European Journal of Education Studies
ISSN: 2501 - 1111
ISSN-L: 2501 - 1111
Available online at: www.oapub.org/edu

DOI: 10.46827/ejes.v12i11.6380 Volume 12 | Issue 11 | 2025

EXAMINING THE INTENTION OF UNDERGRADUATE MATHEMATICS EDUCATION STUDENTS TO USE AI IN THEIR ACADEMIC WORK: AN APPLICATION OF THE UTAUT MODEL

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Abstract:
The emergence of generative Artificial Intelligence (AI) is disrupting every sector of the global economy and the information society. The education industry, similarly, has both educators and students exploring ways to utilize AI. This study investigates the adoption of AI in higher education among undergraduate mathematics education students using the four constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The research focuses on Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, and their influence on students' Behavioural Intention to adopt AI tools. Gender was included as a moderating variable in the relationships between these constructs and behavioural intention. A sample of 142 undergraduate mathematics education students participated in an online survey to measure their perceptions and intentions of AI adoption in their academic work. The findings revealed that all four independent variables and gender had significant direct effects on Behavioural Intention to use AI. This indicates that students perceive AI tools as valuable for enhancing academic performance, easy to use, influenced by social factors such as peers, and supported by adequate facilitating conditions such as technical infrastructure. However, gender did not emerge as a significant moderator in any of the relationships between the UTAUT constructs and Behavioural Intention. This suggests that male and female students exhibit similar adoption patterns toward AI technologies in this context. These results contribute to the growing body of literature on technology adoption in education by confirming the applicability of the UTAUT model within a mathematics education-focused cohort of students while highlighting that gender differences may not play a critical role in shaping intentions toward AI adoption. Future research could explore additional moderating variables or extend this analysis across other disciplines for broader generalizability.

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Keywords: Artificial Intelligence (AI), Artificial Intelligence Adoption, Mathematics Education, Undergraduate Students, Unified Theory of Acceptance and Use of Technology (UTAUT)

1. Introduction

Artificial Intelligence (AI) is evolving rapidly, and it is presenting both unprecedented opportunities and significant challenges, particularly within educational contexts (Aldreabi, Dahdoul, Alhur, Alzboun & Alsalhi, 2025). As AI tools become increasingly sophisticated and available, understanding determinants of their adoption by future professionals, such as undergraduate students, is paramount (Aldreabi *et al.*, 2025; Russell & Norvig, 2016). The integration of AI into various academic disciplines and daily learning activities necessitates a robust framework for analysing user adoption and behavioural intention. The Unified Theory of Acceptance and Use of Technology (UTAUT), initially proposed by Venkatesh, Morris, Davis & Davis (2003), provides a comprehensive framework for examining these dynamics. This model synthesizes elements from eight prominent theories of technology acceptance, providing a powerful tool for predicting user behaviour in diverse technological environments (Williams, Dwivedi, Lal & Schwarz, 2009). Its applicability extends beyond traditional organizational settings, proving valuable in understanding technology adoption in education (Faraon, Ronkko, Milrad & Tsui, 2025). This introductory section sets the stage for a deeper exploration into how undergraduate students perceive and utilize AI, leveraging the UTAUT model to dissect the multifaceted factors influencing their integration of AI technologies into their academic pursuits.

The subsequent sections will delve into the core constructs of the UTAUT model and their specific relevance to AI adoption among undergraduate students. The study explores how students' beliefs about AI's value in augmenting their academic work (Performance Expectancy), the perceived ease of using AI tools (Effort Expectancy), the influence of peers and instructors (Social Influence), and the availability of resources and support (Facilitating Conditions) collectively shape their intention to use AI (Adigun, Tijani, Haihambo & Enock, 2025). By applying the UTAUT model, this study aims to provide a nuanced understanding of the enablers and barriers to AI adoption, offering insights crucial for educators and policymakers seeking to foster effective AI integration in higher education.

