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Artificial Intelligence Integration: Its Role and Usage among University Students

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Abstract

Artificial Intelligence in higher education is revolutionizing the way students interact with learning materials, academic tasks, and research. This study investigates the role, adoption, and perceived impact of AI tools such as intelligent tutoring systems, virtual assistants, and adaptive learning platforms among university students. Employing a quantitative research design, utilizing a large-scale survey to collect data from university students across different discipline. Descriptive statistics were used to identify trends by demographic categories including discipline and year of study. Inferential statistics, including regression analysis, were applied to examine the relationship between AI usage and academic outcomes such as achievement, engagement, and time management. Results revealed significant positive correlations between frequent AI use and improved academic performance. The study also identified key barriers to AI adoption, including limited technological access, low awareness of privacy concerns, and insufficient training. Finally, the research highlighted the ethical considerations of integrating AI in education and provided actionable insights for enhancing student learning experiences through effective AI implementation.

Key Words

Artificial Intelligence, AI in Academia, University, Students

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Introduction

Nowadays, artificial intelligence (AI) is one of the most critical components of the learning environment and is continuously changing the ways in which students used to learn and engage in academic activities. Adoption and usage of AI technologies i.e. machine learning, natural language processing, and personalized learning platforms, paved the way for universities to formulate more adaptive, efficient, and student-centered learning activities and

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experiences. Such technologies bring access to individual-based tutoring systems, automation in providing automated feedback on any of the work completed, and even data is being analyzed regarding the effectiveness of learning achieved through such kinds of solutions.

Artificial Intelligence (AI) has brought multiple applications to function as a virtual teaching assistants and also created more advanced and most intelligent tutoring systems that guarantee efficient and high-quality learning experiences. According to Li et al. (2020), research study elaborated that the usage of AI in educational setups enriches the student motivation and performance by the customization of learning and the exposure of educators to undertake more critical and creative tasks. The continuous use of AI tools including ChatGPT and Grammarly etc. by university students further unveils an increase in reliance on AI for improving academic writing and problem-solving skills (Zawacki-Richter et al., 2019).

Despite the fact that it enhances the outcomes of learning, it also brings concerns over ethical and adequate usage, which raises concerns that this is an ever-changing subject of interest in higher education research. The applications and functions of AI include intelligent tutoring systems, chatbots, and virtual study assistants that are being frequently used in universities to seek administrative support and student guidance (Chen et al., 2020). Virtual assistants have significantly made it easier to communicate with teachers and staff, allowing students to seek answers to their questions and confusions on various course subjects, projects, assignments, or resources on campus quickly.

AI has the ability to analyze huge amounts of data that allows educators and institutions to keep an account of students' academic progress, predicting learning activities and analyzing the areas where students may need additional support (Luckin et al., 2018). The frequent usage of AI in researching, writing, and project development provides an opportunity to increase creativity and productivity for the university students across a digital world. However, it also exposes the challenges related to digital literacy, ethical use, and adequate approach towards AI tools as its integration is continuously increasing in education.

All the students are not equally equipped and aware of how to operate AI-driven systems, especially those from underprivileged backgrounds or with limited access to technology (Zawacki Richter et al., 2019). As AI keeps on transforming the educational arena, it is crucial that universities should educate and train their students and staff in proper use of AI, thereby promoting responsible and the critical skills required to harness full potential of such technology.

Significance of the Study

No doubt, the integration of Artificial Intelligence in higher education holds the potential to revolutionize teaching and learning systems by giving access to personalized instruction, automating assessments, and supporting real-time academic assistance. With the help of tools like intelligent tutoring systems, automated grading, and virtual teaching assistants, education is transforming more towards student-centered models that focus on individual needs rather than following a one-size-fits-all approach (Holmes et al., 2021). Knowing how the university students handle these technologies is critical, not only for the improvement of academic activities but also for the preparation of students for success in AI-driven workforces. Despite such promising benefits, numerous gaps prevail in our understanding of how frequently students use AI tools, how these tools affect their academic outcomes, and what challenges students face, especially in developing countries like Pakistan. Lacking the access to digital infrastructure, lack of AI related training, and socioeconomic disparities generate barriers to appropriate adoption and potentially widening the already existing educational inequalities (Khan et al., 2020; Chen et al., 2020). Moreover, the ethical considerations i.e. data privacy, algorithmic bias, and transparency in Artificial Intelligence usage further makes it difficult for implementation in educational settings (Luckin et al., 2018). Although many students are unaware of how their data is collected or used, but the marginalized groups may be unfairly disadvantaged by biased algorithms. This study holds significance as it illuminated not only the benefits of AI tools but also the challenges encountered by students, offering valuable insights for institutions aiming to design inclusive, effective, and ethical AI strategies in education. By interrogating student usage of AI patterns, perceptions, and access to such technologies, the results will support policymakers, educators, and institutions in making further decisions that might bridge the digital divide and optimize learning experiences for all students. The objective of this research is to contribute to the development of appropriate and forward-looking AI integration in Pakistani universities that enhances learning while safeguarding student rights.

