Eurasian Journal of Educational Research 110 (2024) 33-52

Eurasian Journal of Educational Research
www.ejer.com.tr

Effectiveness of AI-powered Tutoring Systems in Enhancing Learning Outcomes

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ARTICLE INFO

Article History:
Received: 01 December 2023
Received in revised form: 14 March 2024
Accepted: 30 March 2024
DOI: 10.14689/ejer.2024.110.003

Keywords
AI-Powered Tutoring Systems, Satisfaction, Perceived Usefulness, Facilitating Conditions, Content & Navigation, Student Engagement

ABSTRACT

Purpose: This study investigates the impact of various variables on Saudi Arabian university students' perceptions and attitudes towards AI-powered Tutoring Systems (AI-PTS). This study examines the mediating role of satisfaction in the relationship between perceived usefulness, facilitating conditions, content and navigational ease of use, instrumental value of AI-PTS adoption, and the cost and expectation to use AI-PTS. Moreover, this study looks into the moderating effect of student engagement on the relationship between satisfaction and expectancy in AI-PTS. **Methodology:** A survey questionnaire was used to collect data from 284 students from multiple universities in Saudi Arabia, employing the convenience sampling method. The study employed structural equation modelling (SEM) with PLS to analyse the data and assess the research hypotheses. **Findings:** The results indicate that satisfaction in AI-PTS partially mediates the relationship between perceived usefulness, facilitating conditions, content and navigation (ease of use), task value in AI-PTS attainment, and cost with expectancy in AI-PTS. The study's findings highlight the impact of student satisfaction on their expectations and beliefs regarding the system. Additionally, this study highlights the significant role of interpersonal engagement in reducing the relationship between satisfaction and expectancy in AI-PTS. The findings have significant implications for AI-PTS developers and users in the educational field, highlighting the importance of prioritising satisfaction and engagement. **Implications:** This prioritisation is crucial for enhancing students' ability to effectively utilise the technology. This study contributes to the progress of AI-PTS and Saudi Arabian higher education fields by investigating the factors that influence students' expectations and perceptions of AI-PTS. This study aims to investigate the mediating role of satisfaction and the moderating role of student engagement in understanding the complex process of students' connections with AI-PTS.

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Introduction

AI-Renowned Tutoring Platforms Students' "expectancy" would be a measure of how much they think AI systems will be useful and effective. Regarding this research, "expectancy" could refer to students' perceptions of their comfort level, perceived advantages, and level of competency with AI tutoring technologies. Numerous AI-driven teaching systems have been developed, each with unique benefits and functionalities. However, Butz et al. (2004) describes an intelligent tutoring system that uses Bayesian networks on the Web to help students make decisions about computer programming. Le et al. (2013) examines various AI-enabled tutoring strategies, including programming that uses AI feedback-based tutoring and AI to determine the goals of pupils. In 2019, Gan developed AI-Tutor, a personalised adaptive teaching system that can provide remedial questions and answers based on a cognitive diagnostic assessment that are automatically adjusted. Keleş et al. (2009) notes in the last section that improving query and interface precision might be possible with an agent-based intelligent tutoring system built on the semantic-net concept.

Kojima et al. (2020) and Rızvı (2023) highlight the ability of AI-based tutoring systems to provide personalised instructions and adapt as students' progress. Kojima et al. (2020) and Rızvı (2023) emphasise the importance of incorporating a knowledge graph into systems for generating answers, as well as the significance of designing and implementing such systems to enhance learners' experience. Merkle et al. (2024) discusses the user experience of AI-tutors, highlighting various interaction patterns and noting both advantages, such as immediate feedback, and disadvantages, such as generic answers. The present research examines the impact of expectancy on student engagement with AI-enabled tutoring systems. This study examines the alignment between the system's definition and students' expectations and beliefs, and how this alignment impacts their satisfaction, involvement, and academic performance. As a result, the findings will provide insights into the impact of AI-enabled tutoring programs on students' performance and their response to expectancy in educational settings.

The term "Student Satisfaction with AI-Powered Tutoring Systems" refers to the degree to which students experience positive emotions, such as contentment or delight, when using AI-based tutorial systems. This term encompasses various factors that students use to assess a system, including its effectiveness, user-friendliness, potential for interaction, and user experience. Studies on AI-based tutoring systems have revealed that the AI system influences the level of student engagement and satisfaction (Afzal et al., 2019). Research indicates that AI-powered tutoring systems are highly effective in improving student learning and reducing the amount of time required for learning, according to (Kularbphettong et al., 2015). Intelligent solving based systems (SITS) have been recognised for their ability to improve problem-solving skills and increase student interest and motivation in learning (Hooshyar et al., 2018). Cakir (2019) found that web-based intelligent tutoring systems significantly improved students' academic performance and motivation. Therefore, it is crucial to examine the factors that influence student satisfaction in an AI-powered tutoring system. These factors may pertain to system usability, usefulness, effectiveness in learning, and overall user experience. The key objective is to assess students' satisfaction with AI-led student tutoring systems in order to enhance the systems and improve students' learning experiences and outcomes.

