Determinants of Student Adoption of Generative AI in Higher Education

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Abstract: The examination of the impact of Generative AI (GenAI) on higher education, especially from the viewpoint of students, is gaining significance. Although prior research has underscored GenAI's potential advantages in higher education, there exists a discernible research gap concerning the determinants that affect its adoption. In the present study, we aim to enhance our comprehension of the factors influencing the willingness of higher education students to adopt GenAI tools. To achieve this, we have developed an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model incorporating specific GenAI constructs. Our research methodology entailed the selection of a diverse sample of 374 students through random sampling. We then analyzed their data using Structural Equation Modeling (SEM) to gain insights into the complex relationships between various variables. The study found that students are more likely to use GenAI tools when they view them as supplemental resource and effort expectancy. It also revealed that perceived costs negatively impact adoption intentions, highlighting that financial factors are a significant barrier. Interestingly, Factors like information accuracy and hedonic motivation did not significantly affect students' adoption intentions. This study offers key insights for eLearning practitioners on integrating Generative AI (GenAI) tools into educational settings. It emphasizes the significance of resource perception and effort expectancy, demonstrating GenAI's potential to personalize learning experiences. eLearning platforms can utilize GenAI to enhance active learning through engaging methods and streamline course development. Addressing cost barriers is crucial for equitable access and inclusivity. A gradual approach to integration aligned with learning objectives is recommended, along with fostering critical engagement with GenAI tools to enhance digital literacy. Lastly, the study is constrained by its specific context, potential biases in self-reported data, a narrow focus on factors influencing students' intent to use GenAI tools and a cross-sectional design. Future research should encompass a broader range of factors, employ objective measures, and integrate observational data. Longitudinal studies or experimental designs could offer more comprehensive insights into how students' perceptions and intentions develop, thus promoting a more inclusive educational environment for all students.

Keywords: Generative AI, Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), Adoption technologies, Higher education

1. Study Background

In recent years, the rapid advancement of artificial intelligence (AI), particularly generative AI (GenAI), has revolutionized various fields, including education (Bahroun *et al.*, 2023). The emergence of GenAI has sparked widespread interest among students, educators, researchers, and educational institutions globally due to its significant impact on teaching and learning (Faisal Rashid, Duong-Trung and Pinkwart, 2024). GenAI represents a sophisticated technology that leverages deep learning models to generate content that closely resembles human responses to complex prompts. Its ongoing evolution is expected to drive innovation and improvements in higher education, while also presenting new challenges (Michel-Villarreal *et al.*, 2023).

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Multiple types of research have showcased the great potential of GenAI technology in education (for instance, Perera and Lankathilake, 2023; Tafazoli, 2024; Wang *et al.*, 2024). This technology can transform the conventional learning experience by offering personalized learning opportunities and adapting the educational content to cater to student's needs and abilities.

Furthermore, it promotes collaboration and peer interaction by producing contextually relevant prompts and responses, resulting in a dynamic learning environment that enhances student engagement and understanding (Chan and Zhou, 2023a).

GenAI technology can greatly improve personalized learning experiences by leveraging artificial intelligence (AI) and machine learning (ML) techniques to adapt educational activities based on student's preferences, backgrounds, and requirements (Maghsudi *et al.*, 2021; Fernandes, Rafatirad and Sayadi, 2023). By employing GenAI methods, educational platforms can accurately capture students' characteristics, recommend suitable content, develop customized curricula, and facilitate effective learner connections, ultimately enhancing performance evaluation and motivation for learning (Maghsudi *et al.*, 2021).

Additionally, the integration of AI and ML in personalized learning environments enables the continual refinement of unique profiles for individual students through learning data analytics, deep learning, and explainable AI, ensuring a more personalized and effective learning experience (Shawky and Badawi, 2019; Montebello, 2021).

GenAI technology is poised to significantly impact higher education by automating regular tasks, enhancing productivity, and creating new types of work and industries (Chan and Colloton, 2024). While students generally have a positive attitude towards GenAI in teaching and learning, recognizing its potential for personalized support and research capabilities (Chan and Hu, 2023), challenges persist. Universities exhibit significant variation in policies regarding GenAI use, with only a third having implemented specific guidelines (Xiao, Chen and Bao, 2023). Concerns include issues of academic integrity, ethical dilemmas, accuracy, privacy, and the potential transformation or obsolescence of certain jobs due to the continuous evolution of GenAI tools(Chan and Hu, 2023; Alier, García-Peñalvo and Camba, 2024).

In conclusion, effectively addressing these challenges requires a balanced approach leveraging GenAI benefits while mitigating its potential negative impacts on education and society (Arantes, 2024). This study examines factors influencing students' adoption of GenAI tools in higher education using a modified Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. The results show that supplemental resource and effort expectancy significantly and positively impact students' intent to use GenAI tools. At the same time, information accuracy and hedonic motivation do not significantly affect students' willingness to use these tools. This research enriches the UTAUT2 model by introducing new variables and provides practical implications for academic institutions.

2. Rationale of Study

To fully leverage the potential of GenAI, it is imperative to shift our academic focus from bemoaning the challenges in education to understanding how students can effectively utilize such tools (Susarla et al., 2023). An essential aspect of this endeavor is comprehending student perceptions and intentions (Chan and Zhou, 2023). Various studies highlighted the importance of exploring student perceptions and their willingness to embrace GenAI. By dissecting the link between these perceptions and usage intentions, we can gain valuable insight into how students interact with GenAI tools and how to tailor them to better meet student needs and preferences (Ivanov *et al.*, 2024).

It is also crucial to delve into the antecedents of adoption intention and actual usage of AI-based teacher bots, including perceived ease of use, usefulness, information accuracy, interactivity, cost, and perceived intelligence (Pillai *et al.*, 2024). This comprehensive exploration sheds light on the elements contributing to student acceptance of AI technologies, which is vital for developing engaging and effective GenAI tools (Alzahrani, 2023).

Ultimately, a profound understanding of these mechanisms can aid in designing and implementing GenAI tools that enhance educational outcomes. Aligning these tools with student needs and preferences can drive more personalized, interactive, and effective learning experiences.