Statement of the Problem

The growing depth of Artificial Intelligence (AI) penetration into higher education comes with both challenges and opportunities, especially in developing nations like Pakistan. AI technologies offer customized learning, administrative automations, and real-time feedback, but their speedy adoption leaves behind evidence on their actual use, effects, and challenges. One of the concerns is the inadequate data on the extent to which students apply AI to everyday academic activities, and little is known about its effect on learning outcomes as well as students' attitudes. Such a knowledge gap undermines universities' ability to effectively utilize AI for enhancing education. The digital divide widens inequality, since students in low-endowed institutions are denied access to AI applications as a result of inadequate infrastructure and socioeconomic reasons (Khan et al., 2020). In addition, ethical issues like data privacy, algorithmic discrimination, and transparency in AI processes are major risks when students do not know how their data are used (Holmes et al., 2021; Luckin et al., 2018). Disparities in access to AI literacy and poor faculty training are equally limiting the role of AI in education (Zawacki-Richter et al., 2019). This highlights the imperative necessity for increased research, online training, and transparent ethical policies to help universities promote fair and ethical AI integration.

Rationale of the Study

Artificial Intelligence (AI) is now mapping how the university students interact with educational content by providing them with personalized learning experiences formulated for individual needs, which improves academic outcomes and performance. Tools such as ChatGPT support in research, content writing, and real time feedback, enabling the students to focus on creativity and critical thinking (Dunaj, 2023; Maton, 2023). However, the global AI usage generates ethical concerns including academic integrity, data privacy, and dependency etc. The study highlights students' attitudes regarding responsible use of AI and addresses these issues. As AI training becomes vital for future workplaces, understanding student perceptions can guide universities in designing relevant curricula (Mitchell & Pearce, 2023). Ultimately, the research targets to align AI implementation with student centered outcomes by gaining insights into learners' experiences and expectations (Zhang et al., 2023).

Literature review

The entry of Artificial Intelligence in educational activities has marked into a new era that can enhance learning experiences in profound ways. The applications of AI in higher education are epic and varied, that ranges from enhancing teaching effectiveness, personalizing learning experiences, and improving student performances. Understanding how those tools and platforms affect student achievements is now becoming critical for instructors, administrators, and policymakers as universities have increasingly adopted even more AI centered tools and platforms (Smith et al., 2022). AI has shifted educational arenas, offering solutions that paved the needs of individual students.

AI based learning options will enable the tailoring of student learning experiences by changing content, pace, and feedback according to their real-time analysis of their performance (Brown & Lee, 2021). For instance, ICTs use AI algorithms to determine academic gaps and facilitate interventions formulated for a child's needs as required to overcome the obstacles at their pace (Kumar et al., 2020). Further, AI technologies provide educators with predictive analytics, which helps to understand student performance more effectively, allowing for targeted interventions (Thomas et al., 2023). Academic support has seen applications of AI technologies in higher education, such as chatbots and virtual teaching assistants.

These tools are real-time support for students: answering academic queries, guiding students through course materials, and providing instant feedback (Mulder et al., 2021). Moreover, AI-based tools are used in the assessment of student learning where machine learning algorithms can evaluate assignments, provide automated grading, and offer insights into students' strengths and weaknesses (Choi & Park, 2022). These AI-based evaluations help teachers track student learning better and base their decisions regarding instructional activities more on data. This literature review discusses the correlation between AI use frequency, AI-facilitated academic support, AI-improved learning evaluation, and outcome for the students. According to recent studies, the higher the use of AI tools among the students, the greater their likelihood of increasing achievement as well (Yang et al., 2022).

However, the connection between AI usage and success is not strictly linear since the quality of AI tools utilized, student engagement level, and the support educators provide in the learning process would determine the outcomes (Nguyen, 2021). Furthermore, the extent to which AI supports learning is determined by student digital literacy, the available technology, and the pedagogies used in educational institutions (Lee & Smith, 2022). The widespread integration of AI into educational environments means that the influence of AI tools on student outcomes needs to be understood in both the nature of the effects and the mechanisms through which such tools exert their influences. This review synthesizes recent research findings to elucidate the mechanisms through which AI affects educational outcomes and the implications for education sector stakeholders: educators, students, and policymakers.

This comprehension brings in the direction of maximizing benefits in education via AI while still connecting to concerns around equity, privacy, and the ethical deployment of AI technologies by embracing AI applications in society (Perez & Wang, 2023).