2. Literature Review

2.1 Integration of Technology in Higher Education

Technology adoption in higher education is an essential part of modern teaching and learning processes, with students engaging with digital tools to enhance academic outcomes, collaboration, and assessment (Ellis, Bliuc & Han, 2012; Hamzat, 2024). The widespread integration of Learning Management Systems (LMS), mobile learning platforms, and the emergence of Artificial Intelligence (AI)-enabled applications have transformed how students access and interact with educational content and courseware. Several studies have explored the factors influencing students' willingness to adopt these technologies, highlighting performance expectancy, effort expectancy, social influence, and institutional support as critical determinants (Venkatesh *et al.*, 2003; Teo, 2011).

Venkatesh *et al.* (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), a widely applied framework in higher education research. Performance expectancy, that is, students' belief that technology use will improve their learning performance, has been consistently reported as the strongest predictor of student technology adoption. For instance, Almaiah, Al-Khasawneh, and Althunibat (2022) found that students were more likely to use e-learning tools that demonstrated clear academic benefits.

Effort expectancy also influences adoption. Mailizar, Burg, and Maulina (2021) observed that students preferred technologies that were easy to use and required minimal technical knowledge. This is particularly important in diverse learning contexts where students may have varying levels of digital literacy. Social influence, particularly from instructors and peers, has also been shown to affect student adoption. Teo (2011) found that endorsement by respected academic figures increased student confidence in using digital tools. Furthermore, facilitating conditions, such as access to devices, reliable internet, and institutional support, are critical for sustained technology usage. In Kenyan universities, Mutisya and Makokha (2016) posited that infrastructural and resource limitations often hinder student access to digital platforms.

With the growing use of AI in education, new concerns around privacy, trust, and ethical use are emerging. Al-Emran, Mezhuyev, and Kamaludin (2020) emphasized the importance of integrating trust and security considerations into technology adoption frameworks to better understand students' intentions.

2.2 Artificial Intelligence

The field of Artificial Intelligence (AI) has seen remarkable advancements, transitioning from theoretical concepts to practical applications across numerous domains. Early research focused on symbolic AI and expert systems, aiming to encode human knowledge and reasoning into machines (Gunning, Stefik, Choi, Miller, Stumpf & Yang, 2019; Russell & Norvig, 2016). This foundational work laid the groundwork for later developments, though limitations in handling uncertainty and scalability became apparent (Nilsson, 1980).

More recently, the resurgence of machine learning, especially deep learning, has revolutionized AI capabilities, enabling breakthroughs in areas like computer vision and natural language processing (LeCun, Bengio & Hiton, 2015; Goodfellow, Bengio & Courville, 2016). Neural networks, inspired by the human brain, can learn complex patterns from vast datasets, leading to highly accurate predictions and classifications (Schmidhuber, 2015).

AI systems enable computers to learn and perform human-like cognitive tasks, such as predictions and decision-making, through processing and analysing very large amounts of data. Higher education sectors worldwide are grappling with the integration of AI tools to enhance learning and teaching (O'Dea & O'Dea, 2023). AI has been identified as one of the key technologies for postsecondary education, with great potential applications of AI tools in learning and teaching in higher education. However, it appears that even though its perceived impact is high, the actual adoption of AI in higher education is relatively low (Celik *et al.*, 2022).

So far, much of the emphasis of the application of AI into education has not been placed on direct and immediate learning and teaching activities, but rather on digital administrative management (Chandra & Suyanto, 2019; Klos *et al.*, 2021) or the administrative workload of academic and support staff (Kumar & Boulanger, 2021; Uto *et al.*, 2020).

2.3 Artificial Intelligence in Higher Education

The integration of Artificial Intelligence (AI) in higher education is reforming how students learn, interact with content, and receive academic support (Patterson, Frydenberg & Basma, 2024). AI-powered tools, such as intelligent tutoring systems, adaptive learning platforms, and automated feedback systems, are being increasingly adopted to enhance student learning experiences. As higher education institutions invest in AI technologies, understanding the factors that influence student adoption becomes critical (Aldreabi *et al.*, 2025).