3. Study Problems and Aims

Recently, there has been a growing focus on the impact of GenAI in higher education. However, there is a need for a comprehensive exploration of the personal and technological factors that influence users' intentions to utilize GenAI, including hedonism, usefulness, and supplemental resource. Existing research primarily addresses concerns related to academic integrity, potentially limiting student engagement with this transformative technology. Despite students' interest, there is a lack of thorough examination of their perspectives on incorporating GenAI into learning environments (Furze *et al.*, 2024). While previous studies have underscored GenAI's potential in higher education (McDonald *et al.*, 2024), there exists a notable research gap regarding the factors influencing its adoption (Gupta and Yang, 2024).

Understanding these adoption determinants is vital for developing tailored theoretical and practical frameworks to optimize GenAI platforms in education. Given that students are primary beneficiaries, our study aims to explore the diverse factors influencing their adoption of GenAI tools. While the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model provides valuable insights into technology adoption, its application in educational contexts must be modified to be more suitable.

To address these gaps, our research proposes a modified UTAUT2 model that incorporates GenAI -specific characteristics. This approach aims to elucidate how elements like hedonic motivation, effort expectancy, and behavioral intention influence the adoption of GenAI tools among higher education students. Additionally, variables such as information accuracy, perceived cost, and the role of GenAI as a supplemental resource will be investigated to determine their impact on adoption behavior. By identifying reliable predictors of adoption, this study seeks to provide nuanced insights and practical recommendations for optimizing GenAI integration in higher education settings.

4. Study Questions

The current study aims to uncover the key drivers behind higher education students' adoption of Generative AI (GenAI) tools. By extending the UTAUT2 model with GenAI-specific components, we will delve into essential variables influencing adoption behaviors. Accordingly, we pose the following pivotal questions: How do specific factors of the UTAUT2 model, namely hedonic motivation, effort expectancy, and behavioral intention, influence the adoption of GenAI tools by higher education students? In addition, how do additional factors, specifically information accuracy, supplemental resource, and perceived cost, contribute to the adoption of GenAI tools by higher education students? Lastly, among these factors, which is the most dependable predictor of higher education students' adoption of GenAI tools?

5. Significance of the Study

This research is paramount for advancing the integration of GenAI tools in higher education. By examining the factors influencing students' overall experience and expanding the user base of GenAI in education, the study aims to enrich students' experience and promote wider adoption of GenAI in education. The anticipated results of this study are expected to bring substantial and far-reaching benefits for the effective implementation of GenAI in education.

The research's model offers a comprehensive understanding of the factors impacting GenAI adoption among higher education students, providing insights into how various factors collectively influence students' acceptance and use of GenAI tools. This study is instrumental in enhancing the localization and adaptation of GenAI design technology specifically for higher education students. By analyzing the factors influencing their adoption of this technology, we aim to improve the user experience and expand the current user base for GenAI tools, leading to a positive and extensive impact on the utilization of GenAI in higher education.

6. Literature Review and Theory Development

There has been a surge in the use and popularity of GenAI tools, which are being utilized in various fields, including education (Chan and Zhou, 2023a). Integrating these technologies in educational settings has transformed the learning landscape and revolutionized how students approach their studies (Mishra, Oster and Henriksen, 2024).

Recent research on the integration of GenAI in higher education suggests a generally positive reception among students (Chan and Hu, 2023). They acknowledge the benefits of personalized learning support, writing assistance, and enhanced research capabilities (Akyuz, 2020). However, concerns have been raised regarding accuracy, privacy, ethical implications, and the potential impact on personal and societal development (Wach *et al.*, 2023). Given that student perceptions significantly influence learning approaches and outcomes; it is important to address their concerns to effectively incorporate GenAI tools in education (Chan and Hu, 2023).

Additionally, students' intention to use GenAI is influenced by information accuracy and cost, highlighting the importance of considering these factors in promoting adoption (Gupta *et al.*, 2024). Educators and students must be involved in assessment reform efforts to emphasize learning processes, critical thinking, and practical applications in the context of the evolving landscape of AI in education. (Pedro *et al.*, 2019; Alam, 2021).

However, for these technologies to be widely adopted, it is crucial to understand students' perceptions and the factors influencing their acceptance (Ivanov *et al.*, 2024). In this regard, The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model provides a detailed framework for examining how students adopt GenAI tools. It considers factors such as effort expectancy, social influence, hedonistic motivation, and facilitating conditions. This comprehensive approach allows for a more thorough analysis of the adoption process (Gulati *et al.*, 2024).

Various academics have employed the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to comprehend users' inclinations toward accepting AI-based products or technologies. Recent research has demonstrated that these aspects have a significant impact on students' attitudes towards GenAI tools (Wang and Zhang, 2023). For instance, several studies (such as Budhathoki et al., 2024; Sobaih et al., 2024; Wang & Zhang, 2023) have emphasized the significance of performance expectancy. This refers to the degree to which students believe using GenAI tools can improve their academic performance. In addition, the ease of use of these technologies, known as effort expectancy, is a significant factor in determining students' willingness to adopt GenAI tools. Social influence, habit, hedonistic motivation, and facilitating conditions are other factors that have a bearing on students' perceptions of these technologies (Nikolopoulou, Gialamas and Lavidas, 2021; Alhur *et al.*, 2022).

The UTAUT2 model is undoubtedly a valuable framework for understanding technology adoption (Faqih and Jaradat, 2021). Still, it can be challenging to apply in practice, especially in educational settings where resources are often limited (Malatji, VanEck and Zuva, 2023). Additionally, the model overlooks the role of technology characteristics, particularly GenAI, such as information accuracy, in technology adoption. Despite these limitations, modifying the model can make it more useful for education. Researchers have extended the UTAUT2 model, and these modifications show promise for understanding and implementing technology adoption in education (Tamilmani *et al.*, 2021). A recent study conducted by Wang & Zhang (2023) aimed to understand the factors that influence Generation Z's (GenZers) willingness to adopt GenAI technology. To achieve this, the study combined the UTAUT2, Technology Readiness Index (TRI) model, and trait curiosity. The study found that hedonic motivation and effort expectancy are positively correlated to using GenAI. However, no significant correlation was found between performance expectations and the willingness to use GenAI technology.

