Artificial Intelligence in Education and Its Influence on Student Self Efficacy and Academic Performance

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ABSTRACT

Artificial Intelligence (AI) has rapidly advanced in recent years, transforming teaching strategies and learning experiences in educational settings. This study explores students' perceptions of AI in education and examines its impact on their self-efficacy and academic performance. A sample of 1100 students from different universities in Multan, Pakistan, was selected. Well-structured questionnaires, including informed consent, demographic information sheet, General Attitudes Towards Artificial Intelligence Scale, General Self-Efficacy Scale, and Academic Performance Questionnaire was employed for data collection. Data was analyzed using PLS-SEM. This study examines the impact of Artificial Intelligence (AI) on students' self-efficacy and academic performance. Findings reveal significant positive relationships among AI, self-efficacy, and academic achievement ($p < 0.05$). Structural equation modeling (PLS-SEM) confirms AI's strong influence on self-efficacy ($\beta = 0.660$, $p < 0.001$) and academic performance ($\beta = 0.562$, $p < 0.001$). The model fit indices (SRMR = 0.065, NFI = 0.884) validate its reliability. Results suggest that AI enhances academic success by fostering self-efficacy through personalized learning experiences. This study highlights how AI can be used positively in educational settings. However, further studies should be conducted on how to adapt new technologies more successfully in education.

Keywords: *Artificial Intelligence, Self-Efficacy, Academic Performance, Education*

INTRODUCTION

The study of creating computer systems and programs that can carry out tasks that generally require human intelligence is the subject of the computer science discipline known as artificial intelligence (AI). These exercises include perception, learning, problem-solving, natural language interpretation, and decision-making. AI uses algorithms, statistical models, and computing power to analyze data, make predictions, or perform actions to compete with human cognitive functions (1). Due to its capacity to simulate human intelligence, AI is currently present in a broad array of industries, including healthcare, finance, education, and transportation. AI has the potential to magically transform education system by providing tailored training, flexible feedback, and increased student engagement (2). It has much potential to provide dynamic assessments, enable tailored learning, and promote meaningful interactions in online, mobile, or hybrid learning settings (3). Integrating AI technologies such as smart tools, chatbots and robotics into our everyday lives has become increasingly common. With its ability to replicate human intelligence, AI is now permeating diverse domains, from healthcare and finance to transportation and education. There is growing support for the notion that AI is strategically relevant to education (4). For the past thirty years, there has been a growing use of AI in education (AIEd), which is the consolidation of AI into educational practices. A range of AI technologies, such as human-computer interactions, learning analytics dashboards, adaptive learning systems, teaching robots, and intelligent tutoring systems, have been utilized in this field (2). With the ability to provide antecedently unattainable opportunities in traditional educational settings, AI in education has been acknowledged as a powerful tool for advancing instructional design, technological development, and educational research (5).