The term "student engagement in AI-Generated Tutoring Systems" encompasses the learner's emotional connection, attention, and response to the AI-powered tutoring systems used for acquiring knowledge. This term encompasses different aspects of students' behaviour and engagement in the classroom, including their level of focus and active participation, motivation to learn, and their attitude towards or utilisation of the tutoring system. In recent times, significant progress has been made in the development of computerised tutors capable of monitoring students' engagement and detecting instances of excessive involvement (Binh et al., 2019). Interactive dialogue is commonly used to enhance the enjoyment and engagement of the study process (Graesser et al., 2001). It is evident that current technology can enhance education compared to traditional methods. However, further research is needed to investigate how to create environments that offer improved user experiences and learning outcomes (Sundararajan & Nitta, 2015).

A recent study has focused on the educational benefits of AI teaching systems for improving student engagement. Pande et al. (2021) proposed a hybrid conversational AI approach that enables learners to practice self-reflection while focusing on cognitive goals within joint projects. AI technology was utilized in online learning to predict and enhance the interactive capabilities of teachers and students (Xu et al., 2023). Furthermore, Ayouni et al. (2021) investigated the use of machine learning tools to predict online student engagement levels. The study found that these tools have a positive impact on student motivation and dedication. This study aims to examine the effects of AI-supported education system characteristics, including information access, individualization, feedback mechanisms, and gamification elements, on student engagement. Understanding student engagement in AI-powered tutoring systems is essential for effectively configuring them to improve learning outcomes for users.

Literature Review

The students' perception of the usefulness of AI-PTS is determined by their belief in its ability to enhance their learning. The enabling factors mediate the adoption of AI-PTS. The content and navigation of a system, including ease of use, refer to the organisation and user-friendliness of the system. The importance of tasks in AI-PTS is determined by the ratio of their value to their cost. The aforementioned elements are crucial in determining students' satisfaction with the AI-powered teaching system. Student satisfaction is higher when they perceive the system as applicable, receive necessary support, find the interface easy to navigate, and consider the assigned tasks valuable. The contentedness of individuals ultimately influences their expectations and attitudes towards AI-PTS.

Chen et al. (2022) conducted the present study to investigate the impact of two factors, namely involvement (high rate vs. low rate) and tutor type (human tutor vs. AI tutor), under two conditions: poor and bad writing quality. The results indicate a statistically significant interaction effect between user involvement and tutor type. When the user's level of engagement is low, the AI tutor exhibits superior writing quality compared to the human tutor. However, when the user's level of engagement is high, the type of tutor (human or AI) does not influence our perception of the writing quality. Alam (2023) examines the development, utilisation, and integration of advanced technologies in education, specifically focusing on their incorporation into the curriculum and classroom. Otto et al. (2024) aims to generate research data that explores the applications of AI in higher education. This study presents a case from Germany examining student acceptance of an AI-based feedback system used to assist self-regulated learning in voluntary mathematics courses. The feedback system includes an AI component that enables autonomous and automatic assessment of student tasks. This programme allows students to submit assignments multiple times and seek additional assistance from tutors. Merkle et al. (2024)

demonstrates that the feedback loop between expectations, reality, and motivation plays a significant role in the lack of enjoyment of AI-PTS. Alzyoud et al. (2024) asserts that people perceive trust and expected performance in the context of AI in education as requiring effort to learn.

H1: *Satisfaction in AI-PTS mediates relationship between Perceived usefulness in AI-PTS and Expectancy in AI-PTS*

Saqr et al. (2023) study examines the impact of AI-driven platforms (such as Blackboard, Moodle, Edmodo, Coursera, and edX on the perceived usefulness and ease of use among Saudi university students. The study focuses on AI-based social learning networks, personal learning portfolios, and personal learning environments. This study also investigated the direct effects of these opinions on students' satisfaction and their intentions to use e-learning. In addition, the study also examined the moderating effects of individual characteristics, such as readiness for self-directed e-learning, self-efficacy, and innovativeness, on e-learning intentions. Algahtani and Amirah (2024) examines the impact of LLMs on educational assessment processes, such as test structure, item creation, test administration, and scoring. The programme includes experienced STEM teachers who have utilised an AI-based scaffolding system for scientific writing. This study offers a comprehensive review of AI applications in higher education, including an examination of the ethical implications, challenges, and risks associated with these applications. The implementation of AI is central to the process, while managing users' expectations determines the acceptance of technology and its usage over time (Buschmeyer et al., 2023). Ramis and Loh (2023) posited that the need for mediating the relationship between presence and academic motivation is more significant than the psychological need for acceptance. The statement suggests that satisfaction plays a mediating role in the provision of AI-PTS and reward expectancy. Moreover, additional research is needed to explore the impact of AI on cognitive issues.

