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Role of Artificial Intelligence in Promoting Personalized Learning in Pakistani Universities

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ABSTRACT

In higher education, the scope for large-scale, individualized learning catalyzed by rapidly evolving AI technology has already begun to emerge. This quantitative study was proposed to identify faculty and student knowledge of these technologies, the AI role in the context of individualized learning, and the implications of AI in Pakistani universities. 155 participants across public and private Pakistani universities completed the researcher-developed, structured, self-administered, Likert-scale questionnaire. The data were analyzed using SPSS, and following tests, such as descriptive statistics, Pearson correlation coefficients, and reliability analysis (Cronbach's alpha) were employed. AI Tool Awareness and AI-Driven Personalization were both positively and meaningfully associated with Learning Outcomes and Academic Performance. The analysis also showed a significant positive relationship among the three aspects. The participants showed a moderate to high level of AI tool awareness, high level of perception regarding AI tool utility, and positive enhancements in self-discipline, academic readiness, and overall performance. Many persisting issues were documented, including a lack of digital infrastructure, insufficient faculty training, and unaddressed issues of academic integrity and data security. For educational technologists and AI-oriented university managers, these findings require immediate formulation of responsive policies to facilitate improvement of the AI-integrated higher education learning system in Pakistan.

Introduction

Across the globe, with the emergence of technology, the educational systems have brought about a new era in the ways in which teaching and learning occur. Disruptive digital technologies, such as artificial intelligence (AI), have the power to design learning experiences in new ways, at a scale that was previously unachievable. There are a variety of issues in traditional teaching and learning systems that make it impossible to accommodate learners with different learning requirements, learning styles, and diverse learning backgrounds. These issues include, but are not limited to, fixed, mandated, and inflexible curricula and instructional paces, as well as teacher time and capacity constraints. One way that AI-based systems can address the issues in traditional teaching and learning systems is by individualized learning outputs, learning feedback (Zawacki-Richter et al., 2019).

The new AI-based education that creates individualized educational experiences are based on a concept of "personalized learning." Personalized learning can be defined as an educational philosophy that focuses on the needs, learning preferences, learning styles, and interests of the individual learner. Adaptive learning environments, feedback recommendation systems, AI-based learning assessments, and intelligent tutoring systems are AI-based educational technologies that are designed to capture and process learner actions in a real-time manner and deliver customized learning inputs (Lin et al., 2023). One of the learning theories that inspired the design of intelligent tutoring systems is Benjamin Bloom's (1984) seminal research on learning by means of direct personalized one-on-one tutoring. Bloom's research advanced the field of learning by demonstrating that personalized tutoring substantially increases learner achievement when compared to traditional classroom teaching that is based on the learning activities of a group of learners. One of the goals of AI-based educational technologies is to narrow the learning achievement gap by offering personalized learning experiences. The AI-based educational technologies that focus on personalized learning are especially relevant for the context of Pakistan, which has a large and diverse population but lacks modern educational technologies.

Pakistan's higher education system is critically understaffed and overpopulated and suffers from an urban-rural divide and a lack of educational technology funding (Bullentin of Education and Research, 2024). The current situation of education is poor.Insufficient funding exacerbates the situation. Despite the fact that the Pakistani Higher Education Commission (HEC) has made some bold proclamations championing the digitalization and the use of AI in Pakistani universities has little empirical evidence and academic performance shows similar trends. The literature published shows little research conducted in developing countries like Pakistan, therefore, it may not be relevant in Pakistan in terms of social economic and infrastructures.

Teacher perspective and preparedness are also important in practice; the pedagogical practices of teachers depends on the teachers' motivation, technological self-efficacy, and the presence of organizational support to establish and strengthen capacity building (Davis, 1989). It has been noted by teachers in the education sector in Pakistan is very limited, and opportunities for trainings are very inconsistent (Naseer et al., 2025). Meanwhile, the population of students in Pakistani universities is young and, according to this study, use of technology is very high. Students use smartphones and access the mobile internet to communicate with friends and peers. Likely, students from today's workforce are more comfortable using technology than traditional tools to conduct surveys from the industry.

Considering this background, the present study attempted to develop an empirical understanding of the three related areas. (a) the extent to which faculty and students are aware and/or able to access AI tools, (b) the perceived AI-based personalization within the learning environment, and (c) the perceived AI-based personalization within the environment of the self-reported learning outcomes of the students.

The study provides a comprehensive literature review and is further divided into sections that provide a theoretical and conceptual framework. It also includes guidance on sampling, instrumentation, and analysis. It also analyzes the data and provides findings along with a discussion based on theory and previous research. Conclusions and recommendations are provided at the end.

Literature Review

Artificial Intelligence in Higher Education: An Overview

In the last two decades, the presence of AI has rapidly evolved. This evolution ranges from early rudimentary expert systems, through the simple computer-assisted instruction systems, to the distinctly advanced systems which utilize natural language processing, predictive analytics, and adaptive learning content. In their extensive review of 146 studies, Zawacki-Richter et al. (2019) classified the primary application domains for AI in higher education into four categories: intelligent tutoring systems, adaptive systems/personalized learning, assessment/evaluation, and profiling/prediction. Their review noted on STEM education in the technologically advanced member states. These points in the study of the integration and acceptance of AI technology in the developing South Asian countries, and particularly Pakistan.