AI's affordances in education are possibilities that enable AI tools to provide an enabling environment that enhances learning, teaching, and associated activities (O'Dea & O'Dea, 2023). Research indicates that AI has strong potential in higher education, in particular. AI has long been considered the key technology to unlocking personalised and adaptive learning by enabling the provision of tailored learning content, activities, assessments, and feedback support to students, based on their individual learning capacities, habits, interests, and backgrounds (Major & Francis, 2020).

To date, AI tools have not only been widely adopted in various industries but are also used more in people's everyday lives. Alongside the rapid development of AI, there are concerns about the ethics of AI. In the context of higher education, the ethics of AI often revolve around academic integrity and plagiarism. For AI to be successfully adopted by students, institutions must offer not only reliable infrastructure and support but also transparent communication regarding privacy, ethics, and educational value.

2.4 UTAUT Model

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh and colleagues in 2003, is a widely adopted model for examining students' acceptance and use of technology in higher education. It identifies four basic constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions that influence users' behavioural intention and usage behaviours. In the context of higher education, UTAUT has been applied to explore student adoption of digital learning tools, particularly with the rapid emergence of Artificial Intelligence (AI) technologies.

Performance expectancy, or the belief that using a technology will improve learning outcomes (Adigun *et al.*, 2025; Venkatesh *et al.*, 2003), consistently emerges as the most influential factor in students' intention to use technology (Acosta-Enriquez, Farronan, Zapata, Garcia, Rabanal-Leon, Angaspilco & Bocanegra, 2024; Almaiah *et al.*, 2022). For instance, Nizam, Wahab and Rahim (2021) found that AI-driven learning platforms significantly boosted student motivation and engagement in Malaysian universities. Similarly, in a study by Al-Emran *et al.* (2020), performance expectancy significantly influenced students' use of AI-powered mobile learning applications in Saudi Arabian universities.

Effort expectancy, the ease of using the technology, also affects student adoption, especially AI tools that are user-friendly and require minimal training (Adihun *et al.*, 2025; Mailizar, Burg & Maulina, 2021; Aldreabi *et al.*, 2025). Mailizar, Burg, and Maulina (2021) and Aldreabi *et al.* (2025) demonstrated that students were more likely to use AI-based platforms when they perceived them as user-friendly and requiring minimal technical effort. This is especially relevant in developing countries, where digital literacy levels may vary widely among students. Adigun *et al.* (2025) established that effort expectancy had a direct, significant contribution to perceived behavioural intention of pre-service teachers' adoption and use of AI for inclusive education teaching.

Social influence, while less impactful than performance or effort expectancy, still plays a role, especially in collectivist cultures. Students are often influenced by peers, instructors, and institutional managers. For example, Teo (2011) found that peer recommendations significantly increased the likelihood of students in Singapore using educational technology tools.

Facilitating conditions refer to the extent to which a person believes that an organization and technical infrastructure exist to support the adoption and continual use of a technology (Adigun *et al.*, 2025; Venkatesh *et al.*, 2003), such as access to reliable internet, digital devices, and technical support. Mutisya and Makokha (2016) reported that students in Kenyan universities cited infrastructural limitations as barriers to using e-learning platforms, despite positive attitudes toward them.

In this study, behavioural intention is conceptualized as undergraduate students' intention to adopt and use AI (technologies) for academic work. This study investigates the use of the UTAUT (Venkatesh *et al.*, 2003) as the theoretical foundation for exploring the adoption of AI in higher education, particularly from the students' perspective on AI adoption.

3. Material and Methods

3.1 Research Objectives

This study set out to:

1) Determine the relationship between perceived performance expectancy, effort expectancy, social influence, facilitating conditions, and the intentions of undergraduate mathematics education students to use AI in academic work.
2) Establish the moderating effect of undergraduate mathematics education students' gender on the relationship between perceived performance expectancy, effort expectancy, social influence, facilitating conditions, and intentions to use AI in academic work.