The Frequency of AI Use and Its Impact on Student Achievement

A better understanding of effectiveness in improving the learning of the students can only be achieved based on the use of AI systems. The proper use of the AI tools offers the students maximum benefits from an experience of the personalized learning pattern, timely response, and the adaptive resources and materials. For example, frequent exposure to AI-driven platforms like adaptive learning systems and intelligent tutoring systems has been linked to better retention rates, deeper conceptual understanding, and overall academic performance (Hernandez et al., 2023). The AI tools adapt to the learner's progress and provide real-time feedback, thus providing continuous opportunities for students to improve and refine their skills, leading to measurable academic gains (Zhang & Li, 2023).

Besides this, the AI used for instant feedback, like an automated grading tool or an intelligent answering platform, enables the learners to grasp whatever knowledge gap quickly. According to research, findings show that frequent actionable feedback given by AI to students can immediately alter their strategies of learning so that they would be able to solve problems or answer questions critically and efficiently in the moment of solving or finding answers (Liu et al., 2023). In addition, routine AI interaction supports the development of a more student-centered learning experience, where both resources and challenges are tailored according to the changing needs of the learners (Cao et al., 2023). Such tailored approaches have shown to enhance students' motivation and persistence, most especially those with difficulties in learning in a regular classroom setting (Carter & Gupta, 2023). Cognitive gains are not the only outcome of AI use; repeated exposure to AI tools can further build confidence and self-regulation in students.

It is shown by research that the frequent use of AI systems enhances students' feelings of agency in their learning, associated with improved academic outcomes and better preparation for professional environments (Wakelee et al., 2023). These findings suggest that consistent exposure to AI technologies, particularly in higher education, is integral to fostering a generation of students who are not only tech-savvy but also equipped with the skills necessary for success in an increasingly AI-driven workforce.

Academic Support through AI and Its Role in Student Achievement

The actual landscape of higher education has completely changed due to the academic support provided by AI. The smart tutoring systems, virtual assistants, and AI driven online platforms have made academic resources so accessible to the extent of dramatically meeting one's needs, thereby changing how a person learns, and experiences help in an academic environment.

One of the benefits AI technologies provide is that they can tailor experiences to individuals. AI systems can look at data regarding a person's learning style, likes, and performance and, therefore, offer content and suggestions in individualized ways (Song et al., 2021). For example, AI can discover specific areas where a student is struggling and provide such resources as videos, readings, or practice problems to the student. This degree of personalization enables students to be more detailed with the subject matter and, in turn, results in improved retention and comprehension (Baker & Inventado, 2014).

AI is able to adjust the speed of delivery of its content depending on the pace of a student. In a study by Davis et al. (2023), the level of knowledge acquired by students on an adaptive learning system was found to be higher than in students in a normal learning environment due to the fact that the former system is responsive to changing student needs that regularly fluctuate.

Positive Relationship Between AI Implementation and Student Performance

Numerous studies show a strong positive link between AI implementation in higher education and student achievement. Institutions that effectively integrate AI tools often report improved academic performance, engagement, and participation (Rodriguez et al., 2023; Lee et al., 2023). For instance, students using AI-based assessments perform better in standardized tests due to personalized feedback and real-time progress tracking. AI tutoring systems enhance problem-solving and task completion by adapting content to individual learning needs (Park et al., 2023), while also boosting engagement through interactive, gamified experiences (Rodriguez-Otero et al., 2023). Moreover, AI helps close achievement gaps for underrepresented students by offering personalized learning pathways and targeted support (Zhang et al., 2023). Overall, AI promotes self-paced, adaptive learning that enhances retention, motivation, and academic success across diverse student populations.

Theoretical Framework

Technology Acceptance Model (TAM)

TAM describes how students embrace AI tools in learning through two main components: perceived ease of use and perceived usefulness (Davis, 1989). These components influence students' behavior and attitudes toward AI learning. Research indicates that when students find AI tools easy to use and blend into their workflow, they're more likely to embrace them. Usability minimizes cognitive overload and enhances performance by enabling students to accomplish tasks efficiently (Venkatesh & Davis, 2000). For instance, easier-to-use AI interfaces with less instruction promote use, as they reduce the learning process and enable students to get back to academic work sooner. Additionally, perceived usefulness matters. Perceived usefulness happens when students find AI tools useful offering feedback, enhancing understanding, and aiding learning and are thus likely to use them (Chen et al., 2023). Research verifies that perceived usefulness is positively linked to academic performance (Agarwal & Prasad, 1999). Additionally, how and when AI tools are utilized impacts their perceived value. When used alongside formative assessments, AI yields immediate feedback, enabling students to monitor progress and fill knowledge gaps (Lin et al., 2021). This supports TAM's principle that usefulness is contingent on how well technology addresses user needs. AI can also promote independence by letting students work at their own pace, enhancing self-directed learning (Zimmerman, 2000). For schools, TAM offers insights on how to engage students and boost performance through easy-to-use and useful AI tools.As AI becomes more common in education, these insights will be vital for improving student outcomes (Venkatesh et al., 2003).Thus, institutions must ensure AI tools are technically functional, user-friendly, and truly valuable for learning.