Self-efficacy refers to an individual's confidence in their ability to perform a specific task. Someone who is exceptionally self-efficacious believes they can use emotional and cognitive processes to succeed independently. It is a belief in an internal locus of control (6). Bandura (1989) defines self-efficacy as belief in one's ability to reach singular performance levels that affect various life conditions (7). Several researchers have explained that self-efficacy beliefs are essential determinants of emotions, thoughts, motivation, other psychological states, and behavior in many domains (8, 9). To examine the associations between AI and self-efficacy, we turn to Bandura's Social Cognitive Theory (SCT), that highlights how beliefs in personal efficacy shape motivation and behavior (10). By leveraging the observational and imitative aspects of learning, which AI can facilitate, SCT underscores the importance of self-efficacy in creating personalized feedback and learning experiences. Academic performance, often measured through grades, standardized tests, or assessments, serves as a key indicator of educational achievement (11). Academic performance is an outcome of learning activities (12). Study, memory, and the ability to communicate in writing or orally all fall under academic scores. AI reshapes education by offering individualized learning experiences and adaptive tutoring systems (13, 14). The relationships between AI, self-efficacy, and academic performance are well-grounded in Bandura’s SCT and related educational technology models. In the context of AI in education, SCT suggests that students who believe themselves to use AI tools effectively are more likely to succeed academically. Additionally, the Technology Acceptance Model (TAM) provides a framework for understanding how perceptions of technology impact usage behavior. These systems provide customized study materials and enhance students' self-efficacy, enhancing academic performance (15). Previous studies explored that Self-efficacy affects academic performance significantly (8,16). Increased self-indispensability is associated with positive academic performance and adaptive strategies (17). Granić et al. (2019) reported that students have positive perceptions of AI, which benefits them by recognizing themselves as capable enough or successful while attempting the tasks (18). AI has been utilized in teaching, educational curriculum, and content development and has improved student learning (19). AI promises to revolutionize teaching and learning by offering personalized instruction, adaptive feedback, and enhanced student engagement (2). As AI continues to make strides in education, it is essential to understand how students perceive this technology and how it impacts their self-efficacy and academic performance. AI-driven technology has expanded its influence in classrooms, significantly changing learning dynamics worldwide and having a significant and broad impact. While the potential of this paradigm shift was anticipated within the twenty-first century, the onset of COVID-19 has accelerated its realization unexpectedly (5). According to Lee *et al.* (2022), using AI-based chatbots in the assessment process of open health courses has been shown to enhance students' academic performance, self-efficacy, motivation, and learning attitudes (20). Parsakia et al. (2023) also explored that although chatbots and AI can significantly improve student learning and engagement, their effects are nuanced and varied (21). Various existing literature highlighted several challenges in programming education, including students' struggles to develop computational thinking skills, low self-efficacy in programming, and reduced motivation toward the subject (22-24). AI technology development, its educational applications facilitate meaningful interactions in online, mobile, or hybrid learning environments, offering dynamic assessments and enabling personalized learning, but there is still a lack of educational perspectives in AIEd research (3).

However, the literature shows a pocket-size figure of studies examining the effectiveness of AI in education and its application in this field. To fill this gap in the literature, this current study was designed to explore perceptions of AI and its impact on self-efficacy and students' academic performance. This study's primary objectives is to examine students' perception of AI and its impact on self-efficacy and academic performance in the educational setting. Another objective is to investigate the level of perception of AI, self-efficacy, and academic performance among students. In order to achieve these objectives, we formulated the following hypotheses:

H_1: There would be a significant correlation between the perception of AI, self-efficacy, and academic performance among university students.

H_2: Perception of AI would have a significant effect on self-efficacy.

H_3: Perception of AI would positively affect academic performance.

METHODS

A cross-sectional, causal quantitative study was adopted for 1100 university students (male 528, female 572). Data was collected from May 2024 to December 2024. A random survey methodology was adopted to gather data from a representative sample of students. A random sampling approach was used to ensure that every member of the population had an equal chance of being chosen. This strategy reduces selection bias while also improve sample representatives and statistically valid, allowing for reliable inferences regarding the correlations between the variables being studied.

Ethical approval

IRB of Institute of Southern Punjab, Pakistan approved this study. The research was conducted in accordance with the ethical standards of the institutional research committee and with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

Consent to participate

Informed consent was obtained from all individual participants included in the study. Participants were informed about the purpose of the study, procedures, and their right to withdraw at any time.

Inclusion criteria:

The participants who fulfilled the inclusion criteria in this study were 18-25 and were currently enrolled in different public and private universities in Multan, Pakistan, without any severe psychological illness.

Exclusion criteria:

Exclusion criteria were age less than 18 and greater than 25, with serious psychological illness, and not enrolled.

Instruments

All participants were provided with informed consent, including details about the confidentiality of study and demographic data (gender, socioeconomic status, age, department, and university), along with three psychological scales. The participants were guided to complete the questionnaires accurately. The questionnaire administration took almost 15-25 minutes. Collected data was kept in locked computers under strict supervision for evaluation and analysis.