3.2 Research Hypotheses

From the objectives above, the following null hypotheses were formulated:

HO1: There is no significant relationship between Behavioural Intention and Performance Expectancy.

HO2: There is no significant relationship between Behavioural Intention and Effort Expectancy.

HO3: There is no significant relationship between Behavioural Intention and Social Influence.

HO4: There is no significant relationship between Behavioural Intention and Facilitating Conditions.

HO5: Gender is not a significant moderator of the relationship between Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

3.3 Research Instrument

The questionnaire was adapted/modified from previous studies, especially Alyoussef (2021), Attuquayefo and Addo (2014), and Venkatesh *et al.* (2003) by rephrasing some statements. For instance, the statement "mobile technologies would improve students' performance" in Alyoussef's (2021) study can be rephrased as "AI tools can improve my academic work performance" in this study. The UTAUT questionnaire had 20 items in total in five sections, four items for each construct. The adapted UTAUT questionnaire was designed in a five-point Likert scale ranging from "5 = strongly agree to 1 = strongly disagree." The adapted UTAUT questionnaire was subjected to revalidation to ascertain its reliability coefficient using Cronbach's alpha as follows: Performance Expectancy (α = .887), Effort Expectancy (α = .940), Social Influence (α = .897), Facilitating Conditions (α = .930), and Behavioural Intention (α = .932).

3.4 Data Collection and Analysis

The analysis in this paper included 142 complete and usable responses (51.4%) out of 276 third-year undergraduate mathematics education students in their first semester. Descriptive (means and standard deviations) and inferential (correlation, regression, t- and F-tests) analyses were conducted. A frequency analysis was conducted to investigate students' general characteristics. Then, we performed a correlation analysis. Finally, we investigate the relationship of the predictors on the outcome variable through a multistep regression analysis.

4. Results and Discussion

4.1 Preliminary Results

A preliminary analysis (Table 1) suggests that female undergraduate mathematics education students consistently reported higher mean scores across all technology acceptance variables compared to their male counterparts. For example, in Effort Expectancy, females have a mean of 16.9 (SD = 4.4) while males have a mean of 11.6 (SD = 4.9). This difference is also evident in Social Influence (Female: 15.6, SD = 5.0; Male: 10.5, SD = 4.4), Facilitating Conditions (Female: 16.8, SD = 4.0; Male: 11.0, SD = 4.7), and Behavioural Intention (Female: 17.2, SD = 4.0; Male: 11.4, SD = 4.1). The total sample indicates a relatively high standard deviation for Effort Expectancy (5.7), indicating a wider range of opinions on ease of AI use among all participants. These findings imply that, in this specific sample, females have more positive perceptions and intentions regarding technology adoption than males.

Table 1: Means and Standard Deviations of the Technology Acceptance Variables

Gender	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Behavioural Intention
Female (n = 54)	14.9(4.6)	16.9(4.4)	15.6(5.0)	16.8(4.)	17.2(4.0)
Male (n = 88)	12.3(4.5)	11.6(4.9)	10.5(4.4)	11.0(4.7)	11.4(4.1)
Total (N = 142)	**13.3(4.7)**	**13.6(5.7)**	**12.4(5.2)**	**13.2(5.4)**	**13.6(5.0)**

Note: Standard Deviations (in Brackets)

4.2 Correlation Analysis

To examine the correlation among the variables under study, a Pearson correlation analysis was conducted. All variables have significantly positive bivariate correlations, as shown in Table 2. The results consistently show strong, positive, and statistically significant correlations among all the measured constructs and with Behavioural Intention. This pattern is highly consistent with established technology acceptance theories, particularly the UTAUT model, where Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions are direct determinants of Behavioural Intention to use a technology (Acosta-Enriguez *et al.*, 2024; Venkatesh *et al.*, 2003).

The exceptionally high correlation between effort expectancy and behavioural intention ($r = .93$) is particularly noteworthy. While all factors are important, this suggests that for the sample studied ($N = 142$), effort expectancy is an overwhelmingly dominant predictor of an individual's intention to adopt or use the technology (Adigun *et al.*, 2025).