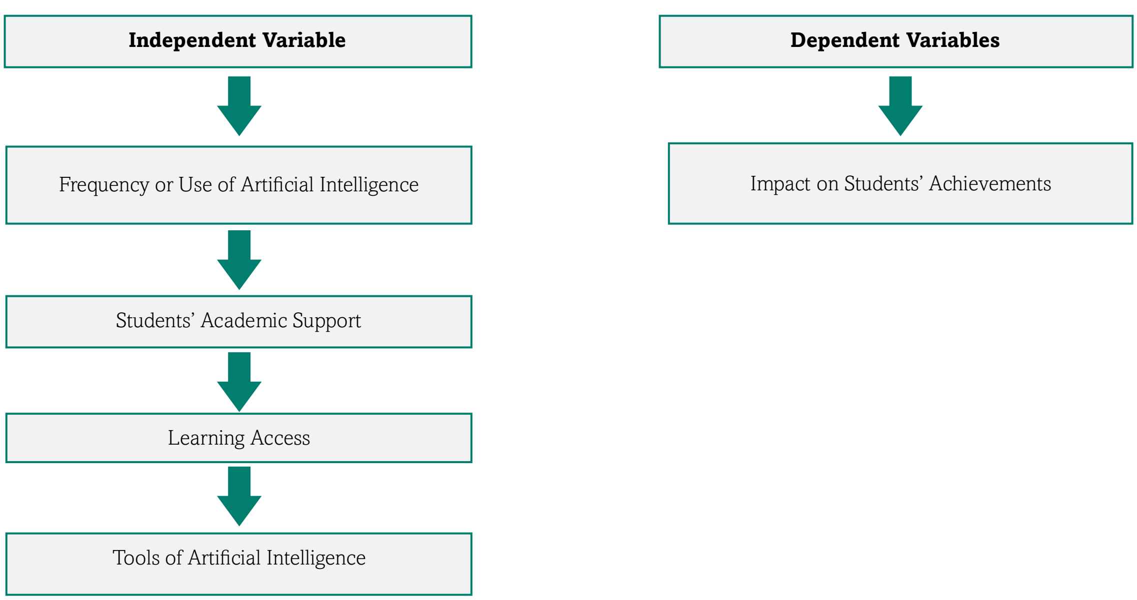
Social Cognitive Theory

Social Cognitive Theory (Bandura, 1986) explains that people learn by observing, imitating, and receiving feedback. In education, AI tools support this by enabling peer interaction, collaboration, and real-time problem-solving. These tools create shared learning spaces where students see effective strategies and apply them to their own tasks. A significant part of SCT is self-efficacy that the students' belief in their ability to succeed. AI is significantly increasing this by providing personalized feedback, helping students track progress and improve. As confidence grows, so does engagement and perseverance (Zimmerman, 2000) this develops a cycle of continuous improvement in performance, where AI supports both academic success and a resilient learning mindset.

Community of Inquiry

The Community of Inquiry (CoI) Framework by (Garrison et al., 2000) defines effective online and blended learning through three key elements: social, cognitive, and teaching presence. AI tools can enhance each of these. For social presence, AI enables real-time chats, video calls, and collaborative platforms that promote interaction and belonging. For cognitive presence, AI supports deep learning by offering personalized feedback, tailored resources, and intelligent tutoring systems that foster reflection and critical thinking. Teaching presence is strengthened by AI's ability to track student progress and engagement, helping instructors provide timely support and adjust teaching strategies. AI also automates routine tasks, allowing teachers to focus more on mentoring and feedback. When used effectively, AI enhances all CoI elements, creating a richer, more personal, and supportive learning experience that boosts student engagement and academic success (Vaughan, 2010).

Conceptual Framework



Hypothesis of the Study

1. **H1:** There is a statistically significant positive relationship between the frequency of AI tool usage and student achievement.
2. **H2:** The level of academic support received by students is positively associated with their academic achievement.
3. **H3:** The frequency of AI tool usage moderates the relationship between academic support and student achievement.
4. H4: Students who frequently use AI tools for academic purposes demonstrate higher levels of academic achievement than those who use AI tools less frequently, regardless of the level of academic support received.