Despite the presence of these studies, there is a lack of research that thoroughly investigates how GenAI tools' positive and negative aspects can effectively predict the core elements of the UTAUT2 model, such as behavioral intention and use behavior. As a result, this article seeks to address this gap in research by extending the UTAUT 2 model to include GenAI.

One potential modification that could be made to the UTAUT2 model is to simplify the constructs and incorporate GenAI-related constructs. This way, the model can capture the essential factors influencing students' acceptance of GenAI tools, making them more accessible and practical for real-world use (Chan, 2023; Chan and Lee, 2023). By streamlining the model, educators and developers can gain valuable insights into students' perceptions of GenAI tools, which can enhance their design and implementation in educational settings (Budhathoki *et al.*, 2024; Chiu, 2024).

Educators and developers should consider the factors influencing technology adoption when creating and implementing GenAI tools. Integrating GenAI-related concepts, such as information accuracy, and viewing GenAI as a supplemental resource (Michel-Villarreal *et al.*, 2023; AlDreabi *et al.*, 2024) within the UTAUT2 model can help address gaps and improve understanding of technology adoption in educational settings.

7. Theoretical Model and Hypotheses

This study expands on previous research by combining UTAUT2 with GenAI characteristics to create a more comprehensive model for understanding technology adoption. This approach provides deeper insight into the factors influencing higher education students' willingness to use GenAI for learning. The upcoming sections will explore these research factors and evaluate their implications for educational practice. Additionally, we will identify potential areas for future research in this rapidly evolving field.

Additionally, Figure 1 illustrates the proposed hypotheses of this research and displays six interrelated pathways. Each pathway represents a specific hypothesis, and the model summarizes each component. Overall, the diagram functions as a visual representation of the hypotheses being examined in the study.

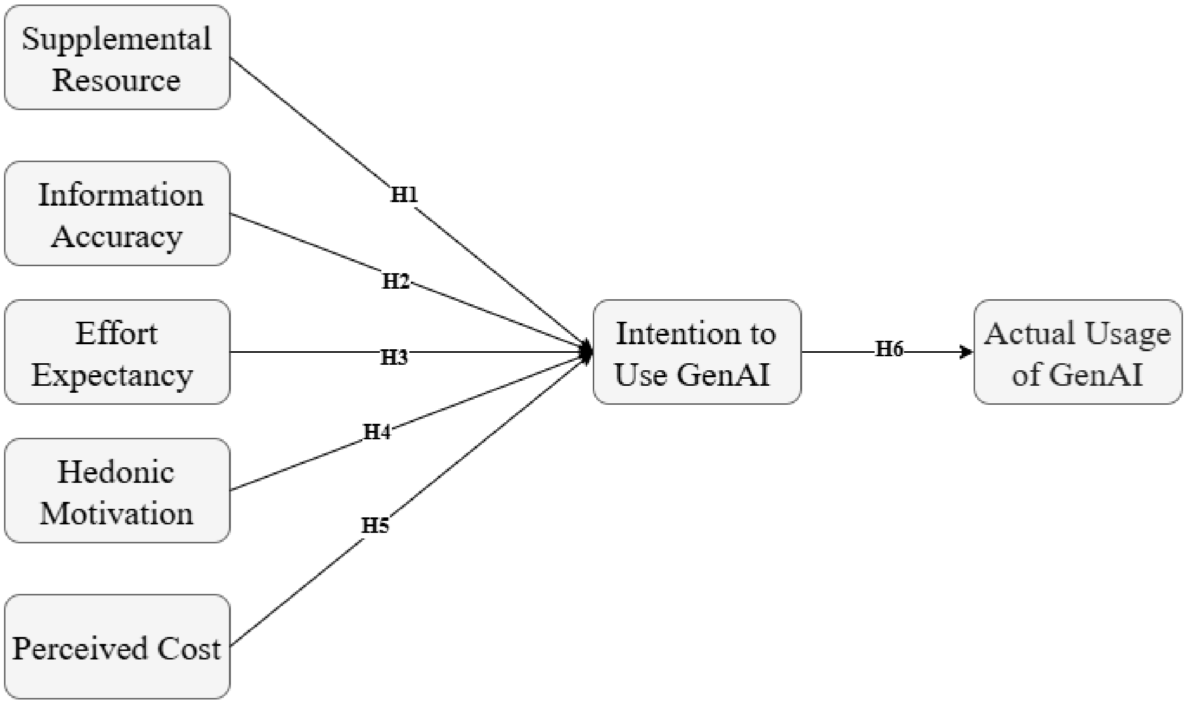

Figure 1*:* Study Model

8. Supplemental Resource

GenAI serves as a supplemental resource for students by utilizing algorithms to produce customized educational resources such as textbooks, eBooks, quizzes, and other creative materials (Alier, García-Peñalvo and Camba, 2024). This technology adapts content to individual learning preferences, enhancing the learning experience (Borah, T N and Gupta, 2024).

There are numerous promising opportunities for students, educators, and researchers in higher education with the use of GenAI (Chiu, 2024). With the aid of GenAI, students can improve their learning and foster critical thinking skills by receiving personalized feedback, explanations, and recommendations (Michel-Villarreal *et al.*, 2023). Research has shown that GenAI can enhance essay-writing skills and serve as a valuable tutoring tool, encouraging lively student debates and discussions (Dwivedi *et al.*, 2023). Furthermore, when used with traditional course materials, GenAI can help reinforce learning and promote independent research (Mai, Da and Hanh, 2024).

GenAI can greatly help medical teaching, particularly in resource-limited settings. GenAI tools enable students to ask queries about medical ideas and receive customized replies to aid them organize their understanding more effectively (Leng, 2024).

Additionally, GenAI tools can aid research by training students in data organization and location for papers and studies. These same tools can also provide direct feedback on diction and grammar to pupils learning a new language, facilitating their language development (Javaid *et al.*, 2023). Studies by Baidoo-Anu & Ansah (2023) Koraishi (2023), Michel-Villarreal et al. (2023) all concur that GenAI is a supplemental resource for higher education students.

