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Unlocking the Future of Education: Empirical Insights into the Adoption of Generative AI in Higher Education

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Abstract:

This study investigates the factors influencing the adoption and use of generative AI technologies (GenAI) in higher education through a comprehensive survey of 592 university professors across the USA and Canada, utilizing both quantitative and qualitative data. The results reveal that educators primarily benefit from using GenAI to create course materials more efficiently and enhance students' learning outcomes. However, significant concerns persist regarding the accuracy of AI-generated content and the privacy and security of data. The qualitative analysis further identified six common themes: efficiency and time-saving, creativity and innovation, engagement with technology, support in research and learning, skepticism or uncertainty, and contextual dependency. Our findings also indicate that perceived enjoyment and performance expectancy are the most crucial drivers for adopting GenAI, whereas perceived risk substantially deters educators from integrating these technologies. Additionally, age and gender were found to significantly impact use behavior and behavioral intention, with age negatively affecting use behavior and moderating the relationship between perceived risk and behavioral intention and gender positively influencing behavioral intention and moderating the effects of social influence and perceived risk. This research substantially contributes to the Information Systems (IS) literature by empirically examining GenAI use in higher education with a large sample size. The study not only highlights the practical benefits and risks associated with GenAI but also provides a nuanced understanding of the psychological factors influencing educators' decisions. These findings offer actionable insights for developers to address educators' concerns and for educational institutions to develop strategies that facilitate the effective and responsible integration of GenAI technologies in academic settings.

Keywords: Generative AI, Higher Education, Educator Adoption, Perceived Risk, Perceived Enjoyment

1 Introduction

Artificial intelligence (AI) refers to the simulation of human cognitive functions by computers to perform activities such as reasoning, identification, understanding, learning, thinking, and problem-solving. Generative AI technologies (GenAI[1]), a sophisticated subset of AI, focus on content generation. GenAI can synthesize new content, ranging from text and images to simulations and interactive environments. According to McKinsey (2023), GenAI have the potential to significantly boost global economic productivity, with estimates suggesting they could add $2.6 trillion to $4.4 trillion annually. They could also substantially impact all industry sectors, including education (Chui et al., 2023). Among the most advanced GenAI are Large Language Models (LLMs), such as OpenAI's GPT series. These models are designed to understand and generate human-like text by processing vast amounts of textual data. LLMs can create cohesive and contextually relevant content across various domains, making them versatile tools for generating narrative text, answering questions, translating languages, and coding. Following the successful launch of ChatGPT by OpenAI in November 2022, several GenAI, such as Microsoft Copilot, Consensus, and Semantic Scholar, have gained attention, especially in education.

Despite the advancements in educational technology, higher education continues to grapple with significant challenges, such as large class sizes, limited resources, and varying levels of student engagement and achievement (Collaço, 2017; Monks & Schmidt, 2011; Rouhiainen L, 2019; Torres & Statti, 2023). Traditional educational tools often fail to accommodate students' diverse learning paces and styles, leading to disparities in learning outcomes (Alzain et al., 2018; ChimpVine, 2023; Romanelli et al., 2009). GenAI have the potential to mitigate these issues by providing adaptive and personalized learning experiences. While AI's role in education has predominantly centered on administrative automation, adaptive learning systems, and basic personalized learning paths, GenAI introduce us to a new era of educational tools. These tools are capable of creating highly engaging, customized content that can revolutionize learning experiences (Bahroun et al., 2023). Generative models can dynamically produce educational materials such as personalized textbooks, interactive simulations, and virtual dialogues, offering an enriched curriculum tailored to each student's unique needs (Alasadi & Baiz, 2023; Bozkurt, 2023; Rouhiainen L, 2019). However, integrating GenAI into education poses several challenges.

[1] In this paper, "GenAI" is a plural term to refer to various technologies, applications, or tools that utilize Generative AI models.

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Concerns include the potential for academic dishonesty and cheating (Williams, 2024), biases in training data leading to unfair or skewed content generation (Yu et al., 2023), and the risk of over-reliance on GenAI hindering creativity and critical thinking (Fryer et al., 2020). Additionally, handling sensitive data with GenAI increases the risk of misuse and compromises data privacy for students and educators (Kadaruddin, 2023). Despite GenAI's ability to generate content rapidly, the accuracy and reliability of the information remain questionable, particularly in specialized or complex areas (Ngwenyama & Rowe, 2024; Walczak & Cellary, 2023).

A successful integration of GenAI into higher education necessitates maximizing its benefits while mitigating its risks. Educators are pivotal in this process, as their acceptance and effective use of GenAI will determine its success (Lim et al., 2023). However, there is a lack of understanding regarding how educators perceive and interact with GenAI in fulfilling their professional tasks, especially in their teaching practices. Previous studies are mainly conceptual papers or have used small or convenient samples to explore this issue. This gap in knowledge highlights the need for comprehensive empirical studies that examine the factors influencing educators' decisions to adopt and use GenAI. This research aims to fill this gap by addressing the limitations of previous conceptual studies and those with small or convenient samples. Empirical insights on the factors influencing educators' decisions to adopt and integrate GenAI help developers and educational institutions better tailor these technologies to meet educators' needs and preferences. These insights will also help develop training programs and support systems that address educators' concerns, boosting their confidence and competence in using GenAI. Ultimately, this will enhance the scalability, personalization, and immersion of learning experiences, addressing many longstanding challenges in higher education and improving student learning experiences.