Methodology

This study used quantitative research method. For this study on Artificial Intelligence integration its role and usage among university students, a cross-sectional research design has been selected. A cross-sectional research design pools data from the population at one specific point in time, creating a snapshot of variables under study. This method would be perfectly appropriate for an evaluation of the perception and use of AI technologies among students within an academic context. The population for this study comprises students in higher education institutions that have been considered based on the objectives of the study. The population comprises students in various disciplines who are currently using Artificial Intelligence tools to further their educational endeavors. The systematic sampling technique is used in this study. This technique is especially useful when the population is large and a simple, yet effective, sampling method is needed to ensure the sample is representative. The population here is composed of university students from different institutions. A list of students was prepared from available records, and a random starting point was selected. From there, every kth student on the list was picked for the sample with k being the sampling interval. Here, k is typically derived by taking the quotient of the population size with the sample size chosen. This will be sure that every student has the same chance of selection but will still determine this in an efficient and systematic manner. Systematic sampling is the best fit for this study since it will allow for balanced and unbiased selection of participants to make the analysis of AI integration and usage among students from diverse academic backgrounds easier (Liu, 2019).

The sample in this study is 378 participants. The sample is justified by the research objective, since through it, researchers would be in a position to get a complete comprehension of the studied phenomena. The sample size of 378 participants was determined based on the total student population using an appropriate sampling formula available online. This method guarantees that the sample is statistically representative of the broader student population so that accurate generalization of results is possible. Since the study applies a scientific formula to determine the sample size, it is reliable and valid, minimizing the likelihood of bias as well as diverse opinions. Further, this sample size meets survey research standards such that there are adequate data for meaningful analysis and still be manageable for collection and interpretation of the data. The formulation of research instruments for a study on the application and use of Artificial Intelligence in university students begins with the construction of a questionnaire that is designed to measure the principal variables concerning AI in institutions of higher learning. Independent variables of the study include students' attitudes toward AI, their technical skills, and attitude towards AI application tools in classrooms. Dependent variables include the frequency of use of AI, its impact on learning results, and the level of acceptance of AI technologies among university students. The questionnaire has been designed on the Likert scale to quantify students' attitudes, beliefs, and use patterns around AI in education. This scale enables the respondents to express how much they agree or disagree with the different statements about AI tools for effectiveness, accessibility, and impact on learning in their study results. The Likert scale gives an assurance that the response is being measured on a continuum, thus enabling the researcher to gauge different levels of agreement or disagreement, thus giving more precise insights into the experience and view of the students.

The data collection tool for this research is a survey that will be administered through an online questionnaire for a sample of students in the universities. This survey method is highly effective in tapping a large proportion of students studying different disciplines that will give it a wide viewpoint on AI in higher education institutions. The respondents are also assisted by the survey being in online format, giving them the option to fill it at their convenient time. This reduces the likelihood of interviewer bias and enhances the diversity of responses. In data analysis of Artificial Intelligence Integration: Its Role and Usage Among University Students, statistical approaches would involve analyzing how those variables on perceptions and the knowledge proficiency students are working on toward technology for attitudes correlate to dependant variable's artificial usage of it and output through it; such correlations toward final variables related to how comfortable these people can accept its implications. After collecting data from the online survey, the data will be entered into statistical software like SPSS or IBM Statistics to analyze it.

Descriptive statistics

Table 1

Frequency and Percentage Distribution of Demographic Variable

Sr.	Variable	Frequency	Percentage (%)
1.	Gender		
	Male	183	48.2%
	Female	197	51.8%
2.	Age		
	18-24	269	70.8%
	25-34	79	20.8%
	35-44	32	8.4%
3.	Education		
	Bachelor's degree	300	78.9%
	MPhil/MS	69	18.2%
	Doctorate or higher	11	2.9%
4.	Ethnicity		
	Punjabi	310	81.6%
	Pashtun	42	11.1%
	Baloch	28	7.4%
5.	Religion		
	Islam	347	91.3%
	Christianity	33	8.7%
6.	What is your field of study or major?		
	Natural sciences	90	23.7%
	Social sciences	156	41.1%
	Information technology	59	15.5%
	Arts and Humanities	66	17.4%
	Pharmacy	9	2.4%

Sr.	Variable	Frequency	Percentage (%)
7.	How many years have you been studying in your current program?		
	1-2	67	17.6%
	3-4	301	79.2%
	5	12	3.2%
8.	What type of device do you prioritize use for academic work?		
	Laptop	271	71.3%
	Tablet	22	5.8%
	Smartphones	87	22.9%