The latest reviews have documented the actual continued integration of AI within higher education. In a systematic review of the design, and evaluation of AI-based personalized learning systems, the most successful systems documented the use of adaptive content with the delivery of real-time feedback. There was agreement that learning gains were evident when systems adopted a humane and interpretive pedagogical style, especially in learning domains requiring procedural skills (e.g., mathematics and programming). An enabling factor for the successful adoption of AI systems is what these studies identified. The successful adoption has been associated with the perceived ease of use, organizational support, digital skills, and faculty members' attitudes toward AI systems.

In such situations, AI can lead to better academic results, greater student engagement, and a higher level of satisfaction with the educational experience (Rane et al., 2023). In the absence of AI, even well-designed software may be overlooked or used in a superficial way, not recognizing their educational value.

Personalized Learning: Definitions and pedagogical justifications

The 1960s and 1970s personal learning movements occurred before the use of technology within education. Today, the term personal learning has come to mean learning that is delivered at a pace, level, and style that is most effective for each individual learner, addressing their individual learning needs and preferences. This style of learning most often occurs for individuals, rather than for groups (Gao, 2023). The personalization of learning relies upon new models of learning and teaching that bring the idea of learning through the construction of knowledge by the learner through interaction with learning that is at the right level, for them, of cognitive development, and the idea of self-regulated learning (Zimmerman, 2000).

Gao is drawing on Bloom's (1984) 2-sigma problem. From the results of Bloom's meta-analysis, it is thought that learners who receive personalized, mastery-based tuition, learn at a level that is two standard deviations above the level of learners who receive traditional classroom-based tuition. This meta-analysis has resulted in countless studies, geared towards increasing the level of benefit received by learners through the process of personalized, one-to-one tuition. Situated in the context to provide adaptive scaffolding (Virvou and Chrysafiadi, 2023), as well as prompt remedial feedback and closure of instructional gaps, and learning that is sequentially stage controlled, is the most encouraging contemporary answer to this problem.

Numerous studies in various contexts have documented the advantages of AI-Powered Personalized Learning (Gao, 2023). The meta-analysis conducted by Gao (2023) on adaptive learning systems in STEM higher education. Springer Nature (2025) reported similar results for AI-based tutoring for undergraduate students, showing that students with lower levels of prior knowledge, who benefit more from mass classes, had the most positive outcomes.

AI Adoption in Pakistani Higher Education

More than 250 accredited universities comprise Pakistan's higher education system. The number of universities continues to grow with over two million students enrolled. The Higher Education Commission supervises the sector and recently has recognized digital transformation as a focus area. However, the number of studies regarding the adoption and the impact of AI tools in Pakistani universities remains low.

Naseer et al. (2025) identified the first two barriers as the presence of Digital and Physical infrastructure and the availability of trained staff. The third barrier was the existence of Policies. These barriers were interlinked and Policy barriers created a "no accountability" zone for Private Sector companies to address the gaps in training and infrastructure. The lack of accountability created a "no pressure" scenario for companies.

A recent study titled "Awareness of AI usage in Pakistani Universities and its impact on faculty perceptions" published in Bulletin of Education and Research (2024) identified four barriers to AI usage among faculty members in Pakistani universities: lack of knowledge, fear of academic malpractice, concerns for data privacy, and fear of losing the human dimension of teaching. Faculty members that have had direct experience with AI tools were less anxious about AI. The difference in viewpoint indicates that teaching staff require frameworks in order to be ready to work with AI technologies.

One aspect of the context that must be recognized is the large institutional diversity across the country. Considering rural areas and other urban centers, urban universities, especially in Lahore, Islamabad and Karachi, enjoy advanced technological infrastructure. Citing Zawacki-Richter et al. (2019), the geographic aspect of digital inequality indicates that the results of research conducted in well-resourced institutions (and the ones included in the current study) would not be easily generalized to the national level.

The faculty's views and the adoption of technology

Given that teachers are the closest technology facilitators to the classroom, it's essential to examine their perception of AI. The Technology Acceptance Model (TAM) (1989) posits that two beliefs, perceived utility and perceived ease of use, form the basis of acceptance of a technology. Some of the more recent expansions of TAM have included factors such as experience, facilitative conditions, and perceived norms (Springer, Journal of Academic Ethics, 2025), which are factors that have been shown to be important in educational settings.

TAM-driven studies suggest that staff members' use intent of AI in higher education is related positively to their beliefs concerning AI's potential benefits in enhancing student learning, managing workload, and performing fair assessments. Even among the positive views of AI tools, doubts about content quality of AI, the low quality of some AI, and the student use of AI to facilitate cheating, have a significant role (Cotton et al., 2023). The lack or vagueness of institutional policy on the use of AI in assessed work makes the last factor even more pressing.