General Attitudes towards Artificial Intelligence scale (AIS)

Schepman (2020) developed AIS to examine general attitudes toward AI (25). This questionnaire consisted of 20 items with five-point likert rating scale (1 = strongly disagree through 5 = strongly agree). This scale is used to assess students' attitudes towards the application of AI in education. While the original scale includes general perceptions of AI, we focused specifically on items related to students' attitudes toward AI in educational settings. This focus aligns with our objectives of exploring the impact of AI on academic performance and self-efficacy in an educational context.It captures various dimensions of attitudes, including perceptions of AI's usefulness, ethical concerns, and its impact on society. Sample items include "I believe AI will improve the quality of education" , "I am concerned about the ethical implications of AI technologies" Scale showed strong reliability in current research, with $\alpha = 0.90$.

General self-Efficacy Scale (GSES)

Schwarzer (1995) developed GSES to measure the overall sense of perceived self-efficacy (26). Participants responded on 4-point scale (1 = Not at all true, 2 = Hardly true, 3 = Moderately true, 4 = Exactly true). Sample items include "I am confident that I could deal efficiently with unexpected events", "I can solve most problems if I invest the necessary effort" This scale exhibited good reliability, with a Cronbach's α coefficient of 0.88.

Academic Performance Questionnaire (APQ)

APQ developed by Birchmeier, assesses academic performance among students as previous studies reported (3, 9). The scale has eight items with responses on a 5-point likert scale. Sample items include "I am satisfied with my current academic performance", "I regularly meet my academic goals" In the current study, the scores of this scale showed a strong reliability of Cronbach's $\alpha = 0.83$.

Statistical Analysis

Descriptive statistics was used to report the demographic profile of respondents, a comprehensive report for all variables used in the present study. Correlation analysis was conducted to determine the direction and strength of the relationship between variables. Measurement model analysis assessed 'individual item reliability, internal consistency reliability, convergent validity, and discriminant validity.' The structural equation model employed to determine the significance of the path coefficients (for the hypothesized direct relationships), R^2 values, effect size, and predictive relevance of the model. Statistical analysis was performed using the SPSS 22 version and PLS-SEM 4 with a significance level of $p < 0.05$. PLS-SEM used in this study so that it can deliver reliable results even with small samples. PLS-SEM creates route coefficients that show the strength and direction of correlations between variables, making it easier to evaluate direct and indirect effects in the model.

RESULT

Demographic Profile Of Respondents

A detailed description of the demographic profile of the respondents is reported in Table 1. A larger proportion of the respondents (52%) were female. Regarding age distribution, the majority fell between 20 and 25, constituting 82.8%, while 17.2% of respondents were less than 20 years old. The socioeconomic status was divided into three categories: middle class (69.2%), upper class (20%), and lower class (10.8%). Additionally, 47.6% of respondents were from Bahauddin Zakariya University, 38.8% from the Institute of Southern Punjab, and 13.6% from Multan Medical & Dental College. The responses came from various fields, with the public health department having the largest percentage (19.2%) of respondents. The departments of business and medicine came next, with 16.4% and 13.6% of the overall.

Table 1. Demographic profile display of participants

Description	*Frequency*	*Percentage*
Gender		
Male	528	48.0
Female	572	52.0
Age		
Less than 20 years	189	17.2
20-25 years	911	82.8
Socioeconomic status		
Upper class	220	20.0
Middle class	761	69.2
Lower class	119	10.8
Department		
Public health	211	19.2
Business	180	16.4
Law	132	12.0
Pharmacy	79	7.2
Medical	150	13.6
Fashion designing	79	7.2
Computer sciences	141	12.8
Economics	128	11.6
University		
Institute of Southern Punjab	427	38.8
Bahauddin Zakariya University	524	47.6
Multan Medical & Dental College	150	13.6

Descriptive analysis of the constructs

The descriptive statistics results, in the form of mean and standard deviation calculated for the constructs for this study, are shown in Table 2. AI has a mean value of 3.20 and a standard deviation of 0.575. Self-efficacy has a mean value of 2.89 and a standard deviation of 0.658, while Academic Performance has a mean value of 3.30 and a standard deviation of 0.660.