2 Related Literature

2.1 GenAI and Education

The integration of GenAI in higher education has brought about a paradigm shift in teaching and learning, presenting unprecedented opportunities and complex challenges (Bansal et al., 2024; Lim et al., 2023; Michel-Villarreal et al., 2023; Ooi et al., 2023; Singh, 2024). Since the first release of ChatGPT, the most popular GenAI application, in November 2022, multiple studies have investigated the benefits of GenAI in higher education (Alasadi & Baiz, 2023; Albdrani & Al-Shargabi, 2023; Chan & Hu, 2023; Harry, 2023;

Kee et al., 2024; Su & Yang, 2023; van den Berg & du Plessis, 2023). Uncovering insights directly from ChatGPT, a study by Michel-Villarreal et al. (2023) identified six benefits of ChatGPT for higher education: (1) 24/7 support and accessibility, (2) personalized learning and tutoring, (3) supplemental learning resources, (4) support for instructors and teaching assistants, (5) innovative and interactive learning experiences, and (6) language learning and communication skills. A study by Chan and Hu (2023) explored university students' views on using GenAI in higher education. The study reveals that students generally have positive attitudes toward ChatGPT and perceive it as a valuable tool with multiple benefits, such as personalized learning support, writing and brainstorming assistance, research and analysis aid, multimedia and creative support, and administrative efficiency. The extant literature also cites using GenAI to improve the teaching and learning experience by boosting collaboration, communication, accessibility, and inclusivity (Cho et al., 2021; Nikolopoulou, 2024).

The ability of GenAI to provide a personalized learning experience has been extensively echoed in the literature (S. Gupta et al., 2024; Kadaruddin, 2023; Qadir, 2023). GenAI can create tailored educational content that aligns with individual learning styles, abilities, and interests, improving students' motivation and interest. A case study by Albadrani and Al-Shargabi (2023) discovered that using ChatGPT to provide personalized learning experiences in data science education enhances student engagement and participation. As students gain a greater sense of control over their education, they are empowered to make decisions and take actions that influence their learning outcomes, leading to increased involvement in the educational process. Using a mixed research approach that combines a case study and an online survey, Kee et al. (2024) found that using GenAI correlates with better time management and reduced anxiety among architecture students. Additionally, it enhances students' digital literacy and holistic competencies, including creativity, initiative, self-management, and stress tolerance. They also discovered that GenAI-driven VR/AR technologies create immersive and interactive learning environments that enhance students' understanding of complex architectural concepts, simulate real-world scenarios, and allow students to practice and apply their knowledge in a safe and controlled environment. Furthermore, the real-time feedback provided by GenAI-driven VR/AR systems allows students to adjust their designs immediately, leading to more refined and well-thought-out projects. As Barros et al. (2023) argue, using GenAI in teaching not only assists educators in generating educational content and developing interactive classrooms but also has the potential to shift educators' roles from traditional instructors, where the

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teachers are primarily a source of information, to facilitators. This new role encourages open discussions and dialogues in the classroom, promotes an inquiry-based learning approach, and incorporates emotional and empathetic components into the learning process. GenAI can also transform the research landscape by automating literature reviews, generating research hypotheses, and analyzing data. Moreover, they can enhance efficiency in administrative tasks like writing reference letters, updating policy reports, and managing communication (Barros et al., 2023).

Despite all these opportunities, integrating GenAI into higher education has several risks and challenges. A study by Yu et al. (2023) identified four key challenges that need to be addressed while implementing GenAI in education: (1) opacity and inexplicability, (2) data privacy and security, (3) individualization and fairness, and (4) effectiveness and reliability. A survey of 399 undergraduate and postgraduate students by Chan and Hu (2023) identified several challenges with using GenAI, including concerns about accuracy and transparency, privacy and ethical issues, weakening of critical thinking and problem-solving skills in students due to over-reliance on GenAI, career anxiety due to the possibility of automating future jobs by GenAI, the potential for GenAI to propagate biases or unethical behaviors if unchecked, and the lack of clear policies governing GenAI use. Lim et al. (2023) outlined four paradoxes of GenAI in education. Firstly, GenAI are described as both a 'friend' and a 'foe,' offering valuable learning assistance but posing challenges in authentic knowledge assessment. Secondly, they are 'capable' yet 'dependent,' proficient in generating responses but limited by the quality and scope of the input they receive. Thirdly, GenAI are both 'accessible' and 'restrictive,' democratizing information but potentially limited by paywalls that affect equitable access. Lastly, despite being banned in some educational settings, GenAI often become even more popular, illustrating the counterproductive effects of such prohibitions. One of the most cited risks in the extant literature is the misuse of GenAI by students for plagiarism or cheating on assignments and assessments (Michel-Villarreal et al., 2023; Van Slyke et al., 2023). A study by Ibrahim et al. (2023) found that while most students plan to use ChatGPT for their assignments and think their peers would approve, indicating that ChatGPT may become a common tool among students, most professors view its use as plagiarism and expect their colleagues to agree. This implies that categorizing ChatGPT as a tool for plagiarism may become the prevailing approach among educators (Ibrahim et al., 2023). Xiao et al. (2023) analyzed ChatGPT policies at the top 500 universities worldwide and found that concerns over cheating, plagiarism, and other academic integrity violations lead some institutions to ban ChatGPT. Despite this, less than one-third of these universities had established ChatGPT policies. Among those with policies, approximately 67.4% integrated ChatGPT into their teaching and learning processes, more than twice the number of universities that opted to ban its use (Xiao et al., 2023).

2.2 Unified Theory of Acceptance and Use of Technology

Our proposed research model draws upon the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT suggests four key factors determine the behavioral intention to adopt technology: *performance expectancy, effort expectancy, social influence, and facilitating conditions* (Venkatesh et al., 2003). Performance expectancy refers to the degree to which an individual believes that using the technology will help them attain gains in job performance (Venkatesh et al., 2012). Effort Expectancy is the degree of ease associated with the use of the technology (Venkatesh et al., 2003). Social Influence pertains to the extent to which individuals perceive that important others believe they should use the new system (Hong et al., 2018). Facilitating Conditions are the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology(Venkatesh et al., 2012). The model also introduced four moderators that influence the impact of these key factors on behavioral intention and use behavior, including gender, age, experience, and voluntariness.