This could imply that if an AI tool is not easy to use, even if it offers significant performance benefits or is socially encouraged, its adoption might be severely hindered.

The strong correlations between the independent variables themselves (e.g., EE with SI and FC) highlight that these factors tend to co-occur or influence each other in the context of technology adoption. For example, an easy-to-use system might naturally garner more social support and require fewer explicit facilitating conditions, or vice versa. The findings underscore the importance of user-friendly AI tools, ensuring adequate infrastructural support, leveraging social networks, and communicating the performance benefits to drive successful AI adoption.

Table 2: Correlations Analysis Results

	Performance Expectancy	**Effort Expectancy**	**Social Influence**	**Facilitating Conditions**	**Behavioural Intention**
Performance Expectancy	1				
Effort Expectancy	.625**	1			
Social Influence	.517**	.818**	1		
Facilitating Conditions	.613**	.824**	.691**	1	
Behavioural Intention	.670**	.930**	.833**	.884**	1
Note: ** = Correlation is significant at the 0.01 level (2-tailed). N = 142					

4.3 Regression Analysis

To examine the effects of independent variables on behavioural intention, a comparative analysis of the factors influencing undergraduate students' intention to adopt AI tools in academic work was conducted using hierarchical regression analysis. Model 1 (F (4,137) = 426.597, p < 0.01) and Model 2 (F (1,136) = 15.952, p < 0.01) had statistically significant differences, as shown in Table 3. Model 3 (F (4, 132) = 0.294, p > .05) had no statistically significant difference from Model 2. This implies that the interaction effects of each independent variable and the respondents' gender on their intention to use AI were not statistically significant.

Table 3: Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R^2 Change	F Change	df1	df2	Sig. F Change	
1	.962a	.926	.924	1.37045	.926	426.597	4	137	.000	
2	.966b	.933	.931	1.30128	.007	15.952	1	136	.000	
3	.966c	.934	.930	1.31500	.001	.294	4	132	.881	2.143

a. Predictors: (Constant), FC, PE, SI, EE
b. Predictors: (Constant), FC, PE, SI, EE: GENDER
c. Predictors: (Constant), FC, PE, SI, EE: GENDER, PE by Gender, SI by Gender, FC by Gender, EE by Gender
d. Dependent Variable: Behavioural Intention

The study employed regression analysis which was conducted in three hierarchical models to examine the influence of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and gender on the adoption of artificial intelligence (AI) by undergraduate students, as well as to explore the moderating role of gender (Table 4). The findings provide important insights into the determinants of AI adoption within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework (Venkatesh *et al.*, 2003; Venkatesh, Thong, & Xu, 2012).

Model 1 serves as the baseline model. It examines the direct effects of the four UTAUT constructs on behavioural intention. The results demonstrated that all predictors were significant and positively associated with students' intention to adopt AI. Performance expectancy ($B = .095$, $\beta = .090$, $t = 2.944$, $p < 0.01$) had a modest but significant effect. This suggests that when students perceive that AI tools enhance their learning performance, they are more likely to adopt them. This finding is consistent with prior research highlighting perceived usefulness as a central factor in technology acceptance (Acosta-Enriquez *et al.*, 2024; Venkatesh *et al.*, 2003). In the academic context, students who see AI as beneficial for efficiency, improved grades, or an enhanced understanding of the content are more willing to integrate it into their studies.

Effort expectancy emerged as the strongest predictor across all three models ($B \approx .408$, $\beta \approx .440$, $t = 8.266$, $p < .001$). This demonstrates that ease of use is a pivotal factor in undergraduate students' adoption of AI. When AI systems are intuitive, user-friendly, and require minimal effort to operate, students are more inclined to use them. Given that AI technologies can be perceived as complex or intimidating, the strong effect of effort expectancy underscores the importance of designing AI platforms that minimize technical barriers. This finding aligns with earlier studies that ease of use is critical in educational technology adoption (Williams, Rana, & Dwivedi, 2015).