Table 2. Descriptive statistic of study variable

Variables	Mean	SD
AI	3.20	.575
SE	2.89	.658
AP	3.30	.660

Note: AI = Artificial Intelligence; SE = Self-Efficacy; AP = Academic Performance

Strength and direction of relationship among variables

The hypothesis on the relationship between AI, self-efficacy, and academic achievement is critical to understand how technology impacts educational results. A significant association indicated that the AI technologies boost students' self-efficacy and lead to greater academic achievement. AI affects self-efficacy and academic performance by customizing learning experiences as shown in Table 3. AI and Self-Efficacy (.687**), AI and Academic Performance (.573**) showed significant relationships. On the other hand, Academic Performance and Self-Efficacy (.566**) also exhibited a significant relationship with $p<0.05$. AI uses adaptive learning systems to personalize training to individual requirements, allowing students to study at their own speed while increasing confidence in their talents and self-efficacy. Furthermore, AI assists students in managing time and focusing on critical learning activities, so enhancing their performance across a variety of academic parameters. This justify our first hypothesis of study.

Table 3: Correlation of artificial intelligence, self-efficacy and academic performance

Variables	***AI***	***SE***	***AP***
AI	-	-	-
SE	.687**	-	-
AP	.573**	.566**	-

Note: *AI = Artificial Intelligence; SE = Self-Efficacy; AP = Academic Performance,* $^{**}P< 0.05$

Assessment of Measurement Model

The PLS algorithm technique was used to assess the validity and reliability of the outer model demonstrated by the factor loading in Table 4 with visual demonstration in Fig. 1 measurement model, which validate that the indicators appropriately reflect the constructs of academic performance, self-efficacy, and AI. The average variance extracted (AVE) analysis was performed to detect convergent validity. The requisite threshold of 0.50 was met, and composite reliability (CR), which prioritized items based on their reliability, was greater than 0.70 (27). Variance inflation factor (VIF) values (ranging from 1.462 to 2.209) remained less than the threshold of 3.3 (28), implying that collinearity and bias were not potential issues in this research. Furthermore, the robustness of the outer model was investigated by utilizing the hetero-trait mono-trait (HTMT) ratio of correlation to assess its discriminant validity (29), as displayed in Table 5. All HTMT values were below the standard 0.85 threshold, suggesting that discriminant validity was satisfied (30).

Table 4: Factors loading, constructs reliability, and validity

Construct	*Items*	*Loading*	*Alpha*	*CR*	*AVE*	*VIF*
AIS	AIS2	0.777	0.901	0.917	0.503	2.209
	AIS5	0.760				2.133
	AIS7	0.702				1.706
	AIS9	0.672				1.639
	AIS11	0.697				1.961
	AIS12	0.743				2.124
	AIS13	0.667				1.713
	AIS14	0.686				1.910
	AIS16	0.694				1.837
	AIS17	0.737				1.952
	AIS18	0.658				1.705
GSES	GSES1	0.747	0.886	0.908	0.523	1.829
	GSES2	0.763				2.038
	GSES3	0.661				1.621
	GSES4	0.710				1.760
	GSES5	0.726				1.891
	GSES6	0.710				1.812
	GSES7	0.707				1.728
	GSES8	0.769				2.045
	GSES9	0.711				1.706
APQ	APQ1	0.647	0.834	0.875	0.501	1.541
	APQ2	0.746				1.881
	APQ3	0.734				1.540
	APQ4	0.646				1.438
	APQ6	0.698				1.633
	APQ7	0.793				1.919
	APQ8	0.675				1.462

Note: *AIS = Artificial Intelligence scale; GSES= General Self-Efficacy scale; APQ = Academic Performance Questionnaire; CR = composite reliability; AVE = average variance extracted; VIF = variance inflation factor*
Loading <0.70; AVE >0.50; CR > 0.70