The UTAUT has been extensively studied in various contexts, such as Internet banking (Rahi et al., 2018; Tarhini et al., 2016), m-commerce ((Marinković et al., 2020; Soh et al., 2020), e-government (Li, 2021; Soong et al., 2020), and learning management systems (Abbad, 2021; Raza et al., 2020; C.-W. Yu et al., 2021). These studies confirm that the UTAUT is a robust and reliable model for understanding technology adoption and use (Momani, 2020). However, there are calls for further research to explore its application in emerging areas, such as AI tools (Venkatesh, 2022). The rapid development of AI technologies, including GenAI, presents unique challenges and opportunities that may not be fully captured by the traditional UTAUT variables. To address this, Blut et al. (2022) suggest that incorporating new variables and mechanisms could improve the model's validity and explanatory power (Blut et al., 2022).

In our study, we propose to extend the UTAUT model to better understand the factors influencing the adoption of GenAI in higher education. In addition to the original UTAUT constructs, we will incorporate *perceived enjoyment* and *perceived risk* as additional variables. Perceived enjoyment has been identified as a significant driver of technology use in contexts where intrinsic motivation plays a crucial role (Gerow

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et al., 2013). Given the interactive and creative potential of GenAI, we hypothesize that perceived enjoyment will significantly influence educators' intentions to use these technologies. Perceived risk refers to the potential negative consequences of using a technology, which can include concerns about data privacy, security, and the accuracy of AI-generated content (Li, 2024). Previous research has shown that perceived risk can be a substantial barrier to technology adoption (Martins et al., 2014). In the context of GenAI, risks such as academic dishonesty, data privacy issues, and over-reliance on AI-generated content must be carefully considered. By extending the UTAUT model to include these variables, our research aims to provide a comprehensive framework for understanding the adoption of GenAI in higher education. This extended model will help developers and educational institutions tailor their strategies to effectively promote the use of GenAI among educators, ultimately enhancing teaching and learning outcomes.

3 Research Model and Hypotheses

Figure 1 shows our research model based on the theoretical foundation discussed in the previous section.

GenAI can potentially transform higher education by offering significant support to educators. These technologies can create course materials more efficiently, personalize content to accommodate diverse learning styles, and streamline tasks such as literature reviews, data analysis, and academic writing. Furthermore, GenAI can assist with academic services like writing reference letters, updating policy reports, and drafting everyday work emails (Barros et al., 2023). These capabilities not only save time but also enhance the quality of educational and administrative outputs. A critical factor influencing the adoption of any new technology is performance expectancy. This concept has been extensively validated in the UTAUT literature, demonstrating a strong correlation with the behavioral intention to use technology (Chao, 2019; Dwivedi et al., 2017). Given the powerful capabilities of GenAI, it is essential to examine how educators' perceptions of GenAI performance expectancy influence educators’ intention to integrate these technologies into their work. Thus, we posit the following hypothesis:

> ***H1:*** *The higher educators perceive the performance expectancy of GenAI, the greater their behavioral intention to use these technologies.*

