcker (1981). Nonetheless, all assessed constructs exhibited Average Variance Extracted (AVE) values that were statistically significant at the 0.05 level and surpassed the threshold of 0.5. To ensure discriminant validity, items below the 0.7 outer loading threshold were removed from the model. Additionally, Composite Reliability (CR) exceeded 0.7, confirming convergent validity. A comprehensive overview of all measures is presented in Table 1.

Table 1: Convergent Validity Assessment of Constructs.

Constructs	Items Outer Loading Range	α	Rho_A	CR	AVE	Outer VIF Range
PU	0.713-0.886	0.892	0.903	0.921	0.701	1.6-3.4
PE	0.712-0.819	0.819	0.837	0.872	0.577	1.5-1.8
FM	0.800-0.863	0.897	0.905	0.924	0.708	2.0-2.6
AU	0.872-0.913	0.922	0.923	0.945	0.81	2.5-3.4
SE	0.700-0.874	0.887	0.888	0.915	0.642	1.4-3.3
CD	0.822-0.902	0.833	0.854	0.899	0.748	1.8-2.1
SL	0.745-0.839	0.8	0.807	0.869	0.624	1.6-2.1
SS	0.782-0.841	0.836	0.837	0.891	0.671	1.6-1.8

Note: PU: Perceived Usefulness, PE: Perceived Ease of Use, FM: Fear of Missing Out, AU: Actual Use of GenAI, SE: Student Engagement, CD: Classroom Disengagement, SL: Student Learning, SS: Student Satisfaction.

Discriminant Validity Assessment

Two established techniques were utilized to ascertain the discriminant validity of the indicators in this study. Firstly, the HTMT criterion, proposed by Henseler et al. (2015), was employed as it addresses potential issues that the Fornell-Larcker criterion might overlook. According to Henseler et al. (2015), if the HTMT value falls at or below 0.90, it indicates satisfactory discriminant validity between two reflective constructs; values exceeding this threshold suggest potential problems with discriminant validity. While Gold et al. (2011) advocate for a threshold of 0.90, Markus (2012) suggests a slightly lower threshold of 0.85. Secondly, the Fornell-Larcker criterion was applied, comparing the Average Variance Extracted (AVE) values with the correlations between latent variables. This method confirms discriminant validity when the square root of each construct's AVE equals the highest correlation with any other construct. Results of the HTMT values (refer to Table 2) and the Fornell-Larcker discriminant validity analysis (refer to Table 3) were obtained using SmartPLS software.

Table 2: Heterotrait-Monotrait Ratio of Correlations Criterion.

	AU	CD	FM	PE	PU	SE	SL
CD	0.517						
FM	0.743	0.466					
PE	0.774	0.577	0.874				
PU	0.829	0.598	0.771	0.817			
SE	0.869	0.736	0.857	0.900	0.864		
SL	0.808	0.776	0.762	0.842	0.744	0.900	

SS	0.659	0.616	0.500	0.630	0.596	0.700	0.662

Note: PU: Perceived Usefulness, PE: Perceived Ease of Use, FM: Fear of Missing Out, AU: Actual Use of GenAI, SE: Student Engagement, CD: Classroom Disengagement, SL: Student Learning, SS: Student Satisfaction.

Table 3: Discriminant Validity (Fornell and Larcker Criterion)

	AU	**CD**	**FM**	**PE**	**PU**	**SE**	**SL**	**SS**
AU	0.900							
CD	0.462	0.865						
FM	0.683	0.414	0.842					
PE	0.691	0.496	0.773	0.760				
PU	0.757	0.523	0.689	0.719	0.837			
SE	0.792	0.639	0.769	0.781	0.772	0.801		
SL	0.691	0.657	0.646	0.685	0.631	0.800	0.790	
SS	0.578	0.517	0.438	0.522	0.513	0.607	0.543	0.819

Note: PU: Perceived Usefulness, PE: Perceived Ease of Use, FM: Fear of Missing Out, AU: Actual Use of GenAI, SE: Student Engagement, CD: Classroom Disengagement, SL: Student Learning, SS: Student Satisfaction.

