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RESEARCH ARTICLE

The impact of artificial intelligence and virtual teachers on students' learning stress and anxiety: A social psychological analysis

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ABSTRACT

This study explores the impact of Artificial Intelligence (AI) and virtual teachers on students' learning stress and anxiety, applying the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The research investigates key factors influencing students' perceptions and usage of AI-driven learning tools, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB). Data were collected from 100 students, revealing generally positive attitudes towards AI tools. The results show that AI's potential to reduce learning stress and improve academic performance (PE) significantly influences students' intention to use these tools in the future (BI). Ease of use (EE) and social support (SI) were also found to positively affect behavioral intention, while facilitating conditions (FC), such as access to necessary resources and technical support, played a crucial role in determining the actual use of AI tools. The study highlights that students are more likely to adopt AI-based educational systems when they perceive them as useful, easy to use, and adequately supported. These findings suggest that fostering positive perceptions, ensuring sufficient resources, and leveraging social influence can significantly enhance the adoption of AI tools, ultimately reducing learning stress and anxiety.

Keywords: artificial intelligence; virtual teachers; learning stress; UTAUT model; educational psychology

1. Introduction

With the widespread application of artificial intelligence (AI) and virtual teachers in education, there is an increasing discussion on how these technologies affect students' psychological experience. Traditional teaching methods, which are often accompanied by greater stress and anxiety, are gradually being supplemented or replaced by AI-driven tools and virtual teachers. This shift has raised concerns about the psychological consequences of these innovations on students. By studying how artificial intelligence and virtual teachers affect students' learning stress and anxiety, this paper aims to reveal the complex interaction between technology and students' mental health based on a social-psychological perspective.

2. Theory base

The integration of Artificial Intelligence (AI) into education has introduced a range of new variables that influence students' adoption of AI-driven learning tools and virtual teachers. These variables include

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personalized support, instant feedback, students' cognition of AI, predictability of the learning environment, technology adaptability, attitude, and data privacy and ethical concerns. To understand how these factors impact AI adoption, we draw upon the Technology Acceptance Model (TAM), a framework initially developed by Davis in 1989[6]. Venkatesh and Davis (2000) gave other explanation about TAM in some fields [18]. TAM is built on core constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATU), Behavioral Intention to Use (BI), and Actual Use (AU). TAM can be used in technology acceptance [9,12]. TAM constructs are interrelated and can influence each other in various ways [11]. For example, personalized support and instant feedback from AI can enhance both PU and PEOU, increasing the likelihood of adoption. This, in turn, improves user experience and encourages continued engagement with AI technologies. Building upon the foundational work of TAM, Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) model to consolidate previous research on technology adoption [19]. UTAUT incorporates key factors like Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Later, in 2012, UTAUT2 was developed to incorporate additional constructs, including Hedonic Motivation (HM), Price Value (PV), and Habit (HT), further refining our understanding of technology adoption behaviors in specific contexts, such as education.

As AI becomes more widely implemented in educational settings, it is essential to explore how these theoretical models apply to students' experiences and perceptions. AI's personalized support and instant feedback, as well as students' cognition of AI, directly influence their adoption of such technologies[13-15]. Therefore, examining these components through the lens of TAM and UTAUT2 offers valuable insights into how students engage with AI-driven tools and how these technologies might affect their academic outcomes and mental health. In the following section, we review the existing literature to explore these factors further and highlight the psychological and cognitive dynamics that shape students' interactions with AI in educational contexts.