Thus, H1: *The perception of GenAI tools as supplemental resource (such as answering queries, generating thoughts, and conducting analyses) has a positive linear impact on higher education students' behavioral intention to use these tools.*

9. Information Accuracy

The construct of information accuracy pertains to how students view the dependability and correctness of information given by AI tools (Dahri *et al.*, 2024). Students' readiness to utilize these tools is affected by their trust in the accuracy of the information. A recent study by Dahri et al. (2024) emphasizes the significance of the information accuracy concept and how it influences the usage of AI tools. In a different examination, Mizumoto & Eguchi (2023) assessed ChatGPT as an automated tool for scoring essays and discovered that it decreased grading time while ensuring consistency in scoring.

Furthermore, it furnished prompt feedback on the writing skills of students. The effectiveness and reliability of ChatGPT showcase the potential of GenAI to transform the process of teaching, leading to better academic results for college and university students. Nevertheless, it is crucial to remember that the accuracy of AI tools is not always guaranteed, and therefore, they must be used cautiously (Chan and Hu, 2023).

In a study by Ding et al. (2023), ChatGPT was used as a virtual tutor to assist in teaching undergraduate-level introductory physics. While it provided an 85% accuracy in answering questions, it occasionally changed its answers from correct to incorrect and vice versa. Students needed clarification about ChatGPT, and almost half trusted its answers regardless of their accuracy.

Thus, H2: *Information accuracy has a positive linear impact on higher education students' behavioral intentions to use GenAI tools.*

10. Effort Expectancy

Effort expectancy is an essential factor in deciding whether someone will use a technology. It means how easy or difficult someone thinks it will be to use a technology. If students think it will be easy to use, they will likely use it (Venkatesh *et al.*, 2003). According to UTAUT2, if technology is easy to use, people will think it requires less effort. Some recent studies have found that people are more likely to use AI services if they think they are easy to use (Wang and Zhang, 2023).

Previous inquiries have yielded helpful insights into utilizing GenAI tools in different scenarios, such as education and research, using various theoretical approaches (Ivanov *et al.*, 2024). Specifically, in education, this factor refers to the level of simplicity exhibited by technology that is perceived by students. In case students consider a system or technology to be user-friendly, they are more likely to recognize its benefits and demonstrate deliberate behavior. As a result, this influences their intention to adopt a specific technology (Budhathoki *et al.*, 2024).

Therefore, it is crucial to consider the perception of effort expectancy when introducing new technologies like GenAI in the educational setting. Students who perceive GenAI tools as simple and easy to use are likelier to engage in deliberate behavior and develop an awareness of the benefits. This, in turn, increases their willingness to adopt the technology and utilize it to its full potential.

Consistent with the research mentioned above, we suggest that: H3: *effort expectancy has a positive linear impact on higher education students' behavioral intentions to use GenAI tools*.

11. Hedonic Motivation

The Unified Theory of Acceptance and Use of Technology (UTAUT) model has been valuable in understanding technology adoption and use. However, it has been criticized for not accounting for the pleasure and enjoyment that comes with using technology (Budhathoki *et al.*, 2024). To address this, the Unified Theory of Acceptance and Use of Technology (UTAUT2) model was introduced in 2012, which includes hedonic motivation as a factor. As defined by Venkatesh, Thong and Xu, (2012), *hedonic motivation* pertains to the satisfaction and enjoyment individuals experience when using cutting-edge technological systems (Venkatesh, Thong and Xu, 2012). Recent studies have revealed a favorable correlation between hedonic motivation and users' inclination to embrace artificial intelligence assistants. Research has also revealed that hedonic motivation has a positive impact on the inclination to embrace and utilize mobile technology, especially for students who value enjoyable and satisfying user experiences (Al-Azawei and Alowayr, 2020).

Moreover, research has found that teachers' intention to adopt mobile Internet for course instruction is positively influenced by the joy they derive from using it (Nikolopoulou, Gialamas and Lavidas, 2021). Similarly, hedonic motivation has been found to impact the acceptance of mobile technology among secondary school teachers and students, with perceived enjoyment significantly affecting students' intentions to accept mobile learning (Açıkgül and Şad, 2021).

Our study proposes that hedonic motivation is essential in how higher education students utilize GenAI tools. The interactive and enjoyable environment created by the conversational aspect of GenAI tools enhances the learning experience and stimulates students, ultimately enhancing their knowledge acquisition.

We propose that H4: *hedonic motivation has a positive linear impact on higher education students' behavioral intentions to use GenAI tools.*

12. Perceived Cost

Per the UTAUT2 model, perceived cost/price is the rational assessment of the anticipated benefits of utilizing technology for the required financial investment (Wang and Zhang, 2023). Lower costs associated with learning or adopting a new technology result in greater perceived benefits, leading to a stronger intention to use it (Al-Adwan and Al-Debei, 2024).

It is a fundamental principle in technology adoption that the perceived benefits of a technology must outweigh its associated costs, as outlined by Venkatesh, Thong and Xu (2012). Therefore, the financial investment necessary to learn or acquire new technology is a crucial factor, as highlighted by Cecilia Ka Yuk Chan and Zhou (2023). Higher perceived benefits of new technology are associated with lower learning or acquisition costs, ultimately increasing the likelihood of technology use.

In other words, investing in technology can pay off in the long run, especially if we take the time to find affordable options (Wang and Zhang, 2023). An individual's motivation and intention to use a service are significantly influenced by its cost. Students might be less likely to use GenAI if the costs are greater than the advantages for them. Research have shown that students' willingness to use educational technology can be negatively impacted by perceived barriers, such as cost (Chan and Zhou, 2023a).

Thus, H5: *The perceived cost has a negative linear impact on higher education students' behavioral intentions to use GenAI tools.*

13. Behavioral Intention

Over the years, researchers in information systems have delved into studying individual behavior and intentions as they relate to technology. This has resulted in the development of various acceptance models for information technology, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Pan and Gao, 2021). The UTAUT2 framework posits that intention is a significant predictor of behavior, influenced by seven fundamental constructs. This theory emphasizes the power of intentions in shaping actions, indicating that individuals are more inclined to act when they genuinely believe their efforts will yield favorable outcomes (Silverman *et al.*, 2016)

In examining the success of information systems, researchers look at actual system usage. The user's willingness to utilize the system can then be understood as their intention to use it. According to experts in technology acceptance, behavioral intention to use directly translates to actual system usage. Most studies aimed at validating technology acceptance models have found this relationship to hold true (Mardiana, Tjakraatmadja and Aprianingsih, 2015).