5. Structural Model

We follow the guidelines outlined by Joseph et al. (2010) for the evaluation of the structural model. Initially, we examine collinearity concerns, ensuring that Variance Inflation Factors (VIF) remain below 5, and assess the significance of relationships between constructs. Additionally, we evaluate R2 (0.25 – Weak, 0.50- Moderate, 0.75 – Substantial), f-square effect size (>=0.02 is small; >= 0.15 is medium;>= 0.35 is large), and Q^2 (0.02 – Small, 0.15 – Medium, 0.35 - Large) based on criteria by Hair et al. (2011, 2013) and Cohen (2013). Furthermore, we assess the model's fit using the Standardized Root-Mean-Square Residual (SRMR), aiming for ≤0.10 or 0.08 (Hu & Bentler, 1999). All VIF results reported are below the recommended thresholds, signifying the absence of collinearity issues.

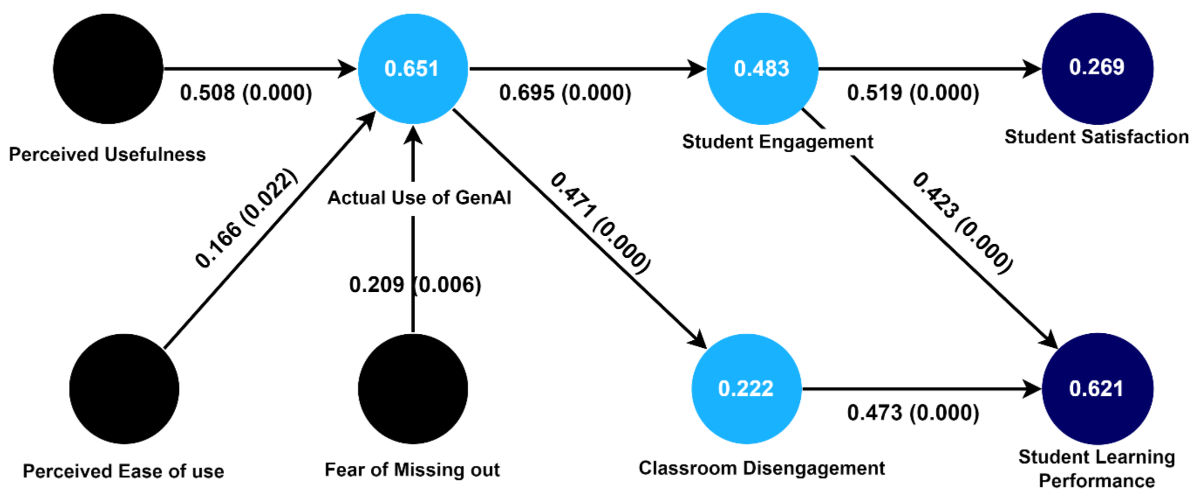

Figure 2: Model Estimation Results

The coefficient of determination (R^2) is employed to measure the proportion of variance in latent dependent variables that is explained by the model, relative to the total variance. This study investigates relationships between Perceived Ease of Use (PE), Perceived Usefulness (PU), Fear of Missing Out (FOMO), and their impact on Actual Use of GenAI (AU). The analysis reveals these factors collectively account for 63.3% of the variability in GenAI utilization, underscoring subjective perceptions and perceived utility in educational technology application. AU moderately connects with Classroom Disengagement (CD) (R-square = 0.214) and significantly impacts Student Engagement (SE) (R-square = 0.627), emphasizing technology's role in shaping classroom engagement and student involvement. Addressing disengagement fosters active participation, comprehension, and interaction, creating a more enriching learning environment. With a high R-square value of 0.676 for Student Learning, Classroom Disengagement and Student Engagement collectively account for 67.6% of the variability in student learning outcomes, emphasizing their significant roles in the context of GenAI use. The positive impact of reduced Classroom Disengagement and increased Student Engagement is reflected in substantial explanatory power for predicting and influencing student learning outcomes.