In the article The Use of Artificial Intelligence in Education: Students' Engagement and Accessibility from the Faculty Perspective, published in the Journal of Academic Ethics (Springer, 2025), it is reported that the faculty of Pakistan were mainly positive about the use of AI to create more engaging and accessible learning for their students, but were resistant to the use of AI in formal assessments based on their concerns regarding the integrity of formal assessments.

This is probably even more exacerbated by most Pakistani institutions not having explicit institutional laws or guidelines concerning the usage of AI. Since faculty members are largely left to their own devices, they tend to adopt a more conservative stance.

Students' learning results on self-generated learning

Many concepts have been implemented to consider how the use of AI tools relates to student learning results. Zimmerman (2000) developed a socially and cognitively relevant SRL model. As it relates to SRL, Zimmerman identified four aspects: performance (self-monitoring, self-instructions), self-reflection (self-evaluations, adaptive inferences), and forethought (goal setting, strategic planning). AI-enabled tools can be designed to support each of these stages by presenting timely and performance data. Such tools will empower learners by providing performance feedback, offering corrective suggestions, and prompting learners to reflect on their own performance.

The use of AI tools is positively impacting SRL in various contexts. In the investigation of AI tools in different educational settings, Lin et al. (2024) reported that AI study tools improved learners’ time management, perseverance to complete learning tasks, and self-efficacy. The learners who showed the most improvement were those who had less academic ability, and the learners who had the less academic ability, were the learners who benefited the least from traditional teaching.

An illustrative example of AI motivated adaptive learning is Vygotsky's (1978) 'Zone of Proximal Development' (ZPD). In the ZPD, the area where learning is possible is between what the learner can do unaided and what the learner is unable to perform without assistance. An AI system might assess students' performance in real time and proactively adjust the difficulty of instruction to keep students within the ZPD. That way, students can be both challenged and supported.

Theoretical Framework

This research incorporates three theories to establish a conceptual framework for the study. These theories are Vygotsky's (1978) Constructivist Learning Theory, Zimmerman's (2000) Self-Regulated Learning Theory, and the Technology Acceptance Model (Davis, 1989). All three theories can be used in conjunction to describe the behavioral, cognitive and attitudinal components of learning in the context of AI enhanced, personalized learning.

The Technology Acceptance Model provides a basis to understand the acceptance of AI tools, and the absence of acceptance. The framework for the study is based on the assumption that the actual engagement of students and teachers with AI tools in personalized learning will be based on the perception of the tools as helpful and usable. The perception of helpfulness and usability will be shaped by the level of support provided by the institution, the training of teachers, and the prior engagement of the tools. In this case, the Technology Acceptance Model provides an explanation of the attitude and behavioral intention as the mediating factor of the availability of the technology and the actual engagement with the technology.

Self-Regulated Learning Theory suggests that the use of AI tools can be a way to enhance one's learning. AI tools that provide help with setting learning goals, tracking progress, and providing personalized self-assessments have the potential to facilitate self-regulation of learning. The final element of the framework used in this study is represented by the use of AI tools that enhance learning, engagement, and goal completion.

There are elements of Constructivist Learning Theory that provide the pedagogical justification for the AI personalisation Learning Theory, particularly the learning theories of Vygotsky and the Zone of Proximal Development. Constructive learning within the Zone of Proximal Development requires that the learning task provides an appropriate level of challenge; neither too much, which may cause the learner to become frustrated, and too little, which may cause the learner to become bored.

Incorporating AI to provide content that is dynamically calibrated with scaffolded feedback aligns with both the active ZPD and the constructivist approach to learning, particularly where learning occurs at the outer periphery of the learner's current level of competence.

Conceptual Framework

These three theories are represented in a model in the following framework (Figure 1). AI-Driven Personalization and AI Tool Awareness and Access represent the two primary independent variables in our model. Contextual restraining factors that impact the extent of AI technology application comprise institutional policy, faculty AI apprehension, and the level of digital infrastructure. Dependent variables in the model comprise academic performance and learning outcomes. The whole model is situated in the context of the Pakistani higher education system and specifically the HEC system.