In this study, "behavioral intentions" refers to students' willingness and determination to integrate GenAI tools into their learning practices. A positive attitude toward these tools indicates students' enthusiasm for incorporating AI technology into their educational endeavors. Previous research has demonstrated that a favorable disposition toward technology usage strongly correlates with its adoption (Ivanov *et al.*, 2024). Similarly, Chatterjee and Bhattacharjee (2020) examined students' behavioral intentions regarding using AI agents or chatbots. Their findings revealed that positive intentions were positively correlated with increased usage of such tools. Consequently, we hypothesize that H6, *the intention to use GenAI has a positive linear impact on higher education students' use of GenAI tools.*

14. Methodology

The study utilized a quantitative cross-sectional approach to explore the utilization of GenAI tools by higher education students in Jordanian public universities during the academic year 2023/2024. It specifically targeted students from three prominent governmental universities: The University of Jordan (1631 students), Jordan

University of Science and Technology (JUST) (1214 students), and Al-Balqa Applied University (350 students). Follow random sampling, a total of 374 students participated in a survey conducted via Google Forms between December 10, 2023, and February 5, 2024, with the support of the student affairs deanships of the universities.

The framework of this study was evaluated using Structural Equation Modeling (SEM), a powerful technique designed for analyzing intricate models with multiple variables and their interconnections(Hair *et al.*, 2021). SEM allows for the simultaneous exploration of both direct and indirect relationships among constructs, deepening our insight into how various factors within the study's model influence the adoption of Generative AI tools (Masud *et al.*, 2024). This methodological approach perfectly aligns with the study's aim to investigate behavioral intention and adoption behavior among students, as SEM effectively integrates measurement and structural components, enhancing the reliability and robustness of the findings.

The questionnaire, initially developed in English and later translated into Arabic, consisted of 23 items that assessed various aspects of the research model, including four demographic questions, incorporating demographic variables such as gender and frequency of GenAI tool usage, essential for interpreting the study's findings. Gender influences technology adoption behaviors, and understanding how often students use GenAI, including whether they opt for free or paid versions, provides insights into access and familiarity in adoption intentions (Table (1). We adapted a previously validated questionnaire from earlier studies, as outlined in Appendix 1. All the scales used in our study have been validated and shown reliability in studies by Chan and Lee (2023), Venkatesh, Thong and Xu (2012), and Dahri *et al.* (2024).

The survey investigated the elements of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), initially designed to analyze technology acceptance in consumer contexts. This framework has been refined to integrate characteristics specific to Generative AI (GenAI), highlighting key aspects such as hedonic motivation, effort expectancy, and behavioral intention. Additionally, it considers crucial factors like information accuracy, perceived costs, and the perception of GenAI as a valuable supplemental resource. This enhanced UTAUT2 framework is particularly suited for higher education environments, where varying motivations and perceived utility influence individual attitudes toward technology. Consequently, it provides a robust theoretical foundation for comprehending the adoption of GenAI tools in educational settings.

Prior to analysis, the data underwent thorough scrutiny for any missing information or anomalies. The sample size was deemed suitable for SEM methodology (Kyriazos, 2018), and an exploratory factor analysis was conducted to effectively consolidate the dimensions linked with each construct.

15. Sample Characteristics

In Table 1, an analysis of the demographic data from the sample is presented, including gender, age, frequency of GenAI tools usage, and whether participants used the paid version of GenAI tools. The sample included 374 students, 52.7% female and 47.3% male. The majority of participants 43.3% fell within the age range of 18-30 years, followed by 31-41 years 31.8%, and ≥42 years 24.9%. In terms of GenAI tools usage, 12% reported using it only once, 23% used it 2-3 times, and 65% used it three times or more. As for whether participants used the paid version of GenAI tools, 56.7% reported using the free version, while 43.3% used the paid version.

Table 1: Sample characteristics

Demographic Data	Categories	Count	Percentage %
Gender	Female	197	52.7%
	Male	177	47.3%
	Total	374	100%
Age	18-30 years	162	43.3%
	31-41 years	119	31.8%
	42 yrs. and over	93	24.9%
	Total	374	100%
How often do you use GenAI tools?	Once times or less	45	12.0%
	2-3 times in week	86	23.0%
	More than 3 times	243	65.0%
	Total	374	100%

Demographic Data	Categories	Count	Percentage %
Do you use the paid version of GenAI tools?	No	212	56.7%
	Yes	162	43.3%
	Total	374	100%

16. Results

The study's data underwent rigorous analysis using IBM SPSS 27 and IBM AMOS 28. As per Hair et al.'s (2019) two-step approach, the researchers conducted confirmatory factor analysis (CFA) to evaluate the measurement model's reliability, validity, and fitness indices. In the second step, they employed robust structural equation modeling (SEM) to examine all hypotheses and comprehensively understand the study's findings.

17. The Study's Reliability and Validity

This study presents a novel measurement model for assessing students' adoption of GenAI tools in higher education. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT) model and GenAI literature, the model was formulated based on the Hair 2019 guidelines. Measurement theory was employed to determine how the latent variables (constructs) are measured, wherein the reflective measurement approach was used due to its suitability for the current context. This approach can effectively capture the nature and nuances of the constructs and provide more reliable and accurate results (Hair et al., 2021).

The model used in this study was rigorously fitted with data, yielding strong fit indices. Specifically, the findings revealed a chi-square value of χ^2 (180) = 565.552, a chi-square to degrees of freedom ratio of χ^2/df = 3.142, a Comparative Fit Index (CFI) of 0.924, a Standardized Root Mean Square Residual (SRMR) of 0.051, and a Root Mean Square Error of Approximation (RMSEA) of 0.076, with a P value exceeding 0.05 (Crawford and Kelder, 2019). To further establish the validity and reliability of the instruments employed, Tables 2 and 3 present findings demonstrating a Cronbach's alpha value greater than 0.70, alongside factor loadings that surpass the recommended threshold of 0.50 (Hair et al., 2021). Additionally, the Average Variance Extracted (AVE) was greater than 0.50 (Kline, 2011), as detailed in Table 3.