H2: *Satisfaction in AI-PTS mediates relationship between Facilitating conditions in AI-PTS and Expectancy in AI-PTS*

The AI-based social platform Ivanov et al. (2023) caters to the needs of students and teachers by offering a unique learning curriculum. Dosky (2024) examines the impact of AI on education and student learning, focusing on its transformative effects on teaching, including personalised learning, smart content, and its influence on student learning outcomes. Also, the focus will be on the impact of Virtual Assistants, such as AI Chatbots and ChatGPT developed by Open AI. This study will also investigate the role of Learning Management Systems in Classroom Management, Behaviour, and Online Discussions. This paper examines the impact of AI-generated content on students and teachers, as well as its accessibility and the associated advantages and disadvantages. The satisfaction and persistence of AI-PTS usage are influenced by factors such as collaboration, effectiveness, and knowledge, as highlighted by (Buba et al., 2024) and (Ngo et al., 2024).

H3: *Satisfaction in AI-PTS mediates relationship between Content & Navigation (Ease of Use) in AI-PTS and Expectancy in AI-PTS*

The study Chine et al. (2022) examines the effectiveness of individualised learning, a hybrid support approach that combines human mentoring and AI tutoring to personalise learning and address students' emotional and cognitive needs. The approach posits that achievement gaps, especially among marginalised students, stem from unequal learning opportunities. It aims to address these inequalities through extended learning programmes such as Ready to Learn. Shoaib et al. (2024) suggests an AI Student Success Predictor that utilises advanced machine learning algorithms to automate grading procedures, predict at-risk students, and forecast possible student retention or dropout. Chaudhry and Kazim (2022) presents a comprehensive perspective on the application of artificial intelligence (AI) in the field of education, encompassing both industrial and academic aspects. The text highlights the focus of recent AIEd research on reducing teacher workloads, promoting student-centred learning, revolutionising assessment methods, and developing intelligent tutoring systems.

H4: *Satisfaction in AI-PTS mediates relationship between Task value in AI-PTS Attainment and Cost and Expectancy in AI-PTS*

The article by Nguyen et al. (2024) not only introduces artificial intelligence in its fundamental form, but also explores its application and significance in higher education. The paper discusses the use of AI technologies and chatbots to engage students, highlighting various opportunities available in this area. The current article focuses on the primary and secondary impacts of AI-assisted education, specifically examining its influence on classroom management and its effects on student engagement, academic achievement, and teacher effectiveness. Darvishi et al. (2024) conducted a randomised controlled trial examining the impact of AI support on students' ability to engage in peer feedback provision. The article emphasizes the significance of AI-based predictive analytics in identifying students at risk of academic failure and improving the likelihood of academic success for all learners (Reethika & Priya, 2024).

H5: *Student engagement in AI-PTS significantly moderates the relationship between Satisfactions in AI-PTS and Expectancy in AI-PTS.*

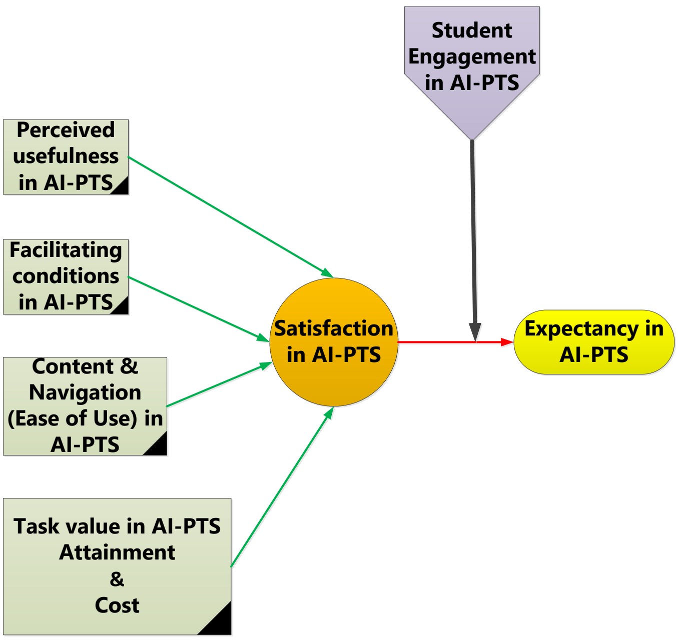

Figure 1: Framework of the study

The study identified mediation effects, indicating that certain variables mediate the relationship between independent and dependent variables. Facilitating conditions mediate the relationship between perceived usefulness and mental engagement, student satisfaction, and learning outcomes.

Moreover, the study found that the third variable moderates the relationships between the observed variables, acting as a mediator. Perceived usefulness, the way students perceive the usefulness of assessment, may be influenced by enabling conditions, indicating that the impact of perceived usefulness on student engagement depends on the level of enabling conditions. The model examines the impact of perceived usefulness, enabling conditions, ease of use, and assignment purposefulness on student satisfaction, engagement, and learning outcomes in AI-enabled Tutoring Systems. The mediation and moderation effects provide a broader perspective for the development of efficient and applicable AI-PTS approaches.

Sampling and Data Collection

The research data was collected from 284 students studying at various universities in the Kingdom of Saudi Arabia. The recruitment method employed was participant pickup, and information was collected using a survey questionnaire. Convenience sampling refers to the process of selecting participants who are readily available and willing to participate in the research. This approach may save time and effort, but there is a potential for biassed responses due to the possibility that the sample may not accurately represent the entire population. On the other hand, in certain situations, it may be employed when the entire population cannot be accessed. In this instance, the accessibility of the case extended beyond individuals with ICT infrastructures to encompass a significant number of university students from Saudi Arabia.