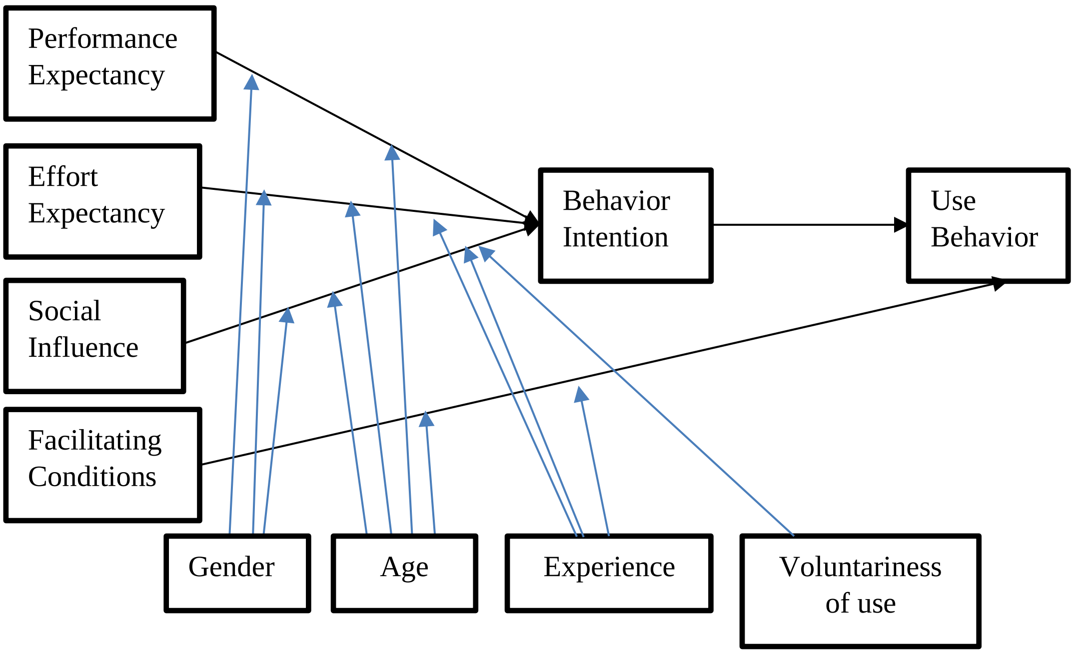

Figure 1. UTAUT model.

3. Literature review and hypothesis

3.1. Literature review

The integration of AI in education has gained significant attention due to its potential to provide personalized support and instant feedback. By analyzing students' learning data, AI systems can deliver tailored learning content and feedback specific to each student. AI-driven virtual teachers, for example, can dynamically adjust teaching materials based on students' learning progress and styles, offering real-time feedback [7]. This personalized support is shown to improve learning efficiency and enhance student motivation[10]. However, the effectiveness of AI-based support is influenced by factors such as the frequency and duration of its use. Frequent and continuous engagement with AI tools can significantly enhance learning outcomes, whereas over-reliance on AI may reduce students' adaptability to traditional teaching methods.

An important factor affecting students' interactions with AI is their cognition and understanding of the technology. Research has demonstrated that students' familiarity with and acceptance of AI are closely related to their learning outcomes and psychological well-being. Students who have a positive attitude towards AI and possess a high level of technological proficiency tend to benefit more from AI support[5]. Conversely, unfamiliarity with or negative perceptions of AI may lead to increased anxiety and decreased motivation[8]. Therefore, educators must focus on enhancing students' awareness and self-efficacy regarding AI to maximize its potential benefits in the learning process.

The predictability of the learning environment is another key factor influencing students' learning experience. AI can enhance the predictability of the learning environment by offering stable learning paths and providing consistent, real-time feedback[2]. This predictability helps alleviate student anxiety, particularly in high-pressure academic settings. However, the effectiveness of AI in creating a predictable learning environment depends on the transparency and stability of AI systems. If AI algorithms are overly complex or opaque, students may become confused, which could reduce the overall effectiveness of their learning experiences.

In addition to cognitive and environmental factors, technology adaptability and students' attitudes toward AI play a critical role in determining the success of AI-driven education. Studies have shown that students' technological proficiency positively correlates with their learning outcomes when using AI tools[3]. However, as AI becomes more widespread, some students may face challenges related to adaptability, such as technical barriers or resistance to new technology. These issues can hinder the effective use of AI tools, underscoring the importance of addressing these barriers in educational settings.

Despite its potential, the use of AI in education also raises significant ethical concerns, particularly regarding data privacy. AI systems rely on large volumes of student data, such as performance and behavioral data, which raises concerns about misuse or exposure of sensitive information. Nguyen et al. (2023) emphasize the importance of transparency and fairness in data usage to protect student privacy[17]. Airaj (2024)[1] stresses the need for ethical frameworks and informed consent to ensure data protection. Bu (2022) warns of the potential risks of inequality and commercial exploitation, advocating for stricter regulations[4]. Naseeb and Bhatti (2024) argue for the inclusion of ethical education in curricula to address these challenges[16]. In summary, these studies underscore the need for ethical AI practices, transparency, and robust safeguards to protect student data.

3.2. Hypotheses

The research indicates that students' belief in AI's ability to enhance academic performance and reduce learning stress significantly influences their intention to use AI tools. This belief, referred to as Performance Expectancy (PE), plays a crucial role in forming Behavioral Intention (BI). When students perceive that AI can improve their learning efficiency and reduce stress, they are more likely to develop a strong intention to use AI in the future. Therefore, personalized support and instant feedback provided by AI can substantially increase students' behavioral intentions, further promoting the adoption of AI technology in education.