Lastly, we report all structural analysis steps. The statistical significance of path coefficients β values is assessed using the t-statistic and p-values derived from the 5000 sub-samples complete bootstrapping test, conducted at a two-tailed 5% error probability level. To validate a hypothesis, both a p-value < 0.05 and a t-value > 1.65 at a 5% significance level are considered. The results of the bootstrapping algorithm are presented in Table 4, providing further confirmation of the statistical significance of path coefficients, contributing to a robust validation of the structural model.

Table 4: Results of Path Analysis and Hypothesis Testing.

Hypotheses	β	VIF	f-square	T statistics	P values
H1	0.184	2.968	0.031	2.522	**0.012**
H2	0.480	2.279	0.275	8.141	**0.000**
H3	0.210	2.734	0.044	2.692	**0.007**
H4	0.792	1.000	1.682	30.494	**0.000**
H5	0.462	1.000	0.272	8.338	**0.000**
H6	0.607	1.000	0.584	12.353	**0.000**
H7	0.643	1.691	0.756	10.599	**0.000**
H8	0.246	1.691	0.110	3.566	**0.000**

Note: *P < 0.05, ** p-value < 0.01; *** p-value < 0.001

Predictive Power and Relevance.

The predictive relevance Q2 was assessed using PLSpredict CVPAT to evaluate the predictive power and relevance of the structural model. The results of the CVPAT analysis are displayed in Table 5.

Table 5: Predictive Relevance.

Variables	Q^2predict	R^2	RMSE	MAE	ALD	t value	p value
AU	0.619	0.633	0.622	0.481	-0.648	7.929	0.000
CD	0.334	0.214	0.824	0.644	-0.201	6.115	0.000
SE	0.674	0.627	0.576	0.444	-0.370	8.296	0.000
SL	0.455	0.676	0.744	0.580	-0.299	7.236	0.000
SS	0.266	0.369	0.866	0.674	-0.186	4.832	0.000

Note: AU: Actual Use of GenAI, SE: Student Engagement, CD: Classroom Disengagement, SL: Student Learning, SS: Student Satisfaction.

In a comprehensive scientific evaluation of a predictive model, the study assessed its performance across the endogenous variables. The model exhibited commendable predictive accuracy, with Q^2 predict values ranging from 0.266 to 0.674, indicating its ability to explain a significant proportion of the variance in the observed outcomes (Hair et al., 1998; Chin, 1998; Chin (2010). Root Mean Square Error (RMSE) values, spanning from 0.576 to 0.866, and Mean Absolute Error (MAE) values, ranging from 0.444 to 0.674, underscored the model's proficiency in minimizing prediction errors and maintaining low average absolute differences between predicted and actual values.

Moreover, the examination of Average Loss Differences $ALD = N1\sum i = 1N(PLSi - IAi)$, revealed consistent superiority of the model over a baseline, with negative differences ranging from -0.186 to -0.648. These results highlighted the model's ability to outperform the baseline on average across the endogenous variables. The statistical significance of these findings, supported by low p-values (0.000), further emphasized the robustness of the model's predictive capabilities. Furthermore, the results presented in Table 5 highlight that the actual use of GenAI and student engagement demonstrate strong predictive power. Finally, regarding the model fit, the Standardized Root Mean Square Residual (SRMR) for this study is 0.070, which is less than the cut-off value suggested by Hu and Bentler (1998). A moderate Normed Fit Index (NFI) of 0.752, an Unweighted Least Squares discrepancy (d_ULS) of 3.259, and Bentler's Comparative Fit Index (d_G) of 1.369, suggesting a comprehensive assessment of the model's appropriateness and performance in capturing the observed data.

In conclusion, the model showcased reliable performance across the endogenous variables, providing valuable insights into outcomes related to the actual usage of GenAI and the overall satisfaction of the students. These collective findings underscore the effectiveness of the PLS model in capturing and predicting intricate relationships with confidence.