Data Analysis and Results

Table 1 presents descriptive statistics for the constructs or variables utilised in the study, including means, standard deviations, minimums, and maximums. The mean represents the average score for each construct, indicating the central tendency of the data. The standard deviation (Std. Deviation) measures the extent to which scores deviate from the mean, indicating the level of variability in the data. The dataset represents the minimum and maximum values for each construct (Field, 2018). The range of the methods of the constructs is from 3.00 to 3.47, indicating a moderate-to-high overall perception across the constructs. The range of sample standard deviations is 0.497 to 0.846, indicating that participants' responses exhibit heterogeneous patterns. EAI-PTS (DV) exhibits the highest standard deviation (0.846), indicating the greatest variability in responses regarding the effectiveness of AI in post-traumatic settings. These minimum and maximum values (1 and 5) indicate that all constructs were rated by the participants over the entire range of the Likert scale used (Bickel, 2007). The descriptive statistics serve as a basis of data analysis providing measurements necessary for the next inferential statistical analysis. Descriptive statistics gives the ability to summarize all the features of a data set concisely and clearly.

Table 1

Descriptive Statistics

Constructs	Mean	Std. Deviation	Minimum	Maximum
(PUAI-PTS)-IV	3.01	0.497	1	5
(FCAI-PTS) -IV	3.26	0.648	1	5
(CN (EU) AI-PTS) -IV	3.47	0.657	1	5
(TVAI-PTS (AC)) - IV	3.21	0.690	1	5
(SAI-PTS)-Mediator	3.00	0.779	1	5
(EAI-PTS)-DV	3.19	0.846	1	5
(SEAI-PTS)- - Moderator	3.17	0.734	1	5

Measurement Model Results

Table 2 displays the assessment of convergent validity for the constructs under investigation. Convergent validity refers to the extent to which measurements of the same construct exhibit strong correlations. The primary indicators include factor loadings, Cronbach's alpha, CR, and AVE. The PUAI-PTS (Perceived Usefulness of AI in PTS) scale demonstrates factor loadings ranging from 0.614 to 0.764. The scale also exhibits a Cronbach's alpha of 0.748, a CR of 0.794, and an AVE of 0.091. The values suggest moderate to high item correlation and severe internal consistency and reliability. The FCAI-PTS (Facilitating Conditions of AI in PTS) exhibits strong reliability and internal consistency, as evidenced by factor loadings ranging from 0.797 to 0.856, a Cronbach's alpha of 0.801, CR of 0.827, and a mean of 0.819. The EU AI-PTS study reports factor loadings ranging from 0.669 to 0.879, a Cronbach's alpha of 0.840, a CR of 0.887, and an ave of 0.811, indicating strong internal consistency. The Trust in AI in PTS, Affective Component (TVAI-PTS (AC)) exhibits factor loadings ranging from 0.697 to 0.870. It has a Cronbach's alpha coefficient of 0.724, a composite reliability (CR) of 0.768, and an average score of 0. The questionnaire demonstrates good internal consistency with a Cronbach's alpha of 0.736. The SAI-PTS (SA of AI in PTS) consists of items with factor loadings ranging from 0.669 to 0.797. It has a Cronbach's alpha coefficient of 0.699, a composite reliability (CR) of 0.741, and an average variance extracted (AVE) of 0.713, indicating moderate reliability. The EAI-PTS (Efficacy of AI in Post-Traumatic Areas) has demonstrated good reliability with a weighted range of 0.697 to 0.911, Cronbach's alpha of 0.811, CR of 0.837, and AVE of 0.800. The self-efficacy on AI in PTS (SEAI-PTS) scale demonstrates acceptable reliability, with a score factor ranging from 0.668 to 0.795, Cronbach's alpha of 0.749, CR of 0.790, and an average of 0.758. High factor loadings, good Cronbach's alpha, strong composite reliability, and AVE values above 0.50 show that the constructs have strong convergent validity. The results are consistent with the criteria for convergent validity and reliability as outlined by (Hair et al., 2010) and (Fornell & Larcker, 1981).