H1: Performance expectancy (PE) → Behavioral intention (BI)

Students' perceptions of the ease of use and convenience of AI tools, known as Effort Expectancy (EE), also play a pivotal role in shaping their behavioral intentions. If students perceive AI tools as easy to use and adaptable to their needs, they are more likely to develop positive intentions to use them. As AI technology continues to evolve and educational tools become more user-friendly, students are less likely to feel overwhelmed, which fosters stronger behavioral intentions to engage with AI.

H2: Effort expectancy (EE) → Behavioral intention (BI)

The influence of Social Influence (SI)—such as support and encouragement from peers, teachers, or other social groups—significantly affects students' behavioral intentions to use AI tools. When students receive positive recommendations and encouragement from their social circle, they are more likely to form the intention to use AI in their learning. Social influence can alleviate students' anxiety, especially when faced with academic pressure, and motivate them to actively engage with AI-driven learning environments.

H3: Social influence (SI) → Behavioral intention (BI)

Behavioral Intention (BI) is a strong predictor of Use Behavior (UB), meaning that students who develop strong intentions to use AI tools are more likely to translate these intentions into actual usage. Encouraging students' intention to use AI tools and demonstrating the benefits of AI technology can significantly increase their actual use behavior, helping to integrate AI into their daily learning routines.

H4: Behavioral intention (BI) → Use behavior (UB)

Finally, the success of AI adoption in education also depends on the Facilitating Conditions (FC), such as access to necessary resources (e.g., devices, internet connectivity) and technical support. When educational institutions provide the necessary infrastructure and support, students are more likely to overcome potential barriers and engage with AI tools effectively. Facilitating conditions are crucial to ensuring that students can fully utilize AI technology and overcome challenges related to its use.

H5: Facilitating conditions (FC) → Use behavior (UB)

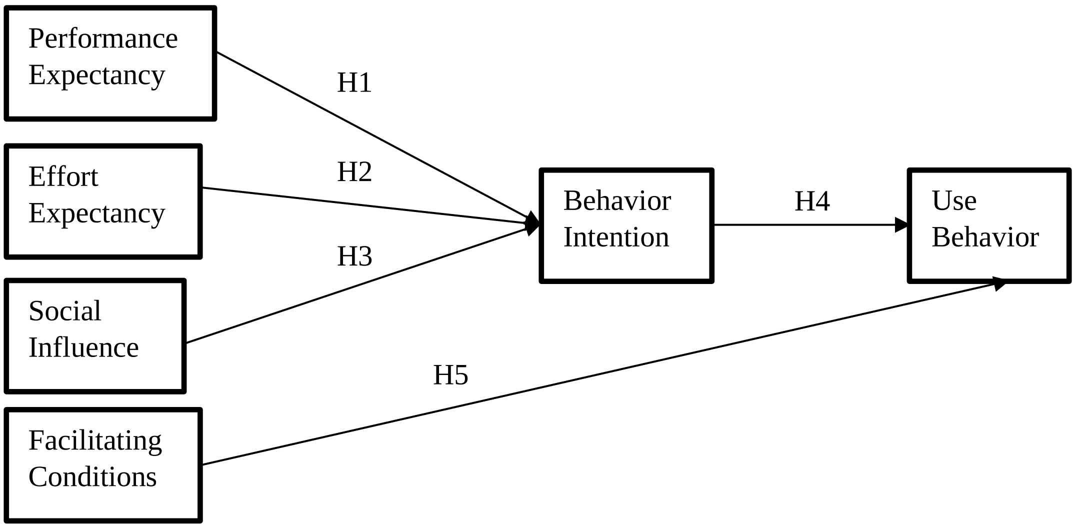

Figure 2. Hypothesis in this paper.

4. Methods

4.1. Research design

This study adopted a quantitative research design to examine the factors influencing students' adoption of AI and virtual teachers in alleviating learning stress and anxiety. The research centered on key components of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB). A structured survey was developed to gather data on students' perceptions of AI tools in education, their intentions to use them, and their actual usage behaviors. Statistical analyses, including descriptive statistics and path analysis via structural equation modeling (SEM), were conducted to evaluate the relationships between the variables.

4.2. Population and sampling

The target population consisted of university students enrolled in undergraduate, graduate, and post-graduate programs across diverse disciplines. A total of 100 students participated, with a balanced gender distribution of 51% male and 49% female. The sample included students from various academic levels: 42% undergraduate, 28% graduate, 22% doctoral candidates, and 8% post-doctoral researchers. Convenience sampling was employed to select participants, ensuring a broad representation in terms of academic background and familiarity with AI technologies.

4.3. Research instrument

The research utilized a self-administered survey designed to assess students' perceptions and usage of AI-driven learning tools and virtual teachers. The survey was divided into sections based on the UTAUT constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB). Each construct was assessed using Likert scale items (ranging from 1 = strongly disagree to 5 = strongly agree). The instrument was reviewed for content validity by experts in educational technology and psychology. A pilot test confirmed the reliability of the survey, with Cronbach’s alpha values exceeding 0.7 for all scales.