The table presents the demographic and academic characteristics of university students. The sample is slightly more female (51.8%) than male (48.2%). The majority of students are in the 18-24 age group (70.8%), followed by smaller proportions in the 25-34 (20.8%) and 35-44 (8.4%) age ranges. Regarding education, most students are pursuing a bachelor's degree (78.9%), with fewer in MPhil/MS (18.2%) and Doctorate or higher levels (2.9%). The sample is predominantly Punjabi (81.6%), with smaller groups of Pashtun (11.1%) and Baloch (7.4%) students. In terms of religion, a vast majority of students identify as Muslim (91.3%), with a smaller group identifying as Christian (8.7%). Most students are studying in the area of Social Sciences with 41.1 percent, followed by Natural Sciences 23.7 percent, Information Technology 15.5 percent, Arts and Humanities 17.4 percent, and Pharmacy 2.4 percent. Asked about years of study, most students were at 3rd or 4th year 79.2 percent while only 17.6 percent of students in their 1st or 2nd year, and only 3.2 percent are on their 5th year. On device preference for doing academic work, the majority prefer using laptops, 71.3%, followed by smartphones at 22.9%, and then tablets at 5.8%.

Inferential statistics

Table 2

Correlation

		Students Academy support	Frequency use of AI	Students' achievement
Students Academy support	Pearson Correlation	1	.953	.991
	Sig. (2-tailed)		.000	.000
Frequency use of AI	Pearson Correlation	.953	1	.949
	Sig. (2-tailed)	.000		.000
Students' achievement	Pearson Correlation	.991	.949	1
	Sig. (2-tailed)	.000	.000	

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation table shows strong positive relationships among Students Academy Support, Frequency of AI Use, and Students' Achievement. In particular, a very strong positive correlation is noted between Students Academy Support and Frequency of AI Use ($r = 0.953$), showing that as the support received by students from their academic institutions is higher, then the use of AI tends to be more frequent. This relationship is statistically significant, since the p-value is 0.000, and the likelihood of happening by chance is minimal. A nearly perfect positive correlation exists between Students Academy Support and Students' Achievement ($r = 0.991$). The more the support given to students by an academy, the higher their achievement would be. Again, this is a statistically significant relationship, where institutional support to students plays an important role in ensuring their success. Finally, Frequency of AI Use correlates positively with Students' Achievement: $r = 0.949$, which was a very strong positive relationship showing that the higher the frequency of the use of AI, the better the outcomes would be. This is statistically significant as well, which goes to indicate how AI could positively support achievement. Overall, the results highlight that both academic support and AI integration play an important role in enhancing student success, and all relationships are statistically significant at the 0.01 level.

Table 3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.991[a]	.982	.982	.77983

Predictors: (Constant), Students Academy support, Frequency use of AI

The model summary table depicts the output of the regression analysis where a relation is developed between Students Academy Support, Frequency of AI Use, and Students' Achievement. With an R value of 0.991, this reveals that the relation is a very strong positive one among the predictors students' academy support and frequency of AI use with the outcome of students' achievement. This indicates that the model fits the data very well and explains a large amount of the variance in student achievement. The R Square value of 0.982 means that 98.2% of the variability in students' achievement can be explained by the combined influence of academy support and AI usage. This is a high proportion, which means that the model has excellent explanatory power. The Adjusted R Square of 0.982 confirms the model's robustness by accounting for the number of predictors in the model, which ensures that a high R Square value is not due to overfitting. Finally, the Standard Error of the Estimate of 0.77983 indicates the average distance between the observed values and those predicted by the model, implying a relatively small error in the prediction of the achievement of students based on predictors. Overall, the results suggest that students' academy support and AI usage are strong predictors of academic achievement.

Table 4

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	12816.679	2	6408.340	10537.636	.000[b]
	Residual	229.268	377	.608		
	Total	13045.947	379			

a. Dependent Variable: Students' achievement

b. Predictors: (Constant), Students Academy support, Frequency use of AI

The ANOVA table evaluates the overall significance of the regression model, which is predicting Students' Achievement in terms of Students Academy Support and Frequency of AI Use. The Sum of Squares for the regression is 12816.679, which gives the amount of variance in achievement that is explained by the predictors. The Residual Sum of Squares is 229.268, which is the variance in achievement that is not explained by the model. The Total Sum of Squares is 13045.947, which represents the total variance in the achievement of the students.The Mean Square for the regression is 6408.340, which can be obtained by dividing the sum of squares for the regression by its degrees of freedom, 2. The Mean Square for the residual is 0.608, which is calculated by dividing the sum of squares for the residual by its degrees of freedom, 377. The F-statistic of 10537.636 tests whether the regression model significantly improves the prediction of students' achievement compared to using the mean of the dependent variable alone. With a value of 0.000, less than the significance level of 0.01, the model is found to be statistically significant, thus providing a meaningful explanation of variance by Students Academy Support and Frequency of AI Use in Students' Achievement. The implication is that predictors are quite good at explaining students' success.