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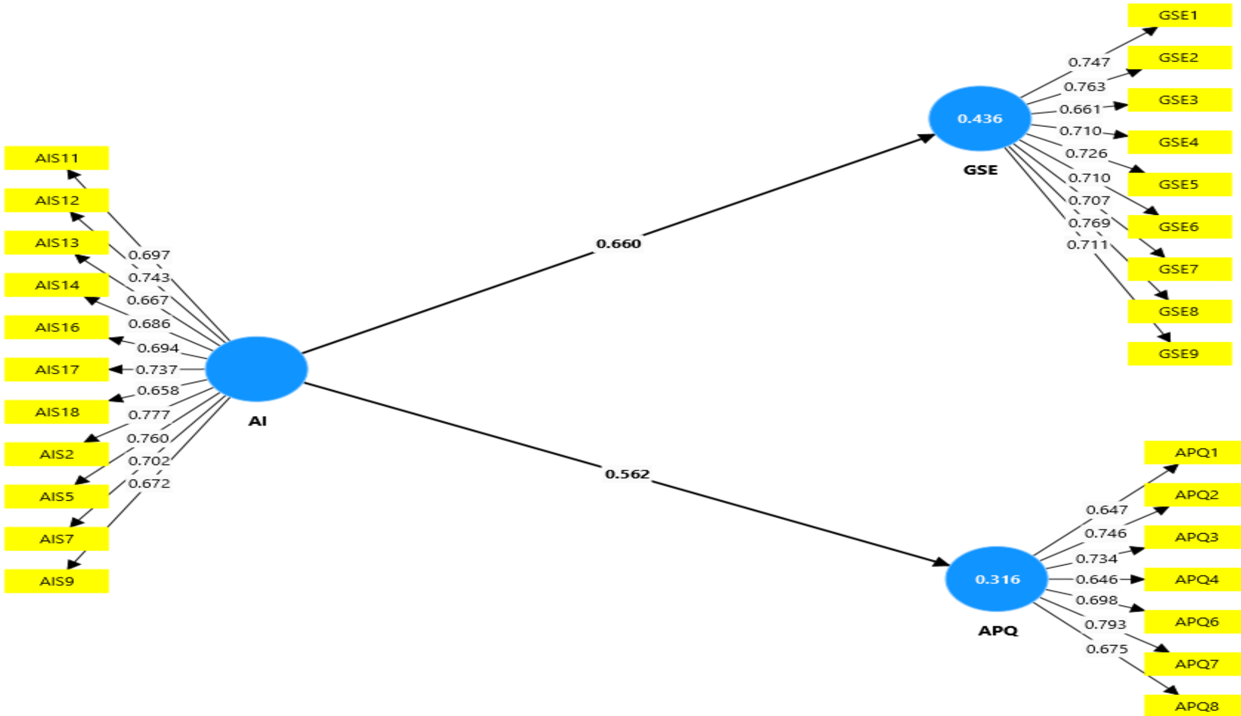

Figure 1: Validity and reliability of the outer model by PLS-SEM

Table 5: Discriminant validity (HTMT)

Constructs	*APQ*	*AIS*	*GSE*
APQ	-	-	-
AIS	0.629	-	-
GSES	0.672	0.730	-
Note: *APQ = Academic Performance Questionnaire; AIS = Artificial Intelligence scale; GSES= General Self-Efficacy scale*			

Assessment of Structural Model

Following compliance with the outer model's criteria, we assessed the goodness of fit of the inner model by computing the significance of path coefficients (beta values), t-values, and R^2 using a bootstrapping method with a 5,000 subsample and $p<0.05$ as shown in Table 6 (31). We found a positive and significant direct association between AI and Academic Performance ($\beta = 0.562$, $t = 10.744$, $p < 0.001$) and AI and Self-Efficacy ($\beta = 0.660$, $t = 16.242$, $p < 0.001$) as shown in Fig. 2 structural model. This justify our second and third hypotheses. The link between AI, self-efficacy, and academic performance is complex since AI technologies boost students' academic achievement. Increased motivation, perseverance, and involvement in academic work are correlated with higher levels of self-efficacy and are important factors in better academic achievement. AI technologies improve academic achievements by fostering self-efficacy and individualized learning, which feeds back positively on accomplishment and confidence.