Table 2: CFA and descriptive statistics

Items	Factor Loadings*	α*	M(SD)*	Skewness*	Kurtosis*
SR1	.939	0.937	3.70(.967)	-.179	-.631
SR3	.917				
SR2	.898				
IA1	.935	0.925	3.03(.947)	-.077	-.559
IA3	.840				
IA4	.863				
IA2	.853				
HM3	.923	0.859	3.31(.917)	-.178	-.698
HM2	.864				
HM1	.692				
Int.3	.911	0.851	4.01(.946)	-.093	-.666
Int.2	.835				
Int.1	.693				
PC2	.752	0.795	3.38(.879)	.147	.516
PC1	.786				
PC3	.738				
AU2	.832	0.797	3.86(.903)	-.134	-.481
AU1	.715				
AU3	.721				
EE3	.745	0.745	3.94(.917)	-.100	-.450

Items	Factor Loadings*	α*	M(SD)*	Skewness*	Kurtosis*
EE2	.745				
EE1	.625				

Note: SR: Supplemental resource, IA: Information accuracy, HM: Hedonic motivation, Int.: Intention to use GenAI tools, PC: Perceived cost, AU: Actual usage of GenAI tools, EE: Effort expectancy. α= Cronbach's Alpha coefficient; M(SD)= Mean & Standard deviation. * These values fall within the thresholds established by Kline (2011) and Hair *et al.* (2019, 2021a)

Examining both convergent and discriminant validity indicated that the research instrument exhibited adequate convergent validity (Hair et al., 2021). Furthermore, Tables 3 and 4 confirm that the measurement items possess sufficient discriminant validity, with Composite Reliability (CR) values going beyond the AVE values (Kline, 2011). The AVE values also exceeded the Average Shared Variance (ASV) and Maximum Shared Variance (MSV) values. At the same time, the correlations among the independent variables remained below the threshold of 0.70 (Almén *et al.*, 2018).

Table 3: Study model's validity

Factors	CR	AVE	MSV	MaxR(H)	SR	IA	HM	Int.	PC	AU	EE
SR	0.941	0.843	0.158	0.944	**0.918**						
IA	0.928	0.763	0.195	0.937	0.397	**0.874**					
HM	0.869	0.692	0.165	0.906	0.186	0.348	**0.832**				
Int.	0.857	0.669	0.114	0.890	0.154	0.160	0.175	**0.818**			
PC	0.803	0.576	0.196	0.805	0.133	-0.442	0.329	-0.300	**0.759**		
AU	0.801	0.574	0.114	0.814	0.160	0.250	0.159	0.338	0.247	**0.758**	
EE	0.749	0.501	0.196	0.758	0.170	0.370	0.406	0.201	0.443	0.204	**0.707**

Note: SR: SR: Supplemental resource, IA: Information accuracy, HM: Hedonic motivation, Int.: Intention to use GenAI tools, PC: Perceived cost, AU: Actual usage of GenAI tools, EE: Effort expectancy; Composite Reliability = (CR) > 0.70, Average Variance Extracted = AVE > 0.50, Maximum Shared Variance = AVE > MSV and McDonald Construct Reliability = MaxR(H) > 0.7. The square root of the AVE is displayed as diagonal boldface values. These values fall within the thresholds established by Kline (2011), Hair *et al.* (2019) and Almén *et al.* (2018)

Table 4: HTMT Analysis

Factors	SR	IA	HM	Int.	PC	AU	EE
SR							
IA	0.404						
HM	0.253	0.362					
Int.	0.167	0.178	0.202				
PC	0.138	0.471	0.364	0.313			
AU	0.159	0.267	0.188	0.358	0.273		
EE	0.178	0.354	0.455	0.212	0.468	0.210	

Note: SR: SR: Supplemental resource, IA: Information accuracy, HM: Hedonic motivation, Int.: Intention to use GenAI tools, PC: Perceived cost, AU: Actual usage of GenAI tools, EE: Effort expectancy. These values fall within the thresholds established by Almén et al. (2018)

18. Structural Model

The study utilized Structural Equation Modeling (SEM) to investigate the factors that affect students' intention to use Generative AI (GenAI) tools. The structural model was developed in accordance with the guidelines established by Hair et al. (2021). The findings indicated that the model displayed a satisfactory fit, as assessed against the criteria set forth by Crawford & Kelder (2019): χ^2 (185) = 597.590, χ^2/df = 3.230, CFI = 0.939, SRMR = 0.052, and RMSEA = 0.073, with a p-value exceeding 0.05.

Figure 2 illustrates the finalized structural model, depicting the relationships among several key predictors—including supplemental resource, information accuracy, effort expectancy, hedonic motivation, and perceived cost—along with the intention to use GenAI tools and the actual usage of these tools. Each pathway is annotated with its standardized regression weight (β) and statistical significance level. Significant relationships are marked with solid arrows (*p < 0.05), while dashed arrows indicate non-significant relationships.