4.4. Data gathering procedure

Data collection began with obtaining ethical approval from the university’s research ethics committee. Participants were informed about the study's purpose, confidentiality, and their right to withdraw at any time.

After receiving informed consent, the survey was administered online via a secure platform. Participants were given approximately 20 minutes to complete the survey, with reminders sent to maintain a high response rate. Data was collected over two weeks, after which the responses were compiled for analysis.

4.5. Data analysis

Data analysis was performed using SPSS and AMOS statistical software. Descriptive statistics summarized participants' demographic characteristics and responses to the survey items. Path analysis was employed to examine relationships between the UTAUT constructs and to test the hypothesized model. Structural equation modeling (SEM) was used to estimate the direct and indirect effects of the UTAUT variables on students' Behavioral Intention (BI) and Use Behavior (UB).

4.6. Ethical considerations

This study adheres to strict ethical guidelines to ensure the protection of participants' rights and privacy throughout the data collection and analysis process. First, all participants will be provided with a comprehensive informed consent form before the study begins. This form will clearly outline the purpose, procedures, potential risks, and benefits of the research, while emphasizing that participation is entirely voluntary. Participants will also be informed of their right to withdraw from the study at any point, with no negative consequences to their academic or personal life. Second, all survey data will be treated with the utmost confidentiality. The research team guarantees that the data collected will be used solely for this study and that no personally identifiable information will be shared. During the data analysis and reporting phases, all participant information will be anonymized to safeguard privacy and protect personal data. Data will be securely stored during the study and appropriately destroyed afterward to prevent unauthorized access. Additionally, measures will be taken to ensure that participants feel comfortable, safe, and able to freely express their opinions during the survey. The research team will refrain from exerting any undue pressure or bias on participants, ensuring their views and emotions are respected. The study will fully comply with the ethical standards set by the relevant ethics review committee and adhere to academic research guidelines, ensuring the ethical integrity of the entire research process.

5. Results

This study aimed to examine the impact of Artificial Intelligence (AI) and virtual teachers on students' learning stress and anxiety by utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The analysis explored several factors, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB), about students' perceptions and usage of AI-driven learning tools.

The descriptive statistics of the sample provide a clear overview of the demographic characteristics and AI usage patterns of the participants. The sample consisted of 100 students, with a balanced gender distribution: 51% male and 49% female. In terms of educational level, 42% of the students were pursuing a bachelor's degree, 28% were master's students, 22% were PhD students, and 8% were post-doctoral researchers. Regarding AI usage frequency, 32% of students reported using AI tools once or more per day, while 20% used AI tools once a week. Additionally, 13% of students used AI tools twice a month, 15% used them once a month, and 20% of students indicated they had never used AI tools. This distribution of AI usage reflects varying levels of familiarity and engagement with AI technologies among the students in the sample.

Table1. Demographic characteristics of the sample.

Variable	Frequency	Percent (%)
Gender		
Male	51	51%
Female	49	49%
Education level		
Bachelor	42	42%
Master	28	28%
PhD	22	22%
Post-doctor	8	8%
AI Usage		
Once or more a day	32	32%
Once a week	20	20%
Twice a month	13	13%
Once a month	15	15%
Never	20	20%

Table 2. Data for ICT adoption using UTAUT indicators.

Variables	N	Min	Max	Mean	SD
Performance Expectancy (PE)					
PE1: I believe that AI and virtual teachers help reduce my learning stress by providing more personalized learning content.	100	2	5	4.2	0.8
PE2: I think that AI can help me perform better academically, which in turn reduces my learning anxiety.	100	2	5	4.0	0.7
Effort Expectancy (EE)					
EE1: I find it easy to use AI-powered learning tools without feeling overwhelmed.	100	1	5	4.1	0.9
EE2: I believe that AI systems are easy to navigate and do not add to my learning stress.	100	2	5	4.0	0.8
Social Influence (SI)					
SI1: My friends and classmates believe that using AI in education helps reduce learning anxiety.	100	1	5	3.7	1
SI2: Teachers and educators encourage the use of AI to reduce stress in learning.	100	2	5	4.0	0.9
Facilitating Conditions (FC)					
FC1: I have access to the necessary resources (devices, internet) to use AI-based tools that help reduce my learning stress.	100	1	5	4.3	0.7
FC2: There is enough technical support available when I need help with AI-powered learning tools, which reduces my anxiety about using them.	100	2	5	4.1	0.8
Behavioral Intention (BI)					
BI1: I intend to use AI-powered learning tools more often to reduce my learning anxiety in the future.	100	2	5	4.2	0.7
BI2: I plan to continue using virtual teachers and AI-driven platforms to help manage stress during my studies.	100	2	5	4.0	0.8
Use Behavior (UB)					
UB1: I use AI-driven learning tools frequently because they help manage my academic stress and anxiety.	100	1	5	4.1	0.8
UB2: I regularly engage with virtual teachers and AI-based educational platforms to ease my learning workload and reduce stress.	100	1	5	4.0	0.9