R^2 of model's endogenous variables APQ and GSES were 0.316 and 0.436, respectively, which are moderate. Q^2 of the endogenous variable were 0.297 and 0.421, all above zero, indicating suitable predictive relevance(27). However, a structural model is deemed a good fit if the value of SRMR is less than 0.08; our study's findings revealed an SRMR value of 0.065, implying that our inner model is a good fit and reliable for analysis. Normed Fit Index (NFI) value ranges from 0 to 1, indicating a better fit of the model. The value of NFI is 0.884 in our model, which means a reasonable fit.

Table 6: Direct path analysis by SEM

Path	***β***	***SD***	***t***	***p***	***LLCI/ULCI***
AIS → APQ	0.562	0.052	10.744	0.02*	0.439/0.650
AIS → GSES	0.660	0.041	16.242	0.01*	0.565/0.729
Constructs			**APQ**		**GSE**
Coefficient of determination (R^2)			0.316		0.436
Predictive relevance (Q^2)			0.297		0.421
Model fit					
SRMR			0.065		
NFI			0.884		

***Note**: P> 0.05* (2-tailed); SD = standard deviation; LL CI= lower limit confidence intervals; ULCI = upper limit confidence intervals; AIS= Artificial Intelligence scale; GSE= General Self-Efficacy; APQ= Academic performance questionnaire*

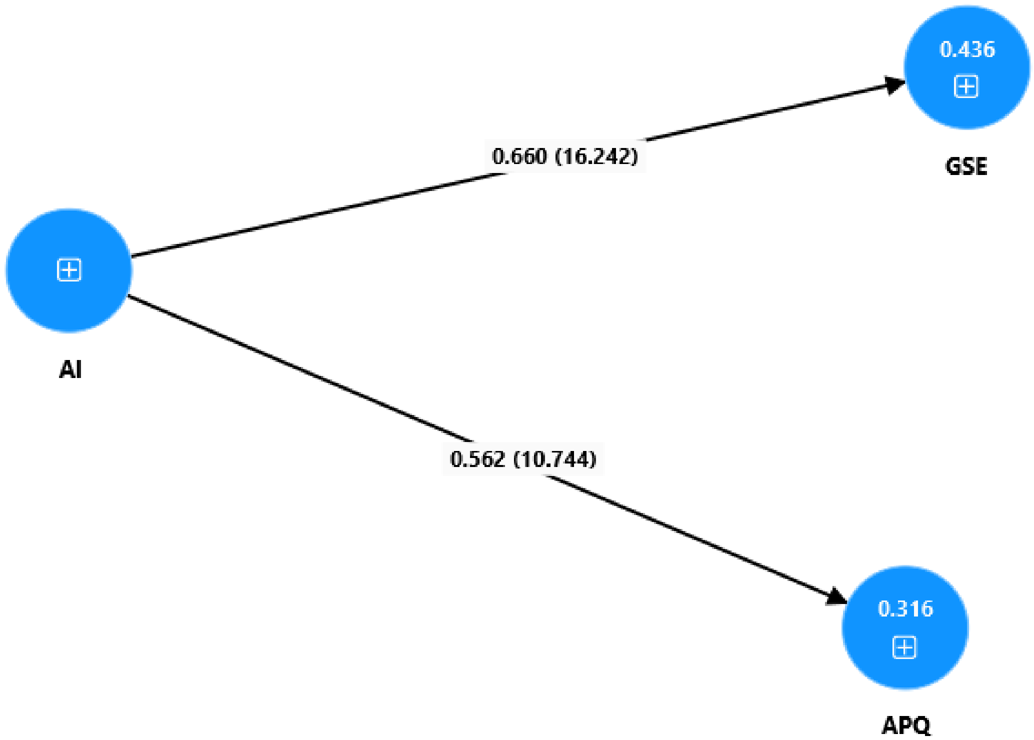

Figure 2. Structural equation model by PLS-SEM

Source: *Authors' work -PLS-SEM structural model output*

DISCUSSION

The principal objective of this study was to measure the perception of AI and its impact on Self-Efficacy and Academic Performance among university students. The results found that students positively perceive AI in the education context for improving their academic performance. They understand that their learning can be increased by adopting AI in educational settings. Similar results were found in other studies showing that AI technology can increase students' learning outcomes by providing them with a customized learning environment (2, 32).