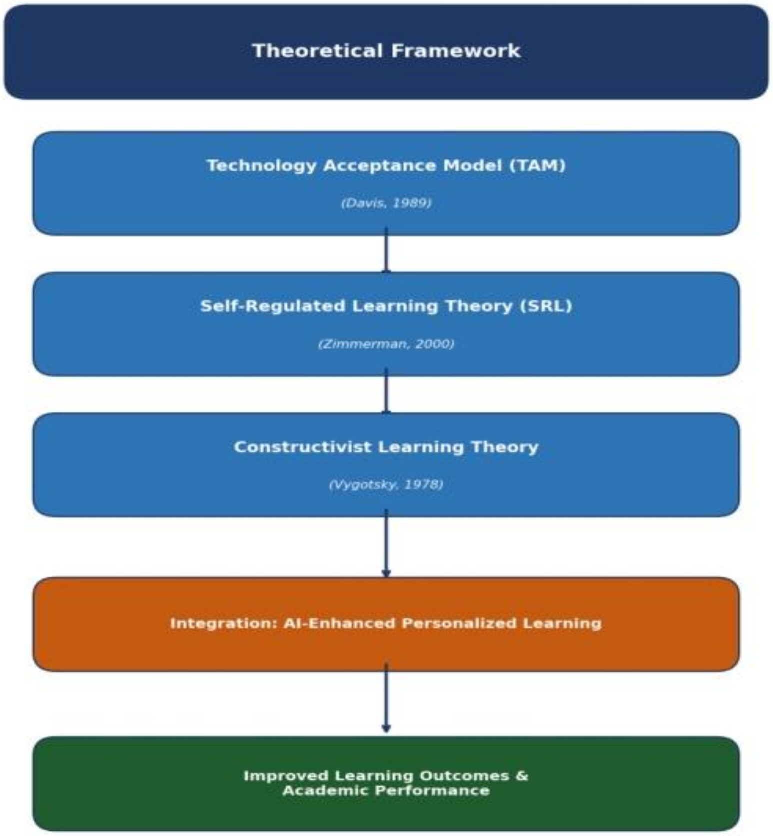

Figure 1. Theoretical Framework Flowchart: TAM, SRL Theory, and Constructivist Learning Theory

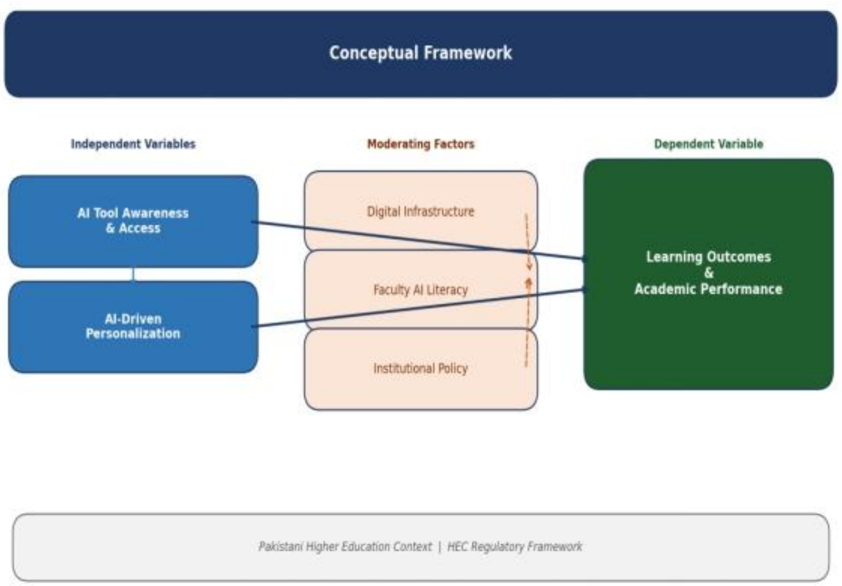

Figure 2. Conceptual Framework Diagram: AI-Enhanced Personalized Learning in Pakistani Universities

Research Questions

From the theoretical framework as well as the empirical research gaps, this study attempted to answer these three questions:

RQ1: What is the awareness and access to AI learning tools among teachers and university students in Pakistan?

RQ2: In what way does AI personalization influence Pakistani university students' perceptions of their learning and their academic success?

RQ3: What impact do AI technologies, personalized AI education, and the awareness of Pakistani university students have on learning and academic success?

Methodology

Research Design and Philosophy

This study was based on positivist philosophy. Positive thinking considers social realities to be quantifiable and establishes statistical relationships among variables based on data collected in a structured manner (Bryman, 2016). Data collection involves the preparation of measurement variables and formulation of relevant hypotheses based on available theories and previous studies. In this research, data were examined to evaluate the presence or absence of hypothesized relationships in the context of Pakistani universities (Creswell & Creswell, 2018).

This quantitative research adopted various research designs like correlational design. The descriptive design in this research determined the central tendency and the dispersion of the attitudes of the respondents within the Three Constructs (AI Tool Awareness and Access, AI-Driven Personalization, and Learning Outcomes). The correlational design, on the other hand, examined the three constructs to determine if a non-causal relationship existed among the constructs and, if so, to determine the nature of that relationship.

Population and Sampling

The target market was made up of undergraduate and graduate students and academic staff from the public and private universities of Pakistan. The criteria for participants were: that they were either students or staff of a registered university in Pakistan and that they were familiar with at least one of the AI learning and/or productivity tools. The criterion focused on the difficulties that the study would face in having the sample represent the population of Pakistan. Because of the sample criteria, the participants were able to provide quality and reliable responses to the study (Etikan et al., 2016).

A total of 155 respondents contributed in the study. This number was adequate and met the requirements for the population of the study as described in Krejcie and Morgan (1970). Participants were selected from six universities UMT, UOE, LCWU, UCP, UOL, and several other universities in Lahore. By including both private and public universities of Lahore, the sample added to the variety of degrees as well.