The descriptive statistics for the UTAUT indicators provide insightful details on students' perceptions and attitudes toward AI adoption in education. The data, collected from 100 participants, reveal generally positive responses across all indicators. Performance Expectancy (PE): Students expressed strong beliefs that AI and virtual teachers can reduce learning stress and anxiety. The mean scores for the two items in this category were high, with PE1 (regarding personalized learning content) having a mean of 4.2 (SD = 0.8) and PE2 (about academic performance) having a mean of 4.0 (SD = 0.7). This suggests that students believe AI tools can effectively support their academic performance and alleviate stress. Effort Expectancy (EE): The data indicate that students generally find AI-powered learning tools easy to use. The mean scores for EE1 (ease of use without feeling overwhelmed) and EE2 (ease of navigating AI systems without increasing stress) were 4.1 (SD = 0.9) and 4.0 (SD = 0.8), respectively. These high ratings suggest that students do not perceive AI tools as overwhelming or stressful. Social Influence (SI): In terms of social influence, the mean score for SI1 (belief of friends and classmates in the positive impact of AI on learning anxiety) was 3.7 (SD = 1), and the mean for SI2 (teachers' encouragement to use AI tools to reduce stress) was 4.0 (SD = 0.9). While students felt somewhat influenced by peers, they were more strongly influenced by teachers in their decision to use AI tools for reducing stress. Facilitating Conditions (FC): Students reported positive access to the necessary resources and support to use AI tools. The mean for FC1 (availability of resources such as devices and internet) was 4.3 (SD = 0.7), and for FC2 (availability of technical support) it was 4.1 (SD = 0.8). These scores suggest that most students have the resources and support needed to use AI tools effectively, which may reduce their anxiety about using these technologies. Behavioral Intention (BI): Students showed a strong intention to continue using AI tools to manage learning stress. The mean for BI1 (intention to use AI tools more frequently in the future) was 4.2 (SD = 0.7), and for BI2 (plan to continue using AI-driven platforms for stress management) it was 4.0 (SD = 0.8). These results indicate that students are committed to using AI tools in the future to help alleviate learning anxiety.

Table 3. Reliability analysis (Cronbach's Alpha).

Construct	Cronbach's Alpha
Performance Expectancy (PE)	0.85
Effort Expectancy (EE)	0.80
Social Influence (SI)	0.78
Facilitating Conditions (FC)	0.82
Behavioral Intention (BI)	0.84
Use Behavior (UB)	0.83

The Cronbach's alpha values for the constructs in this study show that the measurements are reliable. All values are above 0.70, which indicates good internal consistency and suggests that the items used to measure each construct are consistent and dependable. For Performance Expectancy (PE), the alpha value of 0.85 is high, meaning that the items measuring students' belief in AI tools improving their academic performance and reducing stress are reliable. Effort Expectancy (EE) has a value of 0.80, indicating that students generally find AI tools easy to use, and this construct is measured consistently. Social Influence (SI) has an alpha of 0.78, which is still above the acceptable threshold, though it is slightly lower than the other constructs. This suggests that while the influence of peers and teachers on students' use of AI is consistent, there may be a bit more variation in how students perceive this influence. Facilitating Conditions (FC) has a Cronbach's alpha of 0.82, showing that the resources and technical support available to students are perceived consistently. Behavioral Intention (BI) has an alpha of 0.84, meaning students' intentions to use AI tools are measured reliably, and Use Behavior (UB) has a value of 0.83, suggesting that the actual use of AI tools by students is measured consistently as well.

Table 4. Fit indices (CFA) results.