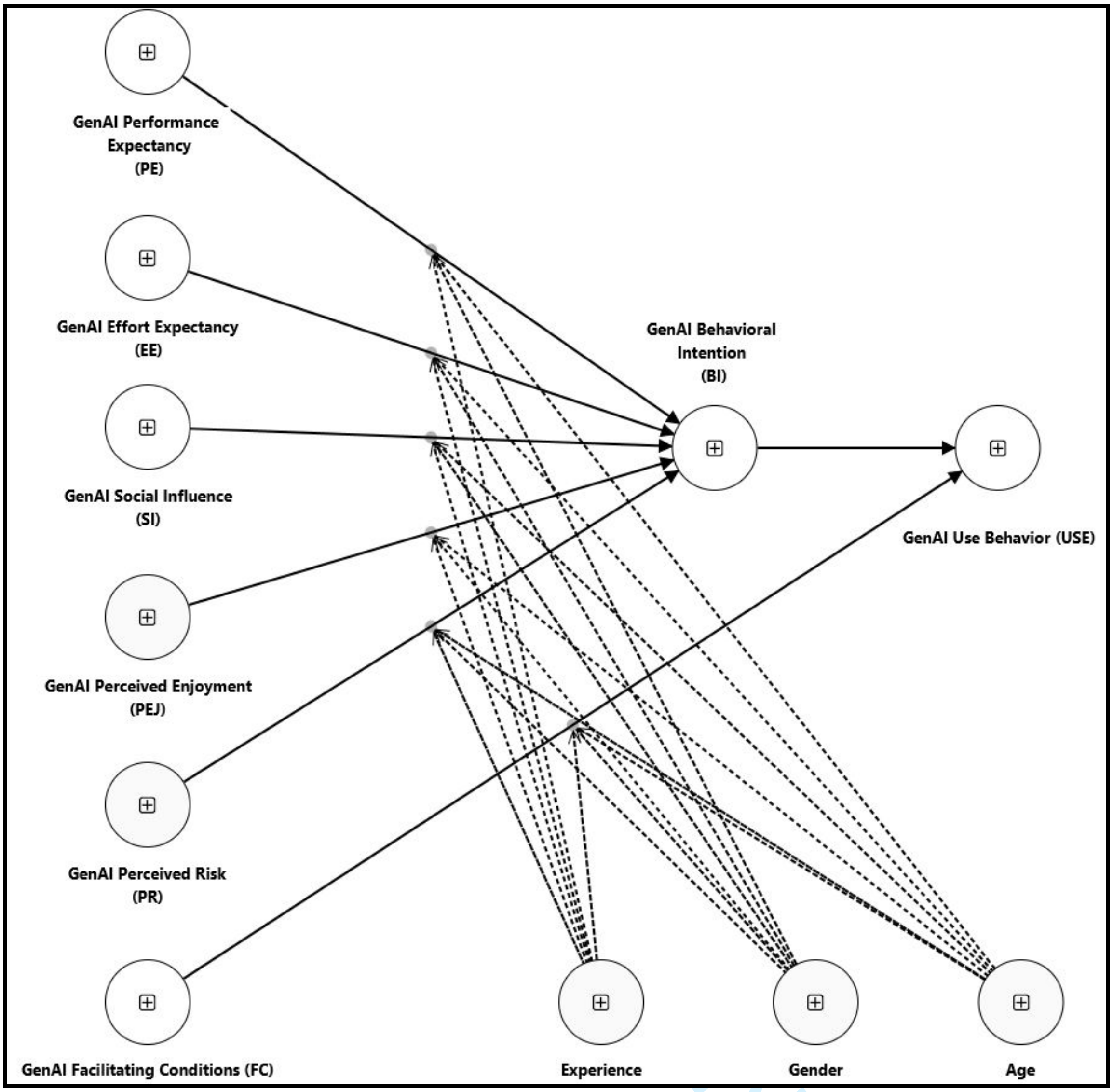

Figure 1. Research Model

Technologies like ChatGPT offer user-friendly natural language interfaces, making them accessible even for non-technical users. These tools support a wide range of functions, including technical assistance, content creation, personal support, learning, creativity, and research, thus catering to diverse user needs. Several studies have demonstrated the significant influence of effort expectancy on users' behavioral intention to use technology in various contexts (Raza et al., 2020; Rumangkit et al., 2023). For instance, Raza et al. (2020) found that ease of use significantly impacts the acceptance of learning management systems among educators. Similarly, Rumangkit et al. (2023) showed that effort expectancy is a critical factor in adopting media support learning. Building on this foundation and accordingly to UTAUT, we propose the following hypothesis:

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H2: *The higher educators perceive the effort expectancy of GenAI, the greater their behavioral intention to use these technologies.*

Social influence is crucial in the adoption of new technologies, as individuals often look to their social environment for cues on whether to adopt new practices (Venkatesh et al., 2012). The existing literature within the UTAUT framework has consistently demonstrated a significant relationship between social influence and behavioral intention to use technology. For instance, a study by Gupta (2024) found that social influence significantly affects both the initial interest and subsequent adoption of ChatGPT among a diverse group of entrepreneurs (Gupta, 2024). Similarly, other studies have shown that social endorsement and peer pressure can play pivotal roles in accepting new technologies in educational settings (Juvonen et al., 2019). As such, the following hypothesis is posited:

H3: *Social influence positively impacts educators' behavioral intention to use GenAI.*

In the context of this study, perceived risk refers to the degree to which an educator believes the adoption and use of GenAI might result in potential adverse outcomes. Integrating GenAI in education poses several risks, such as compromising privacy, producing inaccurate content, and exacerbating biases in data. These concerns are particularly pertinent in teaching, where maximizing the potential of GenAI requires educators to shift their roles from traditional instructors to facilitators. This shift allows students to use GenAI as a primary source of information, which may lead to misuse and over-reliance on these tools. Consequently, this challenges academic integrity and inhibits the development of critical thinking and problem-solving skills (Barros et al., 2023; Williams, 2024).

These risks can significantly impact educators' willingness to adopt GenAI. Previous studies on the UTAUT have been extended to include perceived risk as a determinant of behavioral intention to use technology (Lee & Song, 2013; Teng et al., 2022; Wang & Ma, 2023; Wu et al., 2022). For example, Wu et al. (2022) found that both functional and psychological risks negatively affect students' intention to use AI-assisted learning environments. Similarly, Teng et al. (2022) indicated that perceived risks reduced learners' intention to use an educational metaverse platform called Eduverse. In line with these studies, the following hypothesis is posited:

H4: *The greater educators perceive risks associated with using GenAI, the less their behavioral intention to use these technologies.*

Perceived enjoyment is the extent to which an educator finds using GenAI intrinsically enjoyable and satisfying. The human-like interactive nature of GenAI, combined with their ability to create tailored and reliable content within seconds, fosters a sense of satisfaction and enjoyment among users (Gupta, 2024). The relationship between perceived enjoyment and the behavioral intention to use technology has been well-documented in the literature. For instance, Huwaida et al. (2023) found that perceived enjoyment significantly influences attitudes toward using e-learning platforms, which subsequently affects actual technology use. Similarly, Callii et al. (2018) demonstrated that perceived enjoyment positively impacts the intention to use 3D printer technology among Turkish consumers, suggesting that enjoyment can drive the adoption of innovative tools. These studies collectively highlight the significant impact of perceived enjoyment on users' intention to adopt new technologies. Therefore, we propose the following hypothesis:

> ***H5:*** *The perceived enjoyment of using GenAI positively impacts educators' behavioral intention to use these technologies.*

Facilitating conditions is the degree to which educators believe they have access to adequate resources and technical infrastructure to support the use of GenAI. These conditions include not only the availability of hardware and software but also comprehensive training programs, ongoing technical support, and institutional policies that promote the effective use of GenAI. A lack of awareness about GenAI's capabilities due to inadequate training resources, insufficient technical infrastructure, and limited user support can significantly hinder educators' willingness to adopt these technologies (Michel-Villarreal et al., 2023). Prior studies within the UTAUT framework have consistently confirmed a significant relationship between facilitating conditions and intention to use technology (Ali & Warraich, 2023). As such, we propose the following hypothesis:

> ***H6:*** *Facilitating conditions will positively impact educators' behavioral intention to use GenAI.*

Behavioral intention is the extent to which an educator plans to utilize GenAI in their professional activities, such as lesson planning, student assessment, and administrative tasks. Use behavior, on the other hand, refers to the actual usage of GenAI in these professional duties. Previous research within the UTAUT framework has confirmed the positive relationship between behavioral intention and use behavior

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(for example, see a systematic review by Alghatrifi & Khalid, 2019). Hence, the following hypothesis is posited:

> ***H7:*** *The educators' behavioral intention to use GenAI positively impacts their use of such technologies.*

In this study, we also examine the moderating effects of age, gender, and experience on behavioral intention and use behavior.