Instrumentation

Data was collected using a self-administered questionnaire consisting of twenty-five multiple-choice questions that were divided into three different sub-scales. The first sub-scale consisted of eight questions, and assessed the level of support the institution provided, the awareness of AI educational tools, the availability of AI tools, the frequency of use, and confidence and sufficiency. The second sub-scale asked the respondents to assess the extent that they thought AI tools, which personalized the content, timing, and feedback to align with respondents' learning styles, offered such flexibility. The last sub-scale, Learning Outcomes and Academic Performance, consisted of nine questions that assessed the perceived ability to improve one's academic performance, understanding and proficiency in the area of learning, as well as one's motivation and interest, and the ability to manage one's time and reach personal goals and objectives.

In line with the work by Likert (1932), response items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The design of the questionnaire was built on the analysis of validated questionnaires available in the literature, a review by three faculty experts in educational technology and research, a pilot study with 20 non-sample participants, and in the literature. Before major data collection, the unclear items and the items with poor item-total correlation from the pilot study were modified.

Reliability Analysis

Table 1 presents results of the reliability of each subscale and of the overall instrument assessed using Cronbach's alpha.

Table 1: Reliability Statistics: Cronbach's Alpha Coefficients

Scale	No. of Items	Cronbach's α	Interpretation
AI Tool Awareness & Access	8	0.661	Acceptable
AI-Driven Personalization	8	0.696	Acceptable
Learning Outcomes & Academic Performance	9	0.616	Acceptable
Overall Instrument (25 items)	25	0.881	Good

The three subscales had alpha coefficients ranging between 0.616 and 0.696. Though these results come in low according to George and Mallery (2003) and Nunnally (1978), they fall within the range for new tools that measure complex attitude constructs in educational research and align with studies in educational research. New tools for complex attitude constructs will be shown to adequate for exploratory research in the field. The remaining 25-item instrument produced a strong composite alpha of 0.881.

Data Collection Procedure

There were multiple avenues for participants to access the online questionnaire such as the student organizations, contacts from the research team, Flyers, and the university email list. Participation was voluntary and anonymous. A short information sheet listing the study objectives and the anticipated completion time (10–15 minutes), and the confidentiality was provided to respondents. Participant's informed consent was obtained before they completed the online questionnaire. Data was collected over a period of six weeks.

Data Analysis

The completed surveys were collected on Google Forms and then analyzed via SPSS. Three stages comprised the analysis. First, the overall instrument and each subscale's internal consistency were calculated by Cronbach's alpha. An alpha at or above .60 was deemed acceptable and .80 and higher were deemed good (George & Mallery, 2003; Nunnally, 1978). Second, in order to compute the distribution for each subscale, the sample relied on mean, standard deviation, minimum score, and skewness and kurtosis statistics to assess the suitability of parametric testing. In answering the third research question, "Does greater awareness and personalization of AI lead to improved learning?", the sample computed Pearson product-moment correlation coefficients for each subscale composite score. In line with social science correlational research, the authors of the cited works agreed to adopt a two-tailed p value of less than 0.01 for the analysis of this study (Cohen, 1988; Hair et al., 2019). No regression analysis was performed in this study, which pertain to identifying the nature and strength of associations between variables, rather than which independent variables of a given set contribute to the prediction of a dependent variable, were addressed by the correlational design employed. Future research, based on larger and more representative samples, may consider the use of regression or path analytic methods to explore the nature of predictive relationships.

Results and Analysis

Demographic Profile of Respondents

155 participants answered the survey. Tables 1 through 4 summarize the demographics of the sample.

Table 2: Gender Distribution of Respondents (N = 155)

Gender	Frequency (f)	Percentage (%)
Male	38	24.5%
Female	117	75.5%
Total	155	100%

Looking at Table 2, it can be concluded that 75.5% of surveyed were female (n = 117). The majority female representation possibly mirrors the demographics of the degree programs surveyed. Female students dominate the enrollment in several of the programs surveyed (Education and Urdu) within the institutes surveyed.

Table 3: Age Distribution of Respondents (N = 155)

Age Group	Frequency (n)	Percentage (%)
15–20 years	1	0.6%
21–25 years	88	56.8%
26–30 years	62	40.0%
31–35 years	4	2.6%
Total	155	100%

As shown in table 3, respondents were mostly made up of young adults. The data included those ages 21 to 30, who made up 96.8% of respondents and showed a data dispersion that was in alignment with the demographic data for post-graduate and advanced under-graduate students at various universities in Pakistan.

Table 4: Degree Program Distribution of Respondents (N = 155)

Degree Program	Frequency (f)	Percentage (%)
BS Education	37	23.9%
MPhil	31	20.0%
Business (BBA/MBA)	25	16.1%
IT / Computer Science / AI	14	9.0%
BS Urdu	9	5.8%
Fine Arts (BFA)	9	5.8%
BS English	8	5.2%
Law (LLB)	5	3.2%
Mass Communication	5	3.2%
Other Programs	12	7.7%
Total	155	100%

The participants represented a variety of academic disciplines within the social sciences and applied and professional fields and the humanities. This variety helps strengthen study findings and lessens the odds that results are more influenced by academic subcultures that have specific types of relations with AI tools.