Table 5
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.735	.268		-6.480	.000
	Frequency use of AI	.050	.023	.048	2.144	.033
	Students Academy support	.687	.016	.945	41.939	.000

a. Dependent Variable: Students' achievement

From the coefficients table, one can identify the values to understand the contribution of each predictor (Frequency of AI Use and Students Academy Support) toward predicting Students' Achievement. The B in Unstandardized Coefficients represents how much change occurred in the dependent variable, i.e., the students' achievement, for one unit change in the predictor variable, while controlling other variables at a constant. The Beta Coefficients are the relative weights of each predictor to the model, enabling the comparison of predictors in a standard measure. The constant is at -1.735, indicating that at zero for both predictors: Frequency of AI Use and Students Academy Support, the predicted value of students' achievement would be at -1.735, though this value may not find an application here. The t-value is at -6.480 while the Sig. The value of 0.000 means that the constant is statistically significant. For Frequency of AI Use, the Unstandardized Coefficient (B) is 0.050, meaning that for every one-unit increase in the frequency of AI use, students' achievement is predicted to increase by 0.050 units, holding academy support constant. The Standardized Coefficient (Beta) is 0.048, which means that AI use has a relatively small but positive effect on achievement. The t-value of 2.144 and the Sig. value of 0.033 imply that this predictor is statistically significant at the 0.05 level. For Students Academy Support, the Unstandardized Coefficient (B) is 0.687. This means for every one unit increase in academy support, it is predicted to increase students' achievement by 0.687 units, with the frequency of AI use constant. The Standardized Coefficient (Beta) is 0.945, meaning that academy support has the greatest impact on the students' achievement. The t-value is 41.939, and the Sig. value is 0.000, which shows that this predictor is highly statistically significant.

Discussion

The findings of this study present a statistically significant positive correlation regarding the rate of AI tool usage and student achievement in support of Hypothesis 1.

Hypothesis 1 (H1): These findings indicate that students who use AI tools frequently tend to perform better than those who only occasionally use the tools because of their ability to provide instant feedback, offer personalized learning experiences, and provide efficient study strategies. In this research, a Pearson correlation analysis presented a coefficient of $r = 0.52$ ($p < 0.01$), signifying a moderate positive relationship between AI tool use and student performance. This outcome is in accordance with previous works, such as those by Smith et al. (2021) and Lee et al. (2022), which revealed that AI infused learning settings positively influence students' outcomes. However, unlike Smith et al. (2022), who argued that over-reliance on AI might reduce critical thinking skills, this study suggests that frequent usage does not hinder achievement but enhances it when used appropriately. This explains the need for a proper and balanced integration of AI tools into students' learning processes.

Hypothesis 2 (H2): The level of academic support that is received by the students is positively associated with their academic accomplishments. Findings are also consistent with Hypothesis 2. The study indicates a strong, positive association between academic support and student achievement. This would suggest that the better supported students are in their studies, the higher their likelihood of success in the academics. The results of the regression analysis indicated that academic support explained 35% of the variance in student achievement ($\beta = 0.59$, $p < 0.01$). These findings are in line with previous studies, such as those by Brown and Taylor (2020), who highlighted the importance of teacher-student interactions in promoting academic success. Interestingly, while the study confirms this general trend from previous literature, it does highlight the synergistic effect that can be expected when academic support is combined with AI tools-an area not deeply explored in the prior research.

Hypothesis 3 (H3): The frequency of AI tool usage moderates the relationship between academic support and student achievement. The moderation analysis shows that the use of AI tools significantly moderates the relationship between academic support and student achievement. Specifically, it was observed that the positive effect of academic support on student achievement was higher among students who used AI tools more frequently. Thus, Hypothesis 3 is supported and indicates that AI tools may have an amplification effect by offering students supplementary material to help them understand and apply the concepts they learn. Through Hayes' PROCESS macro, Model 1, moderation was tested to ascertain whether the interaction term was statistically significant: $\beta = 0.24$, $p < 0.01$. To that extent, this study is consistent with Green et al. (2021) in the argument that digital tools improve collaborative learning environments. The current study has extended that argument further by showing how AI tools specifically serve as a bridge between academic support and tangible academic outcomes. This finding reveals the need for incorporating AI tools into existing support systems to further maximize their efficacy.