Table 2

Convergent Validity

	Loadings	Alpha	Composite Reliability	AVE
(PUAI-PTS)0	0.614	0.748	0.794	0.91
(PUAI-PTS)1	0.633			
(PUAI-PTS)2	0.734			
(PUAI-PTS)3	0.764			
(PUAI-PTS)4	0.719			
(FCAI-PTS)0	0.797	0.801	0.827	0.819
(FCAI-PTS)1	0.856			
(FCAI-PTS)2	0.801			
(FCAI-PTS)3	0.837			
(CN (EU) AI-PTS0	0.864	0.840	0.887	0.811
(CN (EU) AI-PTS1	0.669			
(CN (EU) AI-PTS2	0.711			
(CN (EU) AI-PTS3	0.700			
(CN (EU) AI-PTS4	0.879			
(CN (EU) AI-PTS5	0.864			
(TVAI-PTS (AC)0	0.870	0.724	0.768	0.736
(TVAI-PTS (AC)1	0.764			
(TVAI-PTS (AC)2	0.791			
(TVAI-PTS (AC)3	0.769			
(TVAI-PTS (AC)4	0.734			
(TVAI-PTS (AC)5	0.755			
(TVAI-PTS (AC)6	0.697			
(TVAI-PTS (AC)7	0.847			
(SAI-PTS)0	0.669	0.699	0.741	0.713
(SAI-PTS)1	0.703			
(SAI-PTS)2	0.797			
(EAI-PTS)0	0.874	0.811	0.837	0.800
(EAI-PTS)1	0.864			
(EAI-PTS)2	0.897			
(EAI-PTS)3	0.911			
(EAI-PTS)4	0.697			
(EAI-PTS)5	0.789			
(EAI-PTS)6	0.760			
(SEAI-PTS)0	0.794	0.749	0.790	0.758
(SEAI-PTS)1	0.694			
(SEAI-PTS)2	0.668			
(SEAI-PTS)3	0.795			
(SEAI-PTS)4	0.736			
(SEAI-PTS)5	0.740			
(SEAI-PTS)6	0.694			

Discriminant Validity

Table 3 presents the results of the discriminant validity analysis, which assesses the degree of dissimilarity between constructs. Constructs that are considered distinct in theory also demonstrate empirical differences in terms of discriminant validity. Table 3 displays the VIF values for each construct, as well as the correlations between the constructs. The VIF values indicate the presence of multicollinearity, with lower values suggesting less multicollinearity. (Fornell & Larcker, 1981) confirm the validity of a discriminant when the correlations between constructs are less than the square root of the AVE of each construct. The VIF values below the threshold of 5 indicate acceptable levels of multicollinearity, as recommended by Hair et al. (2010).

Table 3

Discriminant Validity

	VIF	(PUAI-PTS)	(FCAI-PTS)	(CN (EU) AI-PTS)	(TVAI-PTS (AC))	(SAI-PTS)	(EAI-PTS)	(SEAI-PTS)
(PUAI-PTS)-IV	2.01							
(FCAI-PTS) -IV	2.34	0.347						
(CN (EU) AI-PTS) -IV	2.17	0.197	0.118					
(TVAI-PTS (AC)) -IV	2.19	0.247	0.364	0.647				
(SAI-PTS)-Mediator	2.64	0.164	0.297	0.257	0.448			
(EAI-PTS)-DV	----	0.228	0.497	0.349	0.314	0.258		
(SEAI-PTS)-Moderator	-----	0.168	0.547	0.480	0.142	0.347	0.228	

Structural Model Results

Table 4 presents the results of the structural model analysis, specifically the R-squared values. The term R-square (R^2) represents the proportion of the variance in the dependent variable that can be accounted for by the independent variables.

Table 4

R –Square

Endogenous Variable	R Square
(SAI-PTS)	0.749
(EAI-PTS)	0.314

The exogenous variables in this case are (SAI-PTS) and (EAI-PTS). The R^2 value for (SAI - PTS) is 0.749, indicating that 74% of the variation in (SAI-PTS) can be explained by the independent variables (Hair, 2006). Parallelly, the R-square value of (EAI-PTS) is 0.314, indicating a 31% relationship. The independent variable has a significant impact on more than 4% of the variation

(EAI-PTS). This finding suggests a strong relationship between the independent variables and the fluctuation of the dependent variables.

Mediation and Moderation

Table 5 displays the results of the mediation effects. The intervening outcomes measure the indirect effect of the independent variable on the dependent variable through a mediator. This study examines the mediating role of PUAI-PTS on SAI-PTS. The presence of an Enterprise Application Integration-Performance Testing System (EAI-PTS) can be indicated by a beta coefficient of 0.2.14 and a t-statistics value of 3.01. Similarly, other mediating properties, such as FCAI-PTS, CN (EU) AI-PTS, and TVAI-PTS (AC), are also enhanced. The aforementioned results indicate that the independent variables have a notable indirect impact on the dependent variable through the mediator.

Table 5

Mediating Effect Results

	BETA	Standard Error	T statistics	P values	Decision
(PUAI-PTS)-> (SAI-PTS ->(EAI-PTS)	0.214	0.018	3.01	0.00	Supported
(FCAI-PTS) ->(SAI-PTS ->(EAI-PTS)	0.269	0.036	3.24	0.014	Supported
(CN (EU) AI-PTS) ->(SAI-PTS ->(EAI-PTS)	0.187	0.048	2.87	0.016	Supported
(TVAI-PTS (AC)) ->(SAI-PTS ->(EAI-PTS)	0.228	0.033	2.99	0.024	Supported

Table 6

Moderating Effect Results

	Beta	Standard Error	T statistics	P values	DECISION
(SAI-PTS)- >(SEAI-PTS)-> (EAI-PTS)	0.189	0.028	3.64	0.017	Supported

Table 6 presents the findings of the analysis on the moderating effect. Moderation effect studies examine how the relationship between variables changes based on the level of a moderator. The objective of our study was to examine the role of (SAI-PTS) as a mediator between (SEAI-PTS) and (EAI-PTS). The (SAI-PTS) serves as the moderator between (SEAI-PTS) and (EAI-PTS). The Beta coefficient is 0.189 with a t-value of 3.64, indicating that the T statistics value exceeds 1.96 (Hair et al., 2007). When the probability value is 0. The p-value of .017 indicates a significant association.