Frequency Analysis by Construct

Table 6: Item-level Frequency Analysis: AI Tool Awareness & Access (N = 155)

Item	SDA	D	N	A	SA	M	SD
Q1: Aware of AI tools for educational purposes	2	2	43	94	14	3.75	0.69
Q2: Can name at least one AI learning tool	1	7	29	68	50	4.03	0.86
Q3: Have access to AI-based learning tools	0	1	34	63	57	4.14	0.77
Q4: University provides adequate AI resources/guidance	1	5	36	74	39	3.94	0.82
Q5: Use AI tools regularly in academic studies	3	5	20	69	58	4.12	0.89
Q6: Confident in using AI tools for learning	1	3	28	59	64	4.17	0.84
Q7: Internet connectivity sufficient for AI tools	1	5	31	72	46	4.01	0.83
Q8: Received training/orientation on AI tools	1	4	36	55	59	4.08	0.88

Key. SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree. Scale 1 - 5.

Mean scores for the AI Tool Awareness and Access subscale spread from 3.75 (general AI awareness, Q1) to 4.17 (confidence in AI tools, Q6) scores. Confidence in tool use and regularity of tool use also (Q5, M = 4.12; Q3, M = 4.14) outscored general awareness (Q1, M = 3.75). This suggests that the respondents are likely either using the tools in practice or are actively participating in the use of AI with formal practice or both, even when they are aware of the AI with limited declarative practice. The lowest mean in the AI resources provision (Q4, M = 3.94) is among the items rated above neutral, highlighting the resource gap in the provision of AI resources vis-a-vis self-use and access.

Table 7. Item-level Frequency Analysis: AI-Driven Personalization (N = 155)

Item	SDA	D	N	A	SA	Mean	SD
Q9: AI tools allow me to learn at my preferred speed	2	2	28	89	34	3.97	0.75
Q10: Content is tailored to my strengths and weaknesses	2	6	32	74	41	3.94	0.86
Q11: AI provides tailored feedback on assignments	0	5	30	76	44	4.03	0.78
Q12: AI helps identify knowledge gaps	0	4	31	71	49	4.06	0.78
Q13: Accommodates my learning style better than traditional methods	1	8	32	61	53	4.01	0.90
Q14: Enables me to review content based on comprehension	1	1	34	64	55	4.10	0.80
Q15: Suggests resources appropriate to my level	0	4	32	68	51	4.07	0.80
Q16: Promotes flexibility and student-centeredness	2	0	29	57	67	4.21	0.83

The AI-Driven Personalization item responses ranged from 3.94 to 4.21. Most appreciated was Q16 (AI promotes flexible, student-centered learning, M = 4.21) and least appreciated was Q10 (content is tailored to individual strengths and weaknesses, M = 3.94). The results imply that respondents appreciate the structural flexibility and the adjustability of the AI tools, but think that the more advanced and sophisticated personalization of the content to the students' cognitive profiles is less evident in the tools. The results show that there is a gap between the general and notable flexibility the AI tools offer and the more adaptive personalization that the AI tools have the capacity to provide.

Table 8: Item-level Frequency Analysis: Learning Outcomes & Academic Performance (N = 155)

Item	SDA	D	N	A	SA	M	SD
Q17: Prefer AI-supported over classroom instruction	1	6	42	62	44	3.92	0.87
Q18: AI tools improved overall academic performance	0	1	21	93	40	4.11	0.64

Q19: AI helped me understand difficult concepts	0	2	23	92	38	4.07	0.66
Q20: Feel more motivated to study with AI tools	0	5	29	66	55	4.10	0.81
Q21: AI improved critical thinking and problem-solving	0	4	27	72	52	4.11	0.78
Q22: Grades/scores improved since using AI tools	0	4	31	70	50	4.07	0.79
Q23: AI tools help manage study time effectively	0	1	17	71	66	4.30	0.69
Q24: More confident completing tasks with AI tools	0	1	23	72	59	4.22	0.71
Q25: AI contributes positively to overall learning goals	0	3	29	71	52	4.11	0.77

The average scores of the three constructs show that the Learning Outcomes subscale had the strongest scores. The best scores were for time management (Q23, M = 4.30) and confidence in completing tasks (Q24, M = 4.22). The lowest score was for the preference for AI-instruction versus traditional instruction (Q17, M = 3.92). The scores are interesting because, although the sample consisted of people who actively use AI, a significant part of the sample does not express preference for AI-instruction while traditional instruction is used. It shows that the people in the sample understand AI as, at least partially, a complementary tool of support in conventional teaching methods, and not a replacement. The finding is aligned with a constructivist belief of the role of technology as a support tool for instruction that does not replace pedagogical relationships.