4 Research Methodology

This study employs an online survey to validate the research model, a method that is both prevalent and accepted within the Information Systems (IS) (Nardi, 2018). Online surveys are particularly suitable for this study due to their ability to efficiently reach a wide and diverse population. The measurement items were adapted from relevant literature to ensure content validity and tailored to the study's specific context. Constructs, except for perceived risk and perceived Enjoyment, were based on the works of Venkatesh et al. (2003) and An et al. (2023). Perceived risk and perceived enjoyment were built using items from Rahiman & Kodikal (2024) and Gupta (2024), respectively. All items were measured on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree." An open-ended question was also added to the survey to allow respondents to express their thoughts and opinions in their own words without being restricted by predefined items. This can yield rich, qualitative data that might reveal insights not captured by closed-ended questions.

The target population comprised educators (full, associate, assistant, and adjunct professors) across the USA and Canada. Before the main data collection, a pilot study was conducted to test the clarity and length of the survey items. The pilot study provided valuable insights, leading to minor adjustments to enhance clarity and ensure the survey was not overly time-consuming. Data collection was carried out using the Qualtrics platform, ensuring a streamlined and user-friendly experience for respondents. The authors personally managed the survey distribution to ensure broad reach and high response rates. In total, 595 responses were collected, of which 592 were usable. Three responses were omitted due to being trivial, incomplete, or duplicates. Table 1 provides detailed demographic information of respondents.

Table 1. Demographic Information

Variable	Category	Relative Frequency (%)
Age	Under 44	29.58
	44-59	46.37
	60-78	20.42
	79 and older	1.38
	Prefer not to say	2.25
Gender	Male	53.63
	Female	43.77
	Non-Binary/third gender	0.35
	Prefer not to say	2.25
Education	Doctorate degree	48.44
	Master's degree	30.28
	Professional degree	12.46
	Bachelor's degree	7.09
	Prefer not to say	1.73
Field of Teaching	Business & Economics	29.76
	Arts & Humanities	12.98
	Engineering & Technology	11.76
	Education	10.90
	Social Sciences	10.03
	Health Sciences	7.44
	Natural Sciences	5.54
	Mathematics & Statistics	5.36
	Law & Legal Studies	2.25
	Other	2.77
	Prefer not to say	1.21
Experience	More than 10 years	54.67
	7-10 years	17.99
	4-6 years	13.84
	1-3 years	9.52
	Less than 1 year	2.94
	Prefer not to say	1.04

5 Data Analysis and Results

Structural Equation Modeling (SEM) was utilized to assess the research framework, with PLS (Partial Least Squares) being the chosen method for data analysis (SmartPLS v.4.1.0.3). The preference for PLS, a component-based SEM approach, over covariance-based SEM techniques, stems from PLS's less stringent requirements regarding sample size, data distribution, and the distribution of residuals (Chin, 1998). Hair et al. (2022) recommend a two-phase process for thoroughly analyzing PLS-SEM findings, comprising the measurement model assessment followed by the structural model examination. The dataset underwent a thorough examination for missing data, anomalies, and deviations from normal distribution. The proportion of missing data for each variable was below 2 percent. Consequently, based on the guidance provided by Hair et al. (2022), the missing values were addressed by substituting them with the mean values of the respective variables rather than removing the affected cases entirely.

Although PLS does not necessitate normally distributed data, the observed deviations from normality in skewness and kurtosis did not pose significant concerns. The skewness measurements for the variables fell within the acceptable range of -1 to +1.

5.1 Evaluation of the Measurement Model

Following the guidelines by Hair et al. (2022), the evaluation of the measurement model involves assessing convergent, internal consistency reliability, and discriminant validity. Convergent validity was assessed through outer loadings, indicator reliability (communality), and the average variance extracted (AVE). Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability. Discriminant validity was verified through cross-loadings, the Fornell-Larcker criterion, and the heterotrait-monotrait (HTMT) ratio of correlations. Table 2 shows the results of convergent and internal consistency reliability. Except for PR_1, with outer loadings of 0.671 and indicator reliability of 0.450, all items exceed the benchmarks of 0.7 for outer loading, 0.5 for indicator reliability, and 0.5 for AVE (Hair et al., 2022). All constructs met the minimum criteria of 0.7 for Cronbach's alpha and composite reliability. Although PR_1 ("*I am concerned about the privacy and security of my data when using Generative AI tool*") did not meet the outer loading and indicator reliability benchmarks, it was retained because the corresponding construct (PR) met the recommended thresholds for AVE and internal consistency reliability, following the guidelines suggested by Hair et al. (2022).

Regarding discriminant validity, each indicator's loading on its respective construct surpassed any loadings on other constructs, meeting the cross-loadings criterion. The square root of AVE for each construct was higher than its largest correlation with any other construct, satisfying the Fornell-Larcker criterion. Additionally, all HTMT values were below the 0.85 threshold, which is in line with the recommendations of Henseler et al. (2015) (see Table 3 for HTMT results).

Table 2. Convergent and Internal Consistency Reliability Results

Latent Variable	Indicators	Convergent Validity			Internal Consistency Reliability	
		Outer Loadings	Indicator Reliability	AVE	Cronbach's alpha	Composite reliability
		> 0.7	> 0.5	> 0.5	> 0.7	> 0.7
BI	BI_1	0.955	0.912	0.915	0.953	0.953
	BI_2	0.957	0.916			
	BI_3	0.957	0.916			
EE	EE_1	0.918	0.842	0.852	0.913	0.916
	EE_2	0.934	0.872			
	EE_3	0.917	0.840			
FC	FC_1	0.862	0.743	0.698	0.856	0.859
	FC_2	0.827	0.684			
	FC_3	0.824	0.679			
	FC_4	0.828	0.686			
PEJ	PENJ_1	0.948	0.899	0.890	0.938	0.939
	PENJ_2	0.941	0.885			
	PENJ_3	0.942	0.887			
PE	PE_1	0.866	0.750	0.740	0.883	0.885
	PE_2	0.872	0.760			
	PE_3	0.867	0.751			
	PE_4	0.837	0.700			
PR	PR_1	0.671	0.450	0.605	0.784	0.837
	PR_2	0.774	0.599			
	PR_3	0.872	0.760			
	PR_4	0.781	0.610			
SI	SI_1	0.833	0.694	0.739	0.883	0.895
	SI_2	0.890	0.792			
	SI_3	0.856	0.733			
	SI_4	0.857	0.734			
USE	USE_1	0.899	0.808	0.789	0.933	0.933
	USE_2	0.896	0.803			
	USE_3	0.887	0.787			
	USE_4	0.879	0.773			
	USE_5	0.879	0.773			