Discussion

The study aimed to analyse student motivation to use and evaluate AI-Powered Tutoring Systems (AI-PTS) in terms of satisfaction and learning effectiveness. The study investigated the factors influencing students' behaviour, satisfaction, and achievement. These factors included usage value, conditions enabling usage, content and interface usability, and the degree of task promotion. The findings suggest that perceived usefulness is a significant factor in influencing student engagement, satisfaction, and learning outcomes in AI-PTS education. There is a positive relationship between students' perception of the usefulness of AI-PTS and their engagement with the system, resulting in increased satisfaction and improved learning outcomes.

The correlation between assessment of usefulness and student engagement, satisfaction, and learning outcomes highlights the importance of developing AI-PTS that offer tangible benefits for students. The investigation revealed significant variations in the conditions of use, particularly in terms of the availability of information and assistance for proper utilisation of the system. In contrast, there was clear evidence that students' factual processing abilities were consistently strong. The awareness of having the necessary resources and support leads students to view AI-PTS as a reliable tool for their learning, resulting in increased engagement, satisfaction, and learning outcomes. The results clearly indicate that adequate funding for students is crucial in enabling them to effectively utilise AI-PTS.

The study analysed the impact of content and navigation on student engagement, satisfaction, and learning outcomes in AI-PTS. The level of user-friendliness of AI-PTS is a key consideration that impacts learners' information contentment and involvement in the system. When a resource is both applicable and easy to use, it enhances well-being, satisfaction, and engagement. Ultimately, this leads to improved learning outcomes. The impact of task value, defined as the perceived importance or worth of the task in AI-PTS, was clearly evident in the students' evaluation of the system's efficiency and utility. The learners who perceive AI-PTS tasks as useful and recognise their significant role in the learning process actively engage with the site to achieve better outcomes. Therefore, recent studies have observed the transfer of skills. Hence, it is crucial to create tasks in AI-PTS that are both pertinent and fulfilling for students in their pursuit of learning goals and objectives.

The study discovered that certain decision-making processes acted as intermediaries, while certain variables functioned as interveners. The model data suggests that perceived usefulness and facilitating conditions strongly predict student engagement, satisfaction, and achievement. The study found a mediation effect between perceived usefulness and student expectancy, which varied based on the intensity of facilitation conditions. Specifically, the effect of perception of usefulness on student expectancy changed as the level of facilitation conditions increased. The results confirm the importance of understanding the interplay between different elements in order to influence student expectancy and satisfaction in AI-PTS learning.

The investigation revealed that the hypothesis was accepted based on the results. The findings indicate that satisfaction in AI-PTS partially mediates the association between AI-PTS usefulness and AI-PTS expectancy. The application of usefulness in AI-PTS may enhance satisfaction in AI-PTS. When students perceive AI-PTS as beneficial, they are more likely to be satisfied with the system. The impact of AI-PTS on joy is reciprocal, influencing the expectancy for AI-PTS. The satisfaction level of AI-PTS users influences their attitude towards the system and their expectations for its future usage and potential benefits. The mediation effect indicates that student acceptance of AI-PTS is influenced by their perception of the system's usefulness. This perception directly affects their satisfaction with the system and their intention to use AI-PTS in future planting operations. The AI-PTS system proves to be effective when it delivers the desired solutions and a satisfying user experience for students. Students are more likely to have positive expectations about the effectiveness and benefits of it in the future.

The literature review suggests that there is empirical support for the hypothesis and proposition that achievement in AI-PTS partially mediates the relationship between enabling factors and expectancy in AI-PTS. The performance of AI-PTS can be improved by creating a favourable environment for AI-PTS. Students become more satisfied with their learning experience when they discover the available resources and support for efficient learning of AI-PTS. However, the study demonstrates a strong positive association between achievement in AI-PTS and expectancy in AI-PTS. Students who have a positive attitude and high satisfaction with AI-PTS are likely to expect and desire to use the technology in the future to gain its benefits. The impact of students' perception regarding the availability of resources and support for utilising the AI-PTS on their overall system satisfaction indicates that their satisfaction is influenced by the system, which in turn affects their expectations for the future of AI-PTS and the benefits they will enjoy. When a student perceives the system they are studying to have all the necessary resources and support, it can greatly contribute to their happiness and foster positive cognitive beliefs about the system's effectiveness and the promising benefits it holds for their future.