6. Discussion

The aim of this study is to examining the antecedents of fear of missing out, perceived ease of use, and perceived usefulness on actual use of GenAI. The study also evaluates the consequential impact of GenAI's actual usage on classroom disengagement, student satisfaction, and learning outcomes. The findings of the hypothesis testing conducted through PLS-SEM are presented in Table 4 and Figure 2. Notably, all the hypotheses were substantiated by the results.

First, perceived ease of use (H1) and perceived usefulness (H2) were essential determinants for the use of ChatGPT, with perceived usefulness exerting a greater influence on actual usage. This suggests that users are more inclined to utilize GenAI when they perceive it to be useful, aligning with previous research indicating that utility and perceived value are critical factors in technology adoption. The impact of perceived usefulness may stem from users' perceptions that GenAI provides tangible benefits in their tasks or interactions. When users perceive a technology as useful, they are more likely to trust it and find it valuable, ultimately leading to increased usage. This finding corroborates prior studies such as Choung et al. (2023) on the acceptance of AI technologies and Sorwar et al. (2023) on factors influencing the acceptance and adoption of smart home technology. These studies similarly underscore the importance of user perception of usefulness in driving technology adoption.

Secondly, fear of missing out (FoMO) was found to positively influence the actual use of GenAI (H3). This suggests that individuals who experience FoMO are more likely to engage with GenAI. This finding is consistent with the notion that individuals with a higher fear of missing out may be more inclined to adopt and utilize new technologies to stay connected and informed. According to Hayran and Anik, (2021) FoMO often arises from the challenge of keeping pace with current, up-to-date content in real-time. Particularly, individuals with a predisposition to FOMO as a personality trait tend to experience it more intensely, particularly in relation to digital content. The findings of our research align with the conclusions drawn by Casale et al. (2023), who assert that FoMO is directly associated with the fear of missing out on current trends and is characterized by a strong desire to stay informed about important activities others are engaged in.

The actual use of GenAI was strongly associated with student engagement (H4), indicating that GenAI tools play a significant role in enhancing student engagement in educational settings. The analysis reveals a robust positive relationship between the actual utilization of GenAI and student engagement, with a notably high T-statistic of 30.494, signifying strong statistical significance. This suggests that as students actively employ tools like ChatGPT or BARD, their levels of engagement with educational materials and activities significantly increase. The outcomes of this study are consistent with previous studies (Menon & Shilpa, 2023; Choudhury & Shamszare, 2023). Tsao & Nogues (2024) discovered that collaborating with GenAI assisted students in cultivating a more sophisticated understanding of authorship, acknowledging their own roles in the creative process. While ethical apprehensions arose regarding the possibility of students overly depending on this technology, leading to academic dishonesty, unethical authorship, and intellectual stagnation. Hypothesis 5 confirmed this assertion as the actual use of GenAI tools influence classroom disengagement. Therefore, to mitigate these risks, it is essential to restrict the incorporation of GenAI, which can be achieved by emphasizing in-class activities as integral components of student assessment, rather than relying solely on extracurricular activities. This approach ensures a balanced integration of GenAI within the educational framework, promoting responsible usage while fostering students' creative development.

Furthermore, the relationship between student engagement and both student satisfaction (H6) and student learning (H7) were significant, highlighting the importance of fostering student engagement to enhance overall satisfaction and learning outcomes. This underscores the potential of technologies like ChatGPT, GEMINI or BARD to not only facilitate engagement but also contribute to improved educational experiences and academic performance. The outcome of the relationship between student engagement and satisfaction is consistent with the study of Roque-Hernández et al. (2023). Similarly, the study of Alalwan, N. (2022) and Qureshi et al. (2023) is consistent with the outcomes of this study on the relationship between student engagement and student learning performance.