This study explored a significant relationship between AI, self-efficacy, and academic performance among university students. This research is accordant with previous research that concluded that AI has a vital role in educational progress and its ability to enhance self-efficacy and students' academic performance (33). This research emphasized that adopting AI skills can increase students' creativity, which can impact students' learning. Our findings highlighted that the perception of AI has a positive significant affect on students' self-efficacy. A higher level of self-efficacy was found among university students who positively perceived AI use in education. Previous researchers also reported that AI can increase individuals' self-efficacy in multiple fields (34-37).

AI significantly positively impacts students' academic performance. Prior research also found that AI can increase educational accomplishments by suggesting individualized learning ways and quick responses (2, 3). The Framework of the Technology Acceptance Model also describes AI technology as a reliable and modest system that can be very beneficial for learning new behaviors and skills concerning other technologies, including mobile phones and other AI-based communication tools (38-40). We also found significant correlation between students' perceptions of AI, self-efficacy, and academic performance, it is important to note that correlation does not imply causation. The cross-sectional design of this study does not allow us to make causal inferences. Future research should employ experimental or longitudinal study designs to better understand the causal relationship between AI perceptions and academic performance.

This study's results shed light on the importance of AI for increasing university students' self-efficacy and learning outcomes. Students can achieve their target objectives by implementing AI tools in an educational context. Additionally, constructive and positive use of AI can enhance their academic performance. AI researchers must work with policymakers and educators to construct ethical guidelines for implementing AI approaches in education.

CONCLUSION

This study made an essential contribution to implementing AI in educational settings. The results concluded that perceptions of AI significantly impact university students' self-efficacy and academic performance. Self-efficacy and academic performance are impacted by AI since it offers data-driven insights, instantaneous feedback, and personalizes learning experiences. AI adapts training to each student's requirements using adaptive learning systems, letting them study at their own speed, increasing self-efficacy and confidence in their skills. AI boosts motivation and engagement by introducing components like gamification, both of which are essential for academic performance. AI also aids students with time management and concentration on important learning activities, maximizing their success in a variety of academic domains. As students perceive AI as a beneficial tool in educational contexts, new technology can be adopted to enhance student learning outcomes.

LIMITATIONS AND FUTURE DIRECTIONS

This study highlights the positive use of AI in educational settings with certain limitations. Academic performance is influenced by multiple factors beyond students' perceptions of AI, including socioeconomic status, parental education, and access to educational resources. While our study controlled for some of these variables, future research should consider a broader range of factors to better isolate the effects of AI perceptions on academic achievement. This study employed small homogeneous samples that might not represent the different backgrounds of pupils. Future study with wider range of demographics and larger sample size can help better to understand the effects of AI on different groups and circumstances broadly. Understanding best practices for efficient AI deployment can assist institutions in effectively adopting AI technologies. Future research should focus on building extensive training programs for educational institutes to help them use AI tools more successfully. Longitudinal studies should be conducted to examine the long-term effects of AI-based technology in education. Qualitative research with open-ended questions can help in getting a detailed understanding of AI from students' and teachers' perspectives. Main limitation of this study is that we did not thoroughly examine the degree to which AI was integrated into students' educational environments. Future studies should explore how the extent of AI integration in the curriculum moderates the relationship between perceptions of AI, self-efficacy, and academic performance. By overcoming these constraints, future research can give more detailed and useful insights into the role of AI in education, resulting in better practices and outcomes.

DECLARATION

Acknowledgement: We are thankful to all participants who sincerely helped us in this research.

Data availability: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethical approval: Obtained
Consent to participate: Obtained
Consent to publish: Obtained

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