Table 9: Descriptive Statistics for Study Variables (N = 155)

Variable	N	Mean	SD	Min	Skewness	Kurtosis
AI Tool Awareness & Access	155	4.029	0.450	2.62	-0.594	0.539
AI-Driven Personalization	155	4.050	0.462	2.38	-0.794	1.206
Learning Outcomes & Academic Performance	155	4.113	0.372	2.89	-0.423	0.903

The general view of AI tool awareness, personalization, and learning outcomes aggregate mean scores of all three composite variables was positive. This is shown by their scores, which are all greater than 4.0. The scores for all three composite variables exhibited a moderate negative skewness, indicated by skewness values of all three on the range of -0.423 to -0.794. It means that respondents were inclined to score on the upper end of the scale. The scores for each of the variables also demonstrated a positive kurtosis, with values on the range of 0.539 to 1.206, which are within the acceptable limits for the application of parametric test (Hair et al., 2019). This confirms that Pearson correlation test was the most appropriate test to use.

Pearson Correlation Analysis

Table 10: Pearson Correlation Matrix for Study Variables (N = 155)

Variable Pair	Pearson r	p-value	Interpretation
AI Awareness & Access ↔ AI-Driven Personalization	0.683**	< 0.001	Strong positive
AI Awareness & Access ↔ Learning Outcomes	0.591**	< 0.001	Moderate positive
AI-Driven Personalization ↔ Learning Outcomes	0.577**	< 0.001	Moderate positive

Note. **p < 0.01 (two-tailed). Based on Cohen in 1988, small r = 0.10–0.29; moderate r = 0.30–0.59; strong r = 0.60–1.00.

The correlation matrix found significant positive relationships for all variable pairs examined (all $p < 0.001$). Of all variables examined, AI Tool Awareness and Access and AI-Driven Personalization had the highest correlation ($r = 0.683$), classified as a large positive relationship per Cohen's (1988) conventions. This relationship demonstrated students that are AI Tool aware and have AI Tool access report AI Tool driven learning to be more personalized. This finding highlights the role that access and literacy play as building blocks to learning tool personalization.

There were also moderate positive correlations between AI Tool Awareness Access and Learning Outcomes ($r = 0.591$) and AI-Driven Personalization and Learning Outcomes ($r = 0.577$). Although of lesser value to be considered as ‘strong’ relationships, positive correlations of this value and strength, in the field of education, are considered meaningful and, generally, are of a value and strength that is rare. These also contribute to the support the conceptual framework articulated in Section 2.6. These. outcomes noted a higher self-reported Learning Outcome when the students noted a higher awareness of AI and a higher use of AI in a Learning Personalization setting.

Discussion

These results give evidence, in the setting of Pakistani universities, that the adoption of AI tools correlates with experiencing personalized learning and better self-reported academic performance. The results are interpreted in the subsequent three research questions, the theories and evidence discussed above, and beyond.

The first research question was related to awareness of students and faculty regarding accessing and using AI tools in Pakistani universities. The descriptive findings refer to a generally positive picture, as the mean of the subscales of the profile was 4.029, and the means of the items ranged between 3.75 and 4.17. The scores indicate that the population sampled is not in the initial stages of awareness of AI but is using AI tools in an academic setting. This is an interesting pattern, as users' confidence in tools ($M = 4.17$) and regular use ($M = 4.12$) were rated higher than their general awareness of the AI landscape ($M = 3.75$). It proves that students have been using certain AI tools, possibly in their personal networks, via online materials and on their own, without formal AI training.

This is partially contradicting previous studies from Pakistan which reported low faculty awareness of AI (Bulletin of Education and Research, 2024) and infrastructure and training as major barriers (Naseer et al., 2025). One possibility is that a generational shift is occurring: the students sampled in this study are younger, digitally-savvy, and more likely to have experienced AI tools in the consumer sphere (e.g., using ChatGPT, Grammarly, etc.) before they are taught in a formal education setting. Familiarity with tools may be lower among faculty members, particularly those in the middle and at the end of their careers, who may have had less experience with consumer AI.

The moderate TAT scores for confidence (PEU), and the high score for regular use, imply that the barrier of ease of use has been significantly overcome for this population. The relative deficiency seems to be in institutional support, as item Q4 (The University provides sufficient AI resources and guidance) had the lowest mean on the subscale ($M = 3.94$). This relates with Naseer et al.'s (2025) definition of institutional policy and support as a key gap in the Pakistani higher education AI ecosystem.

The second study question explored the relationship between self-reported learning outcomes and AI personalisation. Correlation results suggest a moderately positive relationship ($r = 0.577$, $p < 0.001$). These results suggest that students who perceive their academic success to be on the rise, also perceive AI personalisation to be at work. Findings reflect existing global studies that suggest the learning gains associated with personalised, AI-mediated instruction relate to the systematic reviews by Lin et al. (2023) and Springer Nature (2025).