Lastly, classroom disengagement was found to negatively impact student learning as hypothesized (H8). The detrimental effects of classroom disengagement extend beyond mere lack of attention; it directly impedes students' ability to learn and retain information. Even when students appear to be physically present and engaged, their minds may wander, seeking alternative avenues for quick-shallow understanding and problem-solving. This phenomenon highlights the critical need for proactive measures to combat disengagement in educational settings. Interventions leveraging advanced technologies, such as AI-driven platforms like ChatGPT, offer promising solutions. By providing personalized interactions and fostering active participation, these tools can effectively reengage students and enhance the overall learning experience. Therefore, integrating AI technologies into educational practices is not just a matter of innovation, but a strategic imperative for optimizing student engagement and academic achievement. The findings align with both the theoretical framework of this study and the established body of literature concerning the predictive factors contributing to diminished student learning performance due to classroom disengagement (Wammes et al., 2019; Lawson & Lawson, 2020; Adigun et al., 2023).

7. Summary and Conclusion

In conclusion, this study investigated the antecedents and consequences of GenAI utilization in educational settings. The results demonstrated that perceived ease of use and perceived usefulness significantly influence the actual usage of GenAI, with the latter exerting a stronger impact. Additionally, fear of missing out (FoMO) positively correlates with GenAI usage, indicating that individuals experiencing FoMO are more inclined to engage with such technologies. Moreover, the study revealed a robust association between GenAI utilization and student engagement, emphasizing the pivotal role of these tools in enhancing students' interactions with educational materials.

However, while GenAI offers opportunities to augment student engagement, caution must be exercised to prevent over-reliance and ethical concerns, such as academic dishonesty. To address these challenges, a balanced integration of GenAI into educational frameworks is essential, emphasizing in-class activities alongside extracurricular usage. Furthermore, the study underscores the significant impact of student engagement on both students' satisfaction and learning performance, highlighting the potential of GenAI to not only foster engagement but also contribute to improved academic performance. Conversely, classroom disengagement was found to adversely affect student learning, necessitating proactive interventions to combat this issue.

In light of these findings, integrating GenAI technologies like ChatGPT into educational practices emerges as a strategic imperative for optimizing student engagement and academic achievement. This aligns with existing literature emphasizing the importance of addressing classroom disengagement in order to enhance student learning performance. Overall, this study contributes to our understanding of the multifaceted relationship between technology adoption, student engagement, and educational outcomes, providing valuable insights for educators and policymakers alike.

8. Limitations and Future Research Directions

While this study contributes valuable insights, it is important to acknowledge several limitations that warrant consideration in future research endeavors.

Firstly, the data collection method employed in this study was cross-sectional, which may limit the depth of understanding regarding causal relationships. To address this limitation, future research could incorporate longitudinal studies encompassing surveys and observations to provide a more comprehensive validation of the proposed model over time.

Secondly, the study sample was drawn exclusively from a single university, potentially limiting the generalizability of the findings. Future research should aim to replicate this study across multiple institutions to enhance the external validity of the research model and its associated hypotheses.

Thirdly, the study did not differentiate between students based on their academic year or department affiliation. Given the potential variation in GenAI usage patterns across different academic disciplines, future studies should explore specific faculty cohorts within the university setting. This approach would enable a more nuanced understanding of how GenAI adoption varies across diverse academic contexts and student populations.

Lastly, this study primarily focused on testing direct paths between the key constructs of interest in the proposed model. Future research endeavors could enrich our understanding by investigating indirect paths, such as the potential mediating effects of intermediary variables. By exploring these indirect relationships, researchers can gain deeper insights into the complex mechanisms underlying the adoption and impact of GenAI in educational settings.

Addressing these limitations will not only strengthen the robustness of the research model but also advance our understanding of the multifaceted dynamics surrounding GenAI utilization in academia. By adopting a more nuanced approach to research design and analysis, future studies can make meaningful contributions to the evolving discourse on technology-enhanced learning experiences.

Disclosure statement
No potential conflict of interest was reported by the author(s).

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