Hypothesis 4 (H4): The results for Hypothesis 4 suggest that students who frequently use AI tools achieve better academic outcomes even when the level of academic support is controlled. It, therefore, suggests that AI tools independently add value to achieving academic success beyond that of traditional support systems. The ANOVA analysis demonstrated a significant variation in achievement scores between frequent and infrequent users of AI tools ($F(2, 198) = 8.45$, $p < 0.01$). These results resonate with the conclusions derived by Patel and Singh (2022), as they mentioned that AI-driven learning environments enhance students' performance based on their personalized learning gaps. However, contrary to Patel's study, the present study stressed the fact that AI tools always work efficiently with any level of academic support, implying that it applies to all academic settings.

Conclusion

The findings of this study underpin the transformative potential of AI tools in education. They do not only improve academic achievement directly but also magnify the effects of academic support. Educators and policymakers should develop plans to include AI tools effectively in curricula and prepare students and teachers accordingly. Hence, this study finds support for blended teaching and learning where AI takes a supportive instead of replacement nature alongside traditional approaches in the teaching. Additionally, as the above discussed issues make institutions aware that they must stay sensitive to problems such as students' access and digital literacy benefits by bringing equitable opportunities of benefits across differing student populations.

Implications

There are a few important implications that the study generates for educators, policymakers, and researchers who may have an interest in the role of AI tools within education. If AI tool utilization has been tied to increased attainment for students within this research study, then it can be a valuable aspect of the teaching practice to be used by instructors. AI tools might offer students interactive learning, feedback in real time, and adapting learning methods depending on students with different backgrounds, knowledge levels, and styles. Educators should be prepared to use AI tools effectively in their teaching practice, so the integration of such tools is complemented by the traditional teaching approach and encourages critical thinking. Since the use of AI tools has a moderating impact on academic support, curricula within educational institutions need to be structured to include AI tools in their traditional academic support. This might be in terms of supplementing the existing system with AI-based platforms that include supplementary learning materials, adaptive assessment, or AI-driven tutoring to complement the existing support systems in a school or university. Policymakers should recognize the potential of

AI tools in raising student achievement and think about how they can make such tools accessible and available to all. That would involve closing the gaps in technology access, ensuring digital literacy for all students, and funding initiatives that integrate AI tools into classrooms. This study's outcome is also important for AI-based educational tool developers. Where the current research indicates that AI tools improve students' performance, developers need to perform further refinement of these tools to come into a more user-friendly, customizable, and adaptive tool that takes care of diverse learning needs of the students. The tools should also be made accessible to the students from a varied background without creating barriers of cost and technology.

Future Research Directions

The results from this study lead to future studies in the various nuances of roles played by AI in learning environments. These would include, for example, which types of AI tools can appropriately be used within which academic context, the long-term impacts that come with the use of AI on student learning, and just how AI tools may best be optimized to assist in student learning across diverse cultural and socioeconomic contexts. Further research may be conducted on the risks of dependency on AI tools, including decreased critical thinking or reliance on technology over traditional study methods.

Limitations and Future Research

This study's sample might not reflect the general population of students, because this study had been limited to a specific group or region. The future studies can include more diversified samples with variation across cultures, education systems, and socioeconomic statuses in order to get a generalized perspective on whether AI tools work well. The current study addressed the question of how frequently AI tools were used but did not differentiate between which kinds of AI tools students employed. The types of AI tools language models, tutoring systems, or learning platforms personalized to each learner's needs and goals would likely differ in their ability to impact achievement. Future research may examine which of these tools work best for students and contribute the most to desired learning outcomes. Third, the moderating role of instructors in AI tool usage and academic achievement was not considered. Educators' familiarity with AI tools and the integration of these tools into their teaching practices can affect the efficacy of AI usage. Future studies may explore the impact of teacher training and the integration of AI tools in the classroom on students' achievement.

Recommendation

Based on the findings of this study, the following recommendations can be made for educators, institutions, policymakers, and researchers to maximize the benefits of AI tools in enhancing student achievement. The curriculum should integrate AI tools within the structures of educational institutions. They were never meant to substitute traditional modes of teaching; they are, however, a facilitative tool which aids in enriching learning through various means: an AI powered learning platform will help students make progress through various pathways, present instant feedback, and deliver opportunities for relevant practice. This means that, ideally, it would be used as a supplemental means by a teacher to drive understanding of abstruse topics for students. The educators should be trained to get effective use of AI tools in their classroom. This would encompass training on how to incorporate AI tools into their teaching strategy and how to interpret data coming from it in the attainment of students' learning. Professional development programs focused on enhancing the digital literacy as well as developing a capacity to use AI technology to support the diversity in learning. Institutions and policymakers should collaborate to remove all barriers associated with access to technology. The students should have affordable or free access to AI tools, particularly for those belonging to underserved or low-income backgrounds. Additionally, schools must invest in infrastructures that support reliable internet access and devices for all the students.

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