BI = Behavioral Intention; EE = Effort Expectancy; FC = Facilitating Conditions; PEJ = Perceive Enjoyment; PE = Performance Expectancy; PR = Perceived Risk; SI = Social Influence; USE = Use Behavior

Table 3. Discriminant Validity Results (HTMT)

	BI	EE	FC	PE	PENJ	PR	SI	USE
BI								
EE	0.475							
FC	0.500	0.509						
PE	0.827	0.465	0.568					
PEJ	0.831	0.504	0.443	0.848				
PR	0.445	0.152	0.353	0.359	0.333			
SI	0.607	0.375	0.620	0.736	0.587	0.261		
USE	0.762	0.519	0.564	0.845	0.730	0.431	0.724	

5.2 Evaluation of Structural Model

Based on Hair et al.'s (2016) guideline, evaluating a PLS-SEM structural model involves assessing collinearity issues, coefficients of determination (R^2 values), and the size and significance of the path coefficients. All VIF values are below the threshold of 5 (Hair et al., 2022), indicating that collinearity among the predictor constructs is not a critical issue in the structural model. According to Hair et al. (2016), the R^2 value of behavioral intention (0.739) is considered substantial, while the R^2 value of use behavior (0.585) is relatively moderate. The bootstrapping procedure, using 10,000 samples, was employed to determine the significance of the path coefficients. Table 4 shows all path coefficients and significance levels.

Table 4. Path Coefficients and Significance Levels

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
PE -> BI	0.264	0.266	0.047	5.592	0.000
EE -> BI	0.076	0.077	0.030	2.530	0.011
SI -> BI	0.121	0.118	0.037	3.233	0.001
PEJ -> BI	0.420	0.420	0.041	10.186	0.000
PR -> BI	-0.139	-0.138	0.024	5.702	0.000
FC -> USE	0.217	0.218	0.034	6.338	0.000
BI -> USE	0.602	0.602	0.028	21.571	0.000
Age -> BI	-0.025	-0.026	0.029	0.864	0.388
Age -> USE	-0.129	-0.129	0.032	4.025	0.000
Age x PE -> BI	0.020	0.013	0.070	0.284	0.776
Age x EE -> BI	-0.045	-0.048	0.037	1.231	0.218
Age x SI -> BI	-0.042	-0.045	0.042	1.004	0.316
Age x PR -> BI	-0.071	-0.068	0.033	2.157	0.031
Age x PEJ -> BI	0.092	0.106	0.062	1.499	0.134
Age x FC -> USE	-0.058	-0.058	0.030	1.919	0.055
Experience -> BI	-0.001	0.000	0.032	0.027	0.979
Experience -> USE	-0.020	-0.021	0.036	0.545	0.586
Experience x PE -> BI	-0.003	0.000	0.057	0.045	0.964
Experience x EE -> BI	0.033	0.033	0.042	0.794	0.427
Experience x SI -> BI	0.050	0.046	0.044	1.138	0.255
Experience x PR -> BI	0.034	0.034	0.030	1.140	0.255
Experience x PEJ -> BI	-0.022	-0.022	0.060	0.362	0.717
Experience x FC -> USE	-0.053	-0.053	0.038	1.398	0.162
Gender -> BI	0.082	0.080	0.023	3.517	0.000
Gender -> USE	-0.022	-0.022	0.026	0.825	0.409
Gender x PE -> BI	-0.101	-0.111	0.055	1.860	0.063
Gender x EE -> BI	-0.046	-0.047	0.027	1.676	0.094
Gender x SI -> BI	0.089	0.089	0.039	2.297	0.022
Gender x PR -> BI	-0.074	-0.071	0.027	2.764	0.006
Gender x PEJ -> BI	0.004	0.016	0.048	0.073	0.942
Gender x FC -> USE	-0.020	-0.020	0.028	0.727	0.467

As shown in Table 4, performance expectancy significantly impacts behavioral intention (p = 0.000) with a moderate effect size of 0.264 (H1 supported). Effort expectancy has a significant, though small, positive impact on behavioral intention (p = 0.011) with an effect size of 0.076 (H2 supported). Social influence positively affects behavioral intention (p = 0.001) with a moderate effect size of 0.121 (H3 supported). Perceived enjoyment exerts a relatively large and significant influence on behavioral intention (p = 0.000) with an effect size of 0.420 (H4 supported). Perceived risk significantly impacts behavioral intention negatively (p = 0.000) with a moderate negative effect size of -0.139 (H5 supported). Facilitating conditions significantly influence use behavior (p = 0.000) with a moderate effect size of 0.217 (H6 supported). Behavioral intention significantly predicts use behavior (p = 0.000) with a large effect size of 0.602 (H7 supported).

Regarding moderators, age significantly impacts use behavior negatively (p = 0.000) with a moderate effect size of -0.129. Age also moderates the relationship between perceived risk and behavioral intention (p = 0.031) with a small effect size of -0.071. Gender significantly influences behavioral intention positively (p = 0.000) with a small effect size of 0.082. Additionally, gender moderates the relationship between social influence and behavioral intention positively (p = 0.022) and between perceived risk and behavioral intention negatively (p = 0.006), with small effect sizes of 0.089 and -0.074, respectively.