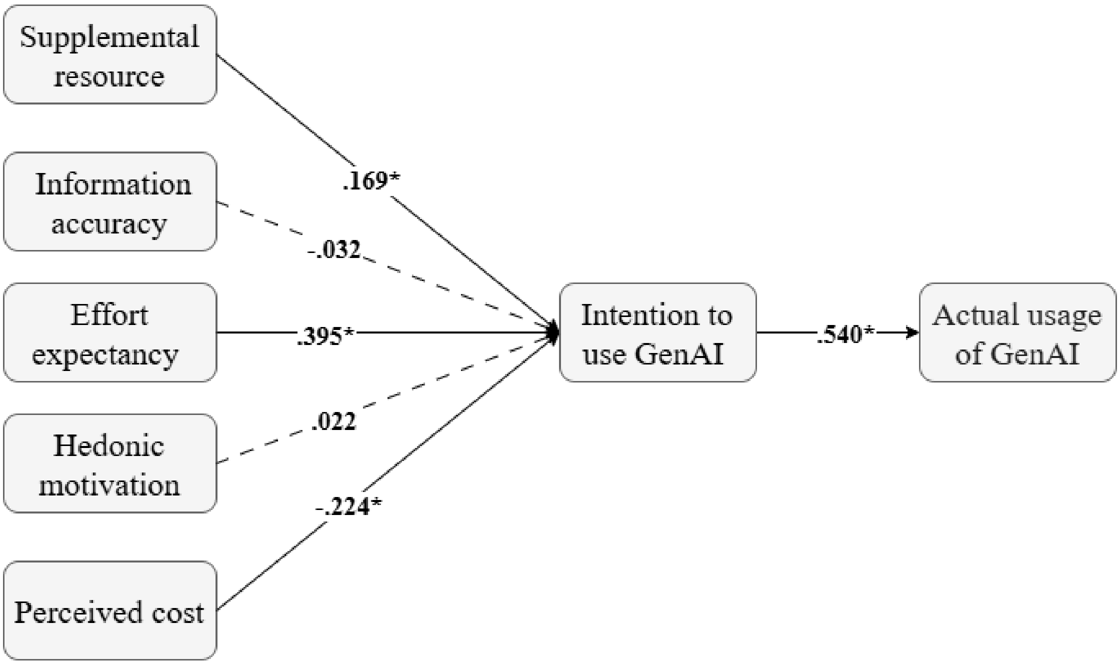

Figure 2*: Structural Model, * P<0.05.*

The results, as presented in Table 5, show that supplemental resource (β = 0.169, p < 0.01), effort expectancy (β = 0.395, p < 0.001), and perceived cost (β = -0.224, p < 0.05) significantly influence students' intention to use GenAI tools, thereby supporting hypotheses H1, H4, and H5. Additionally, the intention to use GenAI tools is a strong predictor of actual usage (β = 0.54, p < 0.001), supporting hypothesis H6.

In contrast, the factors of information accuracy (β = -0.032, p > 0.05) and hedonic motivation (β = 0.022, p > 0.05) do not have a significant impact on students' intention, failing to support hypotheses H2 and H3. Overall, the model accounts for 39% of the variance in students' intention to use GenAI tools and 29% of the variance in their actual usage.

Table 5: Hypotheses testing

Hypothesis	Predictors	Outcomes	S.E.*	t-value	Beta
H1	Supplemental resource	Intention to use GenAI tools	.062	2.867	.169**
H2	Information accuracy	Intention to use GenAI tools	.075	0.417	-.032
H3	Hedonic motivation	Intention to use GenAI tools	.062	0.340	.022
H4	Perceived cost	Intention to use GenAI tools	.114	2.572	.224*
H5	Effort expectancy	Intention to use GenAI tools	.093	4.651	.395***
H6	Intention to use GenAI tools	Actual usage of GenAI tools	.050	9.863	.540***

Note: S.E. = Standard Error, * P<0.05, **P<0.01, *** P<0.001

19. Discussion

This research utilized an adapted version of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to examine the factors influencing students' adoption of generative AI (GenAI) tools. The analysis highlighted several key factors: perceived cost, effort expectancy, hedonic motivation, supplemental resource, and information accuracy.

The findings in Table 5 indicate that students are significantly more inclined to use GenAI tools when they view them as offering valuable supplemental resource, being cost-effective, and being easy to use. Furthermore, Figure 2 illustrates the relationships among these factors and their influence on students' behavioral intentions to adopt GenAI tools in higher education.

The results reveal that effort expectancy and behavioral intention significantly influence students' adoption of Generative AI (GenAI). Conversely, the hedonistic value has little effect on students' willingness to embrace Generative AI. These findings align with previous research conducted by Ivanov *et al.* (2024), McDonald *et al.* (2024), which also emphasized the significance of usability and the availability of supportive resources in technology adoption.

Moreover, the results show that intention behavior has a robust and significant effect on willingness to embrace Generative AI. This finding aligns with previous research (Venkatesh, 2022; Li, 2024; Lu *et al.*, 2024), reinforcing the notion that intention is a critical determinant in technology adoption

The recent shift in focus highlights the importance of educational institutions prioritizing the creation of user-friendly tools that seamlessly fit into students' academic workflows. These institutions must invest in training and support resources that improve students' experiences, enabling them to utilize these tools effectively and navigate their academic tasks with minimal challenges.

The research also highlights vital factors influencing the adoption of Generative AI (GenAI) tools, mainly focusing on information accuracy, supplemental resource, and perceived cost. Findings indicate that students are more likely to use GenAI tools when they view them as cost-effective and offering valuable resources. This aligns with studies by Michel-Villarreal *et al.* (2023) and Wang and Zhang (2023) on the importance of considering GenAI as a supplemental resource for technology adoption in education.

While information accuracy is relevant, students prioritize perceived cost and availability of supportive resources (Chan and Zhou, 2023a). This change in priorities suggests that initiatives to promote GenAI adoption in higher education should place less emphasis on refining precision or enhancing the hedonic value of these tools and more on ensuring they are accessible, user-friendly, and accompanied by robust resources (Hmoud *et al.*, 2023; Li, 2024).

Among the various factors influencing the adoption of Generative AI (GenAI) tools by higher education students, effort expectancy and the availability of supplemental resource have emerged as the most reliable predictors. The findings suggest that students are more inclined to adopt GenAI tools when they view them as user-friendly and recognize the presence of supporting resources, such as tailored examples and information that cater to their learning needs. This observation aligns with existing literature on technology adoption in educational settings, underscoring the importance of accessibility and support structures for effective technology integration (Ivanov *et al.*, 2024; Meakin, 2024).

The focus on effort expectancy indicates that institutions should prioritize making GenAI tools intuitive and easy to use. Students who find these tools straightforward to navigate are more likely to engage with them consistently. Furthermore, the availability of supplemental resource is vital in promoting sustained use. Students benefit significantly from resources that enhance their understanding and application of GenAI tools, which can influence their learning outcomes (Granić, 2022).

20. Study Contributions About Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) Model

The UTAUT2 framework is expanded in this study to incorporate new factors specific to GenAI technologies in higher education. These additional factors, such as supplemental resource and effort expectancy, are vital for understanding students' intentions to adopt GenAI tools, even though they are not explicitly covered in the original UTAUT2 model.

The study utilizes the UTAUT2 model to analyze the adoption of GenAI tools in higher education, shedding light on how existing UTAUT2 variables, like effort expectancy, interact with new GenAI-specific variables, such as supplemental resource.

Furthermore, the research confirms the relevance of existing UTAUT2 variables, like perceived cost and effort expectancy, in the context of GenAI tools, signifying their continued significance in technology adoption.