Based on the results, the hypothesis is confirmed, indicating that the ease of use of content and navigation has a distinct indirect effect on AI expectancy through the mediating role of satisfaction in AI-PTS. The content and navigation of AI-PTS greatly impact customer satisfaction. Students who have access to AI-PTS content that is presented in a logical sequence and has an easy-to-use interface are more likely to have a positive and satisfying experience. For instance, the level of acceptance in the human-machine partnership has a direct impact on the expectations users have for the system. Students who have successfully completed their AI-PTS programme are more likely to have positive expectations regarding the future use and benefits of the system. Such an effect implies that the acceptability of AI-PTS interface which incorporates the extent of content clarity and the friendliness of the navigation is directly related to the degree of student satisfaction which in turn, is associated with their future use and benefits expectations. When students get to access AI-PTS content and they find it well organized and the navigation system is user friendly, they will be more satisfied with their learning experience, and this will continue to create high expectations about the system's system effectiveness and benefits for future use.

According to the research findings, there appears to be a link between how people perceive AI-PTS and their motivation to achieve it. This connection is influenced, to some extent, by the level of satisfaction individuals experience when they attain AI-PTS. The task value has a calming effect on the AI-PTS, enhancing its satisfaction, while the cost continues to rise, further increasing the satisfaction. As a result, the students' behaviours in completing tasks reflect their satisfaction with the overall experience of AI-PTS. Consequently, the prediction of satisfaction in AI-Paced Temporal Stability also impacts the expectations surrounding AI-PTS. Students who have a positive experience with AI-PTS are more likely to feel confident about the future application of the system and the benefits it brings. The mediating effect in this case refers to how students' perception of the balance between the value of the tasks in AI-PTS and the perceived cost of the system greatly impacts their satisfaction with the system. This, in turn, influences their beliefs about the system's future use and their perspective on the benefits it offers. When students recognise the significance and value of the tasks they complete in AI-PTS, their satisfaction with the system may decrease. This could potentially result in them giving a five-star rating and spreading the word about the system's benefits to their friends.

The study's conclusion suggests that there is a significant impact of students' engagement in AI-PTS on the relationship between satisfaction and expectancy in AI-PTS. The interaction between students and AI-PTS plays a crucial role in determining their satisfaction and expectations regarding AI-PTS. This engagement helps to mediate the educational impact of AI-

PTS, ensuring a balanced relationship between learner satisfaction and expectations. The satisfaction levels of students in AI-PTS are significantly higher when there is a strong focus on student engagement, indicating a positive correlation between satisfaction and engagement in AI-PTS. This result emphasises the importance of student engagement with an AI-PTS system in understanding the connection between satisfaction and expectation in AI-PTS. The strong connection between student satisfaction and sense of control becomes even more pronounced when student engagement is high. The result of this is heightened expectations for system utility and performance. However, when student involvement is lacking, the connection between satisfaction and expectancy becomes less strong.

The findings of this moderation analysis indicate that student engagement with AI-PTS is influenced by how the different components of AI-PTS are perceived and how they meet expectations. This finding confirms that the connection between satisfaction and expectation modification varies significantly based on the level of engagement. Furthermore, as these students are deeply engaged, their positive emotions are further strengthened, resulting in increased expectations for the system and a greater recognition of its advantages. Simultaneously, if student engagement is lacking, the connection between student participation and anticipated outcomes becomes less strong.

Theoretical Implications

The study results have significant implications for AI-Powered Tutoring Systems (AI-PTS) and their impact on student learning. Firstly, understanding the factors that affect student satisfaction, engagement, and learning outcomes is crucial for uncovering the drivers behind the effectiveness of AI-PTS. It is important to be mindful of how various factors interact within these systems, including perceived usefulness, effectiveness, and motivation. Besides, the recognition of mediation and moderation diseases highlights the complexity of the relationships between various factors in AI-PTS. This explanation of the structure of learning experiences adds complexity to theoretical models in the fields of educational technology and cognitive science, providing researchers with valuable insights into the workings of AI-driven learning environments.

Practical Implications

The findings have significant practical implications and offer valuable guidelines for designing and implementing AI-Powered Tutoring Systems in educational settings. The quote highlights the importance of designing AI-PTS that are user-cantered, focusing on creating useful and easy-to-use systems that provide users with valuable tasks. It is highly recommended that developers and educators prioritise user-friendly interfaces, personalised learning experiences, and meaningful assignments to ensure learner satisfaction. On the other hand, the mission of providing students with the essential tools and support is clearly emphasised as a key strategy for the successful implementation of AI-PTS. This encompasses not only providing technical assistance, but also imparting effective teaching methods and support systems to facilitate a smoother learning experience for children. Education providers should prioritise investing in training programmes and resources to ensure that students and teachers have the necessary skills to fully utilise AI-PTS. Secondly, the recognition of mediation and moderation effects establishes a foundation for a comprehensive approach to the design and evaluation of AI-PTS. Developers must consider the complex combination of factors and design interventions to optimise learning outcomes. This process involves conducting thorough needs assessments, engaging in iterative testing, and continuously refining AI-PTS to ensure their effectiveness in diverse educational settings.

Limitations and Future Directions

Although this study has its limitations, such as the use of convenience sampling and a narrow focus on a specific population of students, it is important to acknowledge these factors. It would be valuable to explore these variables in various contexts and among different student groups. To enhance the overall scope of the findings from this study. Furthermore, a comprehensive investigation into various factors that may impact student engagement, satisfaction, and achievement would be thoroughly explored through AI-PTS.