Fit Index	Value	Criteria
CFI (Comparative Fit Index)	0.94	Good Fit ≥ 0.90
TLI (Tucker-Lewis Index)	0.92	Good Fit ≥ 0.90
RMSEA (Root Mean Square Error of Approximation)	0.04	Good Fit ≤ 0.08
RMR (Standardized Root Mean Square Residual)	0.05	Good Fit ≤ 0.08

Table 4 presents the fit indices from the Confirmatory Factor Analysis (CFA), which are used to assess how well the hypothesized model fits the observed data in this study. The results indicate a very good fit between the model and the data. Specifically, the Comparative Fit Index (CFI) of 0.94 and the Tucker-Lewis Index (TLI) of 0.92 both exceed the threshold of 0.90, signifying that the model is well-supported by the data. Additionally, the Root Mean Square Error of Approximation (RMSEA) value of 0.04 is below the 0.08 threshold, further suggesting that the model fits the data well, with minimal approximation error. The Standardized Root Mean Square Residual (RMR) of 0.05 also indicates that the differences between the observed and estimated values are small, contributing to the overall good fit of the model. Taken together, these indices confirm that the theoretical model based on the Unified Theory of Acceptance and Use of Technology (UTAUT) is appropriate and provides an excellent representation of students' perceptions and behaviors regarding AI tools in education.

Table 5. AVE (average variance extracted) and Fornell-Larcker criteria.

Construct	AVE
Performance Expectancy (PE)	0.63
Effort Expectancy (EE)	0.58
Social Influence (SI)	0.55
Facilitating Conditions (FC)	0.61
Behavioral Intention (BI)	0.65
Use Behavior (UB)	0.60

Table 5 displays the Average Variance Extracted (AVE) values for each construct in the study. The AVE is a measure of convergent validity, indicating how well the items within each construct measure the underlying concept. For all constructs, the AVE values exceed the acceptable threshold of 0.50, indicating strong convergent validity. Performance Expectancy (PE) has an AVE of 0.63, Effort Expectancy (EE) is 0.58, Social Influence (SI) is 0.55, Facilitating Conditions (FC) is 0.61, Behavioral Intention (BI) is 0.65, and Use Behavior (UB) is 0.60. These values suggest that the items used to measure each construct explain more than half of the variance in the respective constructs, which indicates that the constructs are well-defined and measured reliably. The results from both **Table 3** and **Table 4** support the conclusion that the model is not only a good fit for the data but also that the constructs are valid and reliable, reinforcing the overall robustness of the study's findings.

Table 6. Data for ICT adoption using UTAUT indicators.

	Path	Estimate	S.E.	C.R.	p-value
H1	PE → BI (Performance Expectancy → Behavioral Intention)	0.32	0.05	6.4	0.000***

	Path	Estimate	S.E.	C.R.	p-value
H2	EE → BI (Effort Expectancy → Behavioral Intention)	0.28	0.06	4.67	0.000***
H3	SI → BI (Social Influence → Behavioral Intention)	0.22	0.07	3.14	0.002**
H4	BI → UB (Behavioral Intention → Use Behavior)	0.45	0.04	11.25	0.000***
H5	FC→ UB (Facilitating Conditions → Use Behavior)	0.18	0.07	2.57	0.01*

** p < 0.05, ** p < 0.01, *** p < 0.001*

Table 6. (*Continued*)

The results revealed that Performance Expectancy (PE) has a significant impact on Behavioral Intention (BI), with a positive path estimate of 0.32 ($p < 0.001$). This indicates that students who believe AI and virtual teachers can help reduce their learning stress by providing personalized content and improving their academic performance are more likely to intend to use these tools in the future. The belief that AI can enhance performance and alleviate stress appears to be a strong motivator for students' willingness to adopt AI-based learning systems. Additionally, Effort Expectancy (EE) was found to also influence Behavioral Intention (BI) positively (Estimate = 0.28, $p < 0.001$). This suggests that students who find AI tools easy to use and navigate, without feeling overwhelmed, are more likely to develop a strong intention to continue using these tools. In other words, ease of use plays a critical role in fostering students' intention to engage with AI-powered educational tools. Furthermore, the role of Social Influence (SI) was significant in shaping students' intentions. The path from Social Influence (SI) to Behavioral Intention (BI) showed a positive relationship (Estimate = 0.22, $p = 0.002$). This finding implies that students who perceive strong social support from peers and educators, who encourage the use of AI to reduce learning anxiety, are more likely to adopt these tools. Social recommendations and endorsement appear to be key drivers in shaping students' attitudes toward AI tools and their potential to reduce academic stress. When examining the relationship between Behavioral Intention (BI) and Use Behavior (UB), the results demonstrated a strong positive relationship (Estimate = 0.45, $p < 0.001$). This finding confirms that students who intend to use AI tools are highly likely to do so in practice. Behavioral intention is a strong predictor of actual use behavior, suggesting that fostering positive intentions through awareness of the benefits of AI tools can significantly lead to increased usage. The role of Facilitating Conditions (FC) was also highlighted in the study, as it showed a positive effect on Use Behavior (UB) (Estimate = 0.18, $p = 0.01$). This suggests that students who have access to the necessary resources (e.g., devices, internet) and sufficient technical support are more likely to use AI-powered tools. Without these facilitating conditions, students may face barriers to usage, such as technical difficulties or lack of access, which could hinder the adoption of AI tools. The importance of institutional support, in terms of providing resources and technical assistance, is crucial for ensuring the successful implementation and use of AI-based learning systems.