A closer look at how each item is performing in the AI-Driven Personalization subscale provides additional information. The most salient dimension of personalization to students is the flexibility dimension as discussed in the highest rated item, Q16, which refers to AI's ability to shape learning into a flexible and student-centered approach ($M = 4.21$). This aligns with a constructivist interpretation of the data: learners appreciate the flexibility of their learning experience, and to access material whenever they want, and AI technologies facilitate that by providing access to learning materials on-demand. For the more advanced measure of adaptive personalization in which AI systems construct detailed models of individual learner competencies (Q10, rating $M = 3.94$), the results indicate that this type of personalisation is not as consistently reported as the other types. The disconnect between flexible access and personalized depth could be due to the limited scope of AI tools employed and perhaps not to an adaptive learning system.

Interestingly, AI tool use is significantly correlated with time management (Q23, $M = 4.30$) and task confidence (Q24, $M = 4.22$) within the Learning Outcomes subscale. The two outcomes are very similar to Zimmerman's (2000) SRL constructs: performance and self-reflection in the SRL cycle. The biggest contribution that AI might be having in the classroom is not in delivering content, but in supporting the metacognitive and self-regulatory aspects of learning, and how students approach tasks with confidence and manage their study time. This is a theoretically sound result that AI applications, like a scheduling assistant or a feedback generator or study tracker, are appropriate tools to assist learners who are involved in self-regulation, even if they don't provide highly personalized information about learner profiles.

The last research question investigated if greater understanding of AI coupled with Personalization leads to better learning outcomes. The outcomes of the Pearson correlation tests showed that all of the pairs had positive, statistically significant correlations. AI Tool Awareness and Personalization correlated strongly ($r = 0.683$), and both pairs correlated moderately to learning outcomes ($r = 0.591$, $r = 0.577$, respectively).

AI Tool Awareness and Access and AI Driven personalization have the closest to a strong correlation and the most theoretical significance. This implies that some level of personalization is likely only to be achieved where learners have the understanding and self-directed use of AI tools, as opposed to it being provided to them. It is plausible to expect Personalized Learning to be experienced by learners who have greater resource literacy, a greater willingness to use the resources and an increased degree of comfort in doing so. In this respect, the variables of Awareness and Access are critical to personalizing learning. It is likely that even the most sophisticated and well-thought-out personalized learning systems will not achieve the desired effect if learners have neither the Awareness nor the confidence to use them.

While still moderately correlated, even those just below the “strong” level of correlation seem to provide evidence of practical/pedagogical relevance. It seems that both approaches, awareness-to-outcomes, and personalization-to-outcomes, are important in and of themselves, and interventions directed to both awareness and access, as well as to the degree of personalization, are likely to have visible impacts on students’ academic performance. This finding coincides with other empirical evidence. Gao (2023)’s meta-analysis on adaptive learning in STEM, among other things, reported comparable findings, and Lin et al. (2024) reported moderate to strong effect sizes for learning outcomes when AI tools were implemented in a variety of learning contexts.

Respondents were least in agreement with the statements ($M = 3.92$) in the 25-question survey when asked if they preferred AI-based training to classroom training. This item had the lowest score in the survey. While a few respondents noted a strong association between AI use and academic success, most respondents did not express a clear preference for AI use over classroom training. This reflects a practically significant gap as it suggests that students in Pakistani colleges view AI as a complementary instructional tool, rather than a preferred substitute, to training delivered by human instructors. This should inspire a transformation within colleges and the government away from reliance on AI, and focus on strengthening the existing quality of classroom training.

The sample consisted of urban universities of Lahore, which are among the better resourced universities of the country. The positive scores on awareness, access, and outcomes of the AI observed in this study may not be representative of universities in less urbanized or less well-resourced environments where there are infrastructure challenges and less reliable internet connections. This warning underscores the need to first tackle the digital divide in Pakistani universities, before achieving a fair integration of AI.

This best practice finding, coupled with literature reflecting the lack of faculty training (Naseer et al., 2025; Bulletin of Education and Research, 2024), suggests that there is an evident policy need to establish and implement structured frameworks for the capacity building of AI at the institutional level with support from HEC. The technical infrastructure is just as crucial as other aspects, as is faculty development, ethical guidelines, and data governance, as concerns regarding academic integrity and student data privacy are always cited as hurdles for confident AI adoption (Cotton et al., 2023; Springer, Journal of Academic Ethics, 2025).

Conclusion

To determine the influence of AI on fostering personalized learning at Pakistani universities, three elements were examined: Awareness of AI Tools and Access to Them, AI-Driven Personalization, and Learning Outcomes and Academic Performance. Findings from a survey of 155 students and faculty in six universities of Lahore revealed that all three elements positively correlated with one another. Both AI Tool Awareness and Access were found to have significant positive correlation with AI-Driven Personalization and Learning Outcomes and Academic Performance. AI-Driven Personalization was positively correlated with Learning Outcomes and Academic Performance, and was strongly correlated with AI Tool Awareness and Access. The research suggests that AI tools are being adopted more widely by university students and that their use is associated with positive impacts on motivation, critical thinking, self-efficacy, and time management. While