Moreover, the research outlines practical implications for educational institutions, underscoring the importance of providing comprehensive resources and ensuring the affordability and usability of GenAI tools to facilitate their integration into higher education environments.z

In conclusion, this study enhances the UTAUT2 model by introducing new variables, validating existing ones, critiquing less influential factors, and providing practical insights for implementation in higher education settings.

21. Study Implications

This study aims to explore the factors influencing the utilization of GenAI tools in education, building upon previous studies in this field. Prior research mainly concentrated on identifying the essential variables impacting the use of these tools in various situations. However, this study takes a more comprehensive approach by considering multiple essential elements, such as accuracy of information, supplemental resource, and perceived cost. It seeks to establish a structural model that assesses the most significant factors affecting the adoption of GenAI tools among undergraduate and postgraduate students.

The study also contributes to existing knowledge by extending the UTAUT2 framework to demonstrate the main factors promoting the implementation of GenAI technologies, like Genmini, in higher education institutions. This expansion is important as it highlights the necessity for educational institutions to take various factors into account when making decisions about integrating GenAI tools. By doing so, educational institutions can ensure that the tools are effectively used, enabling their students to benefit from utilizing them in their studies and education.

In contrast, the study's findings present two key practical implications. Firstly, to ensure the effective use of GenAI tools, educational institutions, and developers should prioritize making them more cost-effective, user-friendly, and resourceful. This can be achieved by offering additional resources and support to students, improving the usability of the tools, and ensuring that they are perceived as valuable supplements to traditional learning methods. By addressing these factors, institutions can increase students' willingness to use GenAI tools, promoting their adoption and integration into educational environments.

Secondly, the study highlights the importance of a comprehensive approach to technology adoption in educational settings. While accuracy of information and hedonic motivation are important, they may not be the sole drivers of students' willingness to use GenAI tools. Therefore, institutions should focus on understanding their student's specific needs and preferences, taking into account factors such as perceived ease of use and cost in addition to accuracy and hedonism. By considering the broader context of technology adoption, institutions can develop more effective strategies to encourage the use of GenAI tools among students, ultimately facilitating their integration into the learning process.

22. Limitations

It is important to note that this study has limitations due to its specific context (higher education), potential biases in self-reported data, a narrow focus on factors influencing students' intent to use GenAI tools, and a cross-sectional design, which limits establishing causal or temporal relationships between variables.

23. Conclusion and Further Research

This study investigates the factors that influence the adoption of Generative AI (GenAI) tools among higher education students by utilizing a modified version of the UTAUT2 model. It examines perceived cost, effort expectancy, hedonic motivation, supplemental resource, and information accuracy. The findings indicate that ease of use and the availability of support resources are critical drivers for students' adoption of GenAI tools. This suggests that the adoption of educational technology is primarily influenced by practical utility and accessibility rather than simply by enjoyment or high accuracy.

The research identifies that supplemental resource and effort expectancy are the strongest predictors of students' intentions to use GenAI tools. This highlights that students tend to favor tools that are user-friendly and come with resources that enhance the learning experience. Conversely, information accuracy and hedonic motivation play a lesser role in adoption, indicating a shift in students' perceptions of what is essential in educational technology. These findings enrich the UTAUT2 model by incorporating context-sensitive variables and provide practical insights for educational institutions looking to implement GenAI tools effectively. By addressing these key factors, institutions can foster environments encouraging GenAI adoption and better supporting the learning process.

For future research, it is recommended that studies broaden their focus to explore additional variables and employ a range of methodologies. Incorporating objective measures and observational data could help alleviate the limitations often associated with self-reported findings. Furthermore, conducting longitudinal or experimental studies could yield deeper insights into how students' perceptions and intentions regarding GenAI tools evolve over time. These approaches would foster a more inclusive and comprehensive understanding of effective integrations of GenAI tools, inspiring the audience with the potential for further exploration and ultimately contributing to a more supportive educational environment for various student populations.

Ethics Statement: Participants in the study were thoroughly informed about its nature, purpose, and potential outcomes. Data collection was conducted anonymously, ensuring that no personally identifiable information was gathered or retained. (Ethics approval is not required for our research, and we did not use an AI tool)

AI statement: While preparing this work, the authors utilized Grammarly to enhance readability and language. After using this tool, they carefully reviewed and edited the content as necessary and took full responsibility for the final published article.

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Appendix 1: Questionnaire

Part 1 Demographic Data
1- What is your gender?
Male
Female
2- What is your age?
18-30 years
31-41 years
42 yrs. and over
3- How often do you use GenAI tools?
Once times or less
2-3 times in week
More than 3 times
4- Do you use the paid version of GenAI tools?
Yes
No

Part 2 Items

Second Part	
Supplemental resource (Chan and Lee, 2023)	
SR1	GenAI is valuable for answering queries.
SR2	GenAI helps generate thoughts.
SR3	GenAI helps conduct analyses.
Information accuracy (Chan and Lee, 2023)	
IA1	GenAI tools demonstrate biases in their answers
IA2	GenAI tools develop factually inaccurate answers
IA3	GenAI tools generate answers that are out of context or inappropriate
IA4	GenAI tools generate fake information
Effort expectancy (Venkatesh, Thong and Xu, 2012)	
EE1	GenAI tools are easy to use
EE2	Learning how to use GenAI tools is easy
EE3	Interaction with GenAI tools is unambiguous and understandable
Hedonic motivation (Venkatesh, Thong and Xu, 2012)	
HM1	GenAI tools are enjoyable.
HM2	Interacting with GenAI is pleasant.
HM3	Using GenAI tools is fun.
Perceived cost (Venkatesh, Thong and Xu, 2012)	
PC1	GenAI tools are affordably priced
PC2	They provide good value for the money
PC3	The free plan is better than a paid plan
Intention to use GenAI (Venkatesh, Thong and Xu, 2012)	
Int.1	I intend to use GenAI tools frequently
Int.2	I plan to use GenAI tools daily.
Int.3	I intend to continue using GenAI tools in the future.

Second Part	
Actual usage of GenAI (Venkatesh, Thong and Xu, 2012)	
AU1	The GenAI tools are a pleasant experience.
AU2	I use the GenAI tools currently.
AU3	I spend a lot of time using GenAI tools.

Appendix 2: Structural Model