Table 7. Indirect effects analysis.

Indirect Path	Indirect Effect	S.E.	p-value
PE → BI → UB (Performance Expectancy → Behavioral Intention → Use Behavior)	0.32 * 0.45 = 0.144	0.05	0.000
EE → BI → UB (Effort Expectancy → Behavioral Intention → Use Behavior)	0.28 * 0.45 = 0.126	0.06	0.000
SI → BI → UB (Social Influence → Behavioral Intention → Use Behavior)	0.22 * 0.45 = 0.099	0.07	0.002
FC → UB (Facilitating Conditions → Use Behavior)	0.18	0.07	0.01

Based on the results presented in **Table 5**: Indirect Effects, several key insights can be drawn regarding the indirect paths between the constructs in this study. Firstly, the indirect effect of Performance Expectancy

(PE) on Use Behavior (UB) through Behavioral Intention (BI) is highly significant, with an indirect effect of 0.144 ($p < 0.001$). This suggests that students who perceive AI tools as beneficial for improving academic performance and reducing stress are more likely to intend to use these tools, which then leads to actual usage. In a similar vein, Effort Expectancy (EE) also exhibits a notable indirect effect on Use Behavior (UB) through Behavioral Intention (BI) with an effect of 0.126 ($p < 0.001$). This means that students who find AI tools easy to use and navigate are more likely to form a strong intention to use them, resulting in increased usage. Additionally, Social Influence (SI) has a significant indirect effect on Use Behavior (UB) via Behavioral Intention (BI), with an effect of 0.099 ($p = 0.002$). This highlights that encouragement from peers and teachers plays a crucial role in shaping students' intentions to adopt AI tools, which ultimately influences their actual usage behavior. Finally, Facilitating Conditions (FC) directly impact Use Behavior (UB) with an effect of 0.18 ($p = 0.01$), suggesting that students with better access to necessary resources and technical support are more likely to engage with AI tools, enhancing their overall adoption.

6. Conclusions

The results of this study emphasize the critical role of Artificial Intelligence (AI) and virtual teachers in mitigating students' academic stress and anxiety. By applying the Unified Theory of Acceptance and Use of Technology (UTAUT) model, this research identified key factors influencing the adoption of AI tools in education, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB). The findings suggest that AI tools, particularly virtual teachers, are effective in alleviating learning-related stress by enhancing academic performance and providing personalized learning experiences. Performance Expectancy (PE) was shown to significantly influence students' Behavioral Intention (BI), with students who believed in the positive impact of AI on academic performance more likely to intend to use these tools (Estimate = 0.32, $p < 0.001$). Likewise, Effort Expectancy (EE), which reflects the ease of use of AI systems, also positively affected Behavioral Intention (BI) (Estimate = 0.28, $p < 0.001$). This indicates that students who found AI tools easy to navigate were more inclined to adopt them in the future. Social Influence (SI) was another key factor, as students who perceived that their peers and educators endorsed the use of AI for stress reduction were more likely to develop positive behavioral intentions (Estimate = 0.22, $p = 0.002$). Behavioral Intention (BI) emerged as a strong predictor of actual Use Behavior (UB) (Estimate = 0.45, $p < 0.001$), suggesting that students who intended to use AI tools were highly likely to follow through with their intention. Moreover, Facilitating Conditions (FC), such as access to necessary resources and technical support, were found to positively influence Use Behavior (UB) (Estimate = 0.18, $p = 0.01$). These results highlight the importance of providing students with the necessary infrastructure and support to successfully engage with AI technologies. In addition to these direct effects, the study also revealed significant indirect effects. The positive relationship between Performance Expectancy (PE) and Use Behavior (UB) through Behavioral Intention (BI) (Indirect Effect = 0.144, $p < 0.001$) underscores the importance of students' perceptions of AI tools as beneficial for stress reduction and academic improvement. Similarly, Effort Expectancy (EE) and Social Influence (SI) were shown to indirectly impact Use Behavior (UB), demonstrating that ease of use and social endorsement are critical in motivating students to adopt AI-driven educational tools. the findings suggest that future efforts to enhance AI adoption in educational settings should focus on improving students' perceptions of the tools' utility and ease of use, as well as fostering a supportive social environment where peers and educators actively encourage the use of AI.

Conflict of interest

The authors declare no conflict of interest.