5.3 Common Method Bias

To assess the potential impact of common method bias in this research, we followed a procedure proposed by Kock (2015). This involved calculating variance inflation factors (VIFs) for all latent variables in the model. All VIF values were below the recommended threshold of 3.3, indicating that common method bias did not affect this investigation.

5.4 Open-ended Question Results

As previously noted, despite the advancements in educational technologies, student engagement continues to be a significant challenge within traditional education systems. Generative AI tools offer a promising solution to this issue by facilitating personalized and interactive learning environments. To gather insights on this crucial topic, survey participants were asked the following open-ended question: *"How do you think the use of Generative AI tools in your teaching could enhance student engagement in the classroom?"*

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Out of 592 survey participants, 484 answered the open-ended question. Eight responses were removed because they answered “I don’t know” or “I am not sure.” Therefore, 476 responses were considered for further analysis. To analyze responses, first, a sentiment analysis using Python was done to determine the sentiment of each response. Approximately 49% of responses were found positive, 41% neutral, and 10% negative. Then, a thematic analysis was conducted to identify common themes or patterns in the responses to better understand attitudes toward the use of GenAI in teaching (Braun & Clarke, 2012). Six common themes emerged regarding how GenAI might enhance student engagement in the classroom. Table 5 describes each identified theme with some sample responses.

Table 5. Open-Ended Question Results

Theme	Sample Responses	Summary
Efficiency and Time-saving	"They will save us time and money I feel it will make things more efficient." "I think it can provide more time to do active learning in the classroom." "I think that the use of AI will enhance my teaching by making the grading process faster." "I think it can help give me an easier time setting up lessons." "Primarily access to breadth of knowledge at enormous speed."	Responses suggest that GenAI can help streamline learning processes and save time for both students and teachers.
Creativity and Innovation	"They help students be more creative." "It can make creative projects for students to do in class which can be beneficial for incorporating several components of the curriculum." "I think the use of Generative AI tools can increase student creativity and brainstorming skills which can increase their engagement with their learning material in the classroom." "I can use AI to develop engaging and creative ways to present information." "Asking directly for ideas of how to teach specific topics could lead to more creative pedagogy."	Respondents believe GenAI tools can foster creativity and allow for more innovative approaches to learning and assignments.
Engagement with Technology	"I think using it might be interesting for brainstorming sessions." "Generative AI skills are relevant to my Marketing courses where we discuss tech's impact on business." "As it relates to assignments, I think there may be an increase in student engagement." "I think it could be useful for developing new ways of interacting with content." "I am unsure-though I assume that would be the idea behind the technology."	This theme captures the general enthusiasm and increased relevance when students interact with GenAI.
Support in Research and Learning	"They could create and make learning more interactive and fun." "I think it's an effective way for my students to get help on topics." "It helps me and the teachers actually understand and digest the material." "Going beyond the required learning materials is now possible with AI." "Easy learning experience helps in dealing with complex topics."	Responses indicate that GenAI can aid research, provide up-to-date information, and support learning through various tools.
Skepticism or Uncertainty	"I don't know how AI would actually change student engagement." "I have no idea what AI is supposed to do in a classroom." "I am not convinced AI tools will help much in teaching." "I doubt that AI can truly replace the insights of a seasoned teacher." "Not sure if AI can bring anything new to the table."	Responses express doubt about the effectiveness of GenAI in education or state uncertainty about its benefits.
Contextual Dependency	"Increase relevance, introduce students to methods and tools they can use in real-world scenarios, like finance analysis tools." "Not sure. If this technology is a very fancy calculator, then it might not be suitable for all courses but could be useful in areas like finance or data analysis." "To me, one of the best uses for Gen AI that I've seen is in streamlining data analysis, which is very applicable in fields like finance or economics." "It will allow for better use of time as AI takes over more routine or computational tasks, which can be especially useful in quantitatively heavy disciplines like finance." "If directed properly, Gen AI tools will help students in finance and economics get to grips with complex models more quickly."	Responses emphasize the usefulness of GenAI in specific disciplines or contexts.

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6 Discussion

This study investigates the factors influencing educators' decisions to adopt and use GenAI in their professional activities, including teaching, research, and academic service. Based on the survey of 592 university professors across the USA and Canada, the study reveals several key insights. Most respondents (59.5%) believe using GenAI allows them to create course materials more efficiently. Additionally, 53.4% expect that incorporating GenAI into their curriculum enhances students' learning outcomes. However, over 50% of respondents are neutral or disagree with the statement that using GenAI in research or academic services is helpful. Overall, approximately 72% believe integrating GenAI into their professional activities is beneficial.

Concerning perceived risk, over 80% of respondents express concern about the accuracy of content generated by GenAI. Nearly 70% are worried about the privacy and security of their data. While concerns about plagiarism and over-reliance on GenAI are less pronounced, they are still shared by over half of the respondents.

Regarding perceived enjoyment, a significant portion of respondents (nearly 68%) find exploring the capabilities of GenAI exciting and enjoyable. However, most respondents somewhat or strongly disagree that their institutions provide adequate training and technical support for using GenAI effectively.

Furthermore, almost 65% of respondents believe that their colleagues, important others, or university leadership think they should use GenAI in their work. Likewise, about 64% agree that GenAI is easy to use and learn.

While approximately 69% of respondents intend to use GenAI in teaching, research, or academic service, about 67% actually use GenAI at least occasionally for their learning and self-development, 56% use it for preparing course materials, and 52% integrate it into their teaching methodologies. Conversely, about 33% of respondents never or rarely use GenAI for teaching, research, service, or self-development.

Additionally, the study's results illustrate a comprehensive model detailing the dynamics influencing the adoption and use of GenAI. Perceived enjoyment and performance expectancy are primary drivers, indicating that the enjoyment and benefits associated with GenAI significantly propel educators' intention to use these technologies. Effort expectancy and social influence, while having smaller effect sizes, also positively contribute to behavioral intention, underscoring the importance of ease of use and peer influence in shaping attitudes towards technology adoption. Conversely, perceived risk negatively impacts behavioral intention, highlighting potential concerns that could deter users. Facilitating conditions play a crucial role in actual use behavior, suggesting that adequate support and resources are essential for translating intent into practical usage of GenAI. Overall, the model confirms that both intrinsic motivators and external conditions critically shape the behavioral intention and usage of GenAI.