Social influence was also a significant predictor ($B = 0.191$, $\beta = .202$, $t = 4.999$, $p < .001$). This suggests that peers, instructors, and social networks play a crucial role in shaping students' decisions to adopt AI. For undergraduate students, recommendations from lecturers, endorsements from peers, and institutional encouragement can significantly drive adoption behaviors. This aligns with prior research showing that social expectations are particularly influential in technology use within educational contexts (Acosta-Enriquez *et al.*, 2024; Teo, 2011).

Facilitating conditions were also found to have a statistically significant and strong positive effect on the behavioural intention to use AI ($B = 0.301$, $\beta = .328$, $t = 7.782$, $p < .001$). This suggests that students' access to technical support, training, and reliable infrastructure greatly enhances their willingness to adopt AI. Although the original UTAUT framework emphasised facilitating conditions as a direct determinant of usage behaviour rather than intention, recent studies confirm their importance in shaping adoption, particularly in education, where institutional support is vital (Teo, 2011). For example, when universities provide adequate internet connectivity, training workshops, and resource materials, students are better positioned to adopt AI applications in their learning.

Model 1 explains 92.6% of the variance in behavioural intention. This means that higher levels of perceived performance, ease of use, social pressure, and available support all lead to a greater intention to use AI (Aldreabi *et al.*, 2025; Patterson, Frydenberg & Basma, 2024).

Model 2 expands on Model 1 by introducing gender as an additional predictor variable. The results show that performance expectancy ($t = 3.513$, $p < 0.01$), effort expectancy ($t = 8.701$, $p < 0.001$), social influence ($t = 4.512$, $p < 0.01$), and facilitating conditions ($t = 6.822$, $p < 0.01$) remain significant. Gender has a significant negative coefficient ($B = -1.030$, $\beta = -0.101$, $t = -3.994$, $p < 0.001$). The negative t-value for gender (coded as female = 0, male = 1) suggests that, on average, males have a lower intention to use AI compared to females, holding other factors constant, which supports the findings of Patterson, Frydenberg, and Basma (2024). The model explains 93.3% (R-squared = 0.933) of the variance in behavioural intention. The increase in explanatory power compared to Model 1 is only 0.7%, indicating that the contribution of gender is relatively small.

Model 3 investigates the interaction effects between gender and the four UTAUT constructs. The interaction effects were not significant (all $p > .38$). This implies that the relationship between the UTAUT constructs and behavioural intention does not significantly differ between male and female undergraduate students of mathematics education, despite gender having a direct effect. In other words, male and female students rely on similar decision-making mechanisms, such as performance, effort, social, and contextual evaluations, when deciding whether to adopt AI. This finding is consistent with Venkatesh *et al.* (2012), who noted that as technology becomes more widespread, the moderating role of gender diminishes.

Table 4: Hierarchical Regression Analysis

Predictors	**Unstandardized Coefficients**						**Standardized Coefficients**			***t***			***p***		
	B			***SE***			***ß***								
	Mod.1	**Mod.2**	**Mod.3**	**Mod.1**	**Mod.2**	**Mod.3**	**Mod.1**	**Mod.2**	**Mod.3**	**Mod.1**	**Mod.2**	**Mod.3**	**Mod.1**	**Mod.2**	**Mod.3**
(Constant)	.481	1.826	1.753	.370	.487	.513				1.298	3.750	-3.994	.196	.000	.001
PE	.095	.109	.109	.032	.031	.032	.090	.103	.103	2.944	3.513	3.415	.004	.001	.001
EE	.403	.408	.408	.049	.046	.047	.437	.437	.442	8.266	8.701	3.419	.000	.000	.000
SI	.191	.155	.155	.038	.037	.039	.202	.176	.164	4.999	4.512	8.600	.000	.000	.000
FC	.301	.265	.265	.039	.038	.039	.328	.038	.289	7.782	6.822	3.997	.000	.000	.000
GENDER		-1.030	-1.030		.270	.289		.270	-.101			6.777		.000	.001
PE x Gender			.023			.153			.005			-3.567			.880
EE x Gender			.022			.263			.004			.151			.933
SI x Gender			-.169			.193			-.032			.084			.384
FC x Gender			.020			.215			.004			-.874			.924

a. Predictors: (Constant), FC, PE, SI, EE
b. Predictors: (Constant), FC, PE, SI, EE: GENDER
c. Predictors: (Constant), FC, PE, SI, EE: GENDER, PE by Gender, SI by Gender, FC by Gender, EE by Gender
d. Dependent Variable: Behavioural Intention