These findings, overall, contribute to our understanding of how AI affects student satisfaction, engagement, and learning outcomes. This knowledge is important for improving the development and use of AI-PTS.

Conclusion

The concept of perceived usefulness reflects the level of confidence students have in the ability of artificial intelligence fallible tutor systems (AI-PTSs) to enhance their learning and academic performance. The results of the study showed that the perceived usefulness of AI-PTS had a positive correlation with student engagement, efficiency, and educational achievements. The rise in the perceived value of AI-PTS leads to an increase in student adoption and usage. Students place a high value on the conditions that determine whether they have access to the necessary resources and support to utilise AI-PTS. These conditions are seen as crucial facilitators. The study revealed that the level of facilitating conditions has an impact on students' attitude towards it. If students feel that they have access to all the necessary resources and support, they will find AI-PTS to be user-friendly and will be more inclined to engage with the system. The content and navigation in AI-PTS are designed to be transparent, systematic, and user-friendly, ensuring a seamless user experience. The findings indicate that the AI-PTS has a strong impact on student satisfaction and engagement, highlighting its effectiveness and value. A well-designed and structured interface can greatly enhance user satisfaction and improve engagement levels. In AI-PTS, students perceive the task value as the worth or importance of the assigned work. This includes the efforts and costs they anticipate, such as time and effort. The analysis revealed that the importance placed on the task significantly influenced how students perceived the efficiency and effectiveness of AI-PTS. In the AI-PTS system, when students perceive tasks as valuable and relevant, they approach them with a high level of dedication and achieve improved learning outcomes.

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Appendix: Measurement Scale

Items	Source
Perceived usefulness in AI-PTS	
1. Using AI-Powered Tutoring Systems would improve my skills	
2. Using AI-Powered Tutoring Systems would enhance my effectiveness in learning	
3. Using AI-Powered Tutoring Systems would increase my productivity in learning	
4. Using AI-Powered Tutoring Systems would allow me to accomplish learning tasks more quickly	
5. Using AI-Powered Tutoring Systems would improve the quality of skill tasks I do	
Facilitating conditions in AI-PTS	(Ni & Cheung, 2023).
1. I have resources necessary to use AI-PTS for learning	
2. I can turn to a specific person (group) for assistance with AI-PTS difficulties	
3. Specialized instructions concerning AI-PTSs are always available to me	
4. There is always support when I need help using AI-PTS	
Content & Navigation (Ease of Use) in AI-PTS	
1. I was able to navigate through AI-Powered Tutoring Systems easily from start to finish.	(Neo, 2022).
2. The content in the AI-Powered Tutoring Systems was well-organized and followed a suitable sequence for understanding a topic.	
3. The language and the content of the AI-Powered Tutoring Systems was easily understandable.	
4. The inclusion of web links and visual aids, such as videos & images, in the AI-Powered Tutoring Systems further helped in the clarity of the topic.	
5. I had no problem going through AI-Powered Tutoring Systems on my own.	
6. It was easy for me to become skillful at using the AI-Powered Tutoring Systems.	
Satisfaction in AI-PTS (Mediator)	
1. AI-Powered Tutoring Systems is pleasant to use.	(Cen et al., 2023).
2. AI-Powered Tutoring Systems is wonderful.	
3. AI-Powered Tutoring Systems is fun to use.	
Task value in AI-PTS	(Yurt & Kasarci, 2024).
Attainment	
1. The ability to effectively use artificial intelligence is important to me.	
2. Learning and implementing innovations in artificial intelligence applications are a priority for me.	
3. It is important for me to stay updated on developments related to artificial intelligence.	
4. I attach great importance to strengthening my skills in using artificial intelligence applications.	

Cost	
1. I am inclined to sacrifice time from other activities to learn artificial intelligence applications.	
2. I am not hesitant to invest a considerable amount of time and effort to enhance my skills related to artificial intelligence.	
3. Learning artificial intelligence applications is an easy task for me.	
4. Investing time and effort to learn artificial intelligence applications is worthwhile for me.	
Expectancy in AI-PTS (Dependent Variable)	
1. I can learn the skills that enable effective use of artificial intelligence applications.	
2. My general knowledge about artificial intelligence is more than sufficient compared to many.	
3. I am better than most of my peers in effectively using artificial intelligence applications.	
4. My potential to effectively use artificial intelligence applications surpasses many people in my surroundings.	
Student Engagement in AI-PTS (Moderator)	
1. AI-PTS increased student interaction with teachers 2. It is more comfortable to express issues with AI-PTS to the lecturers than in person. 3. Digital education simplifies communication with instructors. 4. AI-PTS lessons simplify student communication. 5. The frequent occurrence of miscommunication in online courses between lecturers and students. 6. In AI-PTS, student engagement with one another intensifies. 7. In digital education, navigating challenges among learners can become more manageable, such as when working on collaborative assignments.	(Sadegh-Zadeh et al., 2023).