The study also reveals that younger educators use GenAI more frequently than their older counterparts. However, the adverse effect of perceived risk on behavioral intention is more pronounced among younger educators, indicating that they are more sensitive to perceived risks when considering using GenAI. Female educators demonstrate a higher intention to use GenAI compared to their male colleagues. Additionally, the impact of social influence on behavioral intention is more substantial among female than male educators. Furthermore, female educators are more sensitive to perceived risks concerning their intention to use GenAI.

Finally, the analysis of the open-ended questions reveals six common themes regarding the use of GenAI tools in teaching. Educators highlighted that GenAI can streamline learning processes and save time, foster creativity and innovation, and increase student engagement through interaction with technology. Additionally, GenAI was seen as supportive of research and learning, though some educators expressed skepticism about its effectiveness. The usefulness of GenAI was also noted to be context-dependent, particularly beneficial in specific disciplines like finance and economics.

7 Contributions

This research offers both theoretical and practical contributions. By empirically investigating the use of GenAI in higher education with a substantial sample size, this study reveals factors influencing educators' decisions to adopt GenAI. It addresses the limitations of previous conceptual studies and those with small or convenient samples, providing a more robust and generalizable understanding of the phenomenon. Additionally, it applies the UTAUT model to GenAI as an emerging technology, as Venkatesh (2022) suggested. It also extends the model by incorporating perceived enjoyment and perceived risk, thus enriching the IS literature by offering a more comprehensive framework for studying technology adoption.

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Moreover, the findings of the open-ended questions provide valuable insights into educators' perspectives on the use of GenAI in teaching. The analysis revealed six common themes: efficiency and time-saving, creativity and innovation, engagement with technology, support in research and learning, skepticism or uncertainty, and contextual dependency. These themes elucidate the diverse ways in which educators perceive and interact with GenAI, offering a nuanced view that can inform both theoretical models and practical implementations. For researchers, the identified themes offer a foundation for further empirical studies to explore the nuanced impacts of GenAI on various educational outcomes. By highlighting specific areas of concern and interest, such as efficiency, creativity, and skepticism, future research can build on these findings to develop targeted interventions and strategies for effective GenAI integration in education.

Moderators also provide significant insights by highlighting the role of demographic factors in influencing adoption behavior, with age and gender significantly impacting behavioral intention. Specifically, age was found to negatively impact use behavior and moderate the relationship between perceived risk and behavioral intention, while gender positively influences behavioral intention and moderates the effects of social influence and perceived risk. These insights underscore the importance of considering demographic variables in technology adoption studies, suggesting that strategies to promote GenAI adoption may need to be tailored to different demographic groups to be effective.

The practical implications of this study provide educators and educational institutions with valuable guidance on how to integrate GenAI into their teaching strategies effectively. By tailoring training programs and support systems to address the opportunities and challenges identified by this research, institutions can foster a more comprehensive understanding of GenAI's potential. This strategic approach enhances student engagement and enriches learning experiences in higher education. For example, training programs can focus on demonstrating how GenAI can save time and boost creativity in course material preparation, while support systems can address concerns about data privacy.

Furthermore, by identifying educators' perceptions of the benefits, risks, and barriers to adopting and using GenAI, this study provides valuable insights for developers. These insights can help tailor GenAI more effectively to educators' needs and preferences, aiding in developing customized GenAI tools that address educators' concerns and enhance their confidence and competence in utilizing GenAI. For instance, developers can create features that enhance user control over AI-generated content, ensuring accuracy and reliability, or develop secure data handling protocols to alleviate privacy concerns. Additionally, understanding the demographic factors influencing adoption, such as age and gender, allows for the creation of targeted support resources and user interfaces that are more accessible and appealing to diverse educator groups. This holistic approach promotes the effective integration of GenAI and ensures that its implementation aligns with the specific requirements and expectations of educators, ultimately contributing to more innovative and effective teaching practices.

8 Limitations and Future Research Directions

Despite its contributions, this study faces some limitations. Collecting data from universities in the USA and Canada may limit the generalizability of the findings to other regions with different educational cultures and technological infrastructures. Additionally, the empirical analysis relies on self-reported data, which may be subject to biases such as social desirability or response bias. Future research should address these limitations by incorporating more diverse geographic samples and potentially using mixed methods to triangulate findings and reduce biases. Given the human-like interactive nature of GenAI and the fact that data for this study was collected almost 15 months after the initial release of ChatGPT in November 2022, it is no surprise that perceived enjoyment significantly influences behavioral intentions. As such, future research should explore the longevity of this effect.

9 Conclusion

This study, utilizing both quantitative and qualitative data and drawing on the UTAUT model, investigated the factors influencing the adoption and use of GenAI in higher education. Surveying 592 university professors across the USA and Canada, it identified significant benefits, risks, and barriers to integrating GenAI. Key benefits include more efficient course material creation and enhanced student learning outcomes, while major concerns revolve around the accuracy of AI-generated content and data privacy. Barriers to adoption include inadequate training and technical support.

Demographic factors like age and gender significantly influence adoption behaviors, underscoring the need for tailored strategies. The qualitative analysis revealed six common themes: efficiency and time-saving, creativity and innovation, engagement with technology, support in research and learning, skepticism or uncertainty, and contextual dependency. The study also highlighted that perceived

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enjoyment and performance expectancy are the main drivers of GenAI use in classrooms, whereas perceived risk hinders its integration. To effectively integrate GenAI into higher education, it is crucial to enhance its benefits and mitigate its risks, thereby improving scalability, personalization, and immersion in learning experiences and addressing many longstanding educational challenges.

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