From these results, hypotheses HO1 to HO4 were rejected, but failed to reject HO5, and conclude that:

1) There is a significant relationship between Behavioural Intention and Performance Expectancy.
2) There is a significant relationship between Behavioural Intention and Effort Expectancy.
3) There is a significant relationship between Behavioural Intention and Social Influence.
4) There is a significant relationship between Behavioural Intention and Facilitating Conditions.
5) Gender is not a significant moderator of the relationship between Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

5. Recommendations

Prioritizing ethical AI use and responsible integration, the following recommendations are made:

1) Enhance Performance Expectancy by showcasing AI's academic benefits and integrating tools into curricula.
2) Optimize Effort Expectancy through providing user-friendly tools, comprehensive training, and robust support.
3) Leverage Social Influence by encouraging faculty modeling, peer collaboration, and success stories.
4) Enhance Facilitating Conditions by ensuring access to hardware, software, connectivity, and clear policies.
5) Investigate and tailor interventions for gender-specific factors to address gender differences.

This study has shown that integration of AI is bound to take center stage in student learning in higher education. Therefore, future research can investigate undergraduate students' perspectives on the ethical use of AI in their academic work and what specific aspects of their academic work will benefit from the integration of AI.

6. Conclusion

The study investigated the factors influencing undergraduate mathematics education students' behavioural intention to use Artificial Intelligence (AI) in their academic work, grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The research hypothesised that key UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) would significantly predict students' intention to adopt AI. The findings revealed significant relationships between all hypothesized UTAUT constructs and behavioural intention, implying that students are more likely to adopt AI for academic work if they perceive them as beneficial for their academic performance (performance expectancy), easy to use (effort expectancy), if they are influenced by their peers and instructors (social influence), and if they have access to the necessary resources and support (facilitating conditions).

This study contributes to the existing body of knowledge by providing empirical evidence of the UTAUT model's effectiveness in the context of AI adoption in mathematics education. The findings have several implications. First, they highlight the importance of designing AI tools that are user-friendly and offer clear benefits to students' learning outcomes. Second, the results underscore the need for higher educational institutions to foster a supportive environment that encourages ethical use of AI, including providing adequate training, technical support, and promoting positive social norms around AI usage. Third, the study provides valuable insights for educators and curriculum developers, informing the strategic integration of AI into mathematics education curricula to enhance student engagement and learning.

While this study offers valuable insights, it is important to acknowledge its limitations. The research focused on a specific population (undergraduate mathematics education students) and a specific context (academic work), which may limit the generalizability of the findings to other populations or settings. Further studies could investigate the long-term impact of AI adoption on students' learning outcomes and academic performance. Longitudinal studies could track changes in students' attitudes and behaviors over time. Additionally, exploring the moderating effects of demographic variables (e.g., age, prior experience) on the relationships between UTAUT constructs and behavioural intention could provide a more nuanced understanding of AI adoption.

This study provides strong evidence supporting the applicability of the UTAUT model in understanding and predicting undergraduate mathematics education students' intention to use AI in their academic work. The significant relationships between all UTAUT constructs and behavioural intention underscore the importance of considering these factors when designing and implementing AI-based educational interventions. By addressing these factors, educators and institutions can effectively promote the adoption and integration of AI tools to enhance the learning experience and improve academic outcomes. This research contributes to the growing body of knowledge on technology acceptance in education and offers valuable insights for the future of AI in mathematics education.

Conflict of Interest Statement

The author declares no conflicts of interest.

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