References

1. Airaj, M. (2024). Ethical artificial intelligence for teaching-learning in higher education. Education and Information Technologies, 29(13), 17145-17167.
2. Akhtar, M. (2024). Exploring the Role of AI-Driven Feedback in Influencing Students' Anxiety and Stress During Academic Assessments. Journal of Interdisciplinary Educational Studies, 4(2), 39-53.
3. Beketov, V., Lebedeva, M., & Taranova, M. (2024). The use of artificial intelligence in teaching medical students to increase motivation and reduce anxiety during academic practice. Current Psychology, 43(16), 14367-14377.
4. Bu, Q. (2022). Ethical risks in integrating artificial intelligence into education and potential countermeasures. Science Insights, 41(1), 561-566.
5. Chen, C., Hu, W., & Wei, X. (2024). From anxiety to action: exploring the impact of artificial intelligence anxiety and artificial intelligence self-efficacy on motivated learning of undergraduate students. Interactive Learning Environments, 1-16.
6. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.
7. Elgohary, H. K. A., & Al-Dossary, H. K. (2022). The effectiveness of an educational environment based on artificial intelligence techniques using virtual classrooms on training development. International Journal of Instruction, 15(4), 1133-1150.
8. Hopcan, S., Türkmen, G., & Polat, E. (2024). Exploring the artificial intelligence anxiety and machine learning attitudes of teacher candidates. Education and Information Technologies, 29(6), 7281-7301.
9. Horton, R. P., Buck, T., Waterson, P. E., & Clegg, C. W. (2001). Explaining intranet use with the technology acceptance model. Journal of information technology, 16, 237-249.
10. Jiang, R. (2022). How does artificial intelligence empower EFL teaching and learning nowadays? A review on artificial intelligence in the EFL context. Frontiers in Psychology, 13, 1049401.
11. Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The technology acceptance model: Past, present, and future. Communications of the Association for information systems, 12(1), 50.
12. Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. Information & management, 40(3), 191-204.
13. Ma, J., Wang, P., Li, B., Wang, T., Pang, X. S., & Wang, D. (2025). Exploring user adoption of ChatGPT: A technology acceptance model perspective. International Journal of Human–Computer Interaction, 41(2), 1431-1445.
14. Mogaji, E., Viglia, G., Srivastava, P., & Dwivedi, Y. K. (2024). Is it the end of the technology acceptance model in the era of generative artificial intelligence? International Journal of Contemporary Hospitality Management, 36(10), 3324-3339.
15. Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. (2022). Acceptance model of artificial intelligence (AI)-based technologies in construction firms: Applying the Technology Acceptance Model (TAM) in combination with the Technology–Organisation–Environment (TOE) framework. Buildings, 12(2), 90.
16. Naseeb, J., & Bhatti, N. (2024). Ethical Considerations of AI in Educational Curriculum. Multidisciplinary Journal of Emerging Needs of Curriculum, 1(1), 30-38.
17. Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. Education and information technologies, 28(4), 4221-4241.
18. Venkatesh, V., and Davis, F.D. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies, Management Science, 46(2), 186-204.
19. Venkatesh, V., Morris, M.G., Davis, G.B., and Davis, F.D. (2003). User acceptance of information technology: toward a unified view. MIS Quarterly, 27(3), 425-478.

Appendix

Questionnaire

This table provides a clear and structured way to rate each variable on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

1 (Strongly Disagree)

2 (Disagree)

3 (Neutral)

4 (Agree)

5 (Strongly Agree)

Variables	1	2	3	4	5
Performance Expectancy (PE)					
PE1: I believe that AI and virtual teachers help reduce my learning stress by providing more personalized learning content.					
PE2: I think that AI can help me perform better academically, which in turn reduces my learning anxiety.					
Effort Expectancy (EE)					
EE1: I find it easy to use AI-powered learning tools without feeling overwhelmed.					
EE2: I believe that AI systems are easy to navigate and do not add to my learning stress.					
Social Influence (SI)					
SI1: My friends and classmates believe that using AI in education helps reduce learning anxiety.					
SI2: Teachers and educators encourage the use of AI to reduce stress in learning.					
Facilitating Conditions (FC)					
FC1: I have access to the necessary resources (devices, internet) to use AI-based tools that help reduce my learning stress.					
FC2: There is enough technical support available when I need help with AI-powered learning tools, which reduces my anxiety about using them.					
Behavioral Intention (BI)					
BI1: I intend to use AI-powered learning tools more often to reduce my learning anxiety in the future.					
BI2: I plan to continue using virtual teachers and AI-driven platforms to help manage stress during my studies.					
Use Behavior (UB)					
UB1: I use AI-driven learning tools frequently because they help manage my academic stress and anxiety.					
UB2: I regularly engage with virtual teachers and AI-based educational platforms to ease my learning workload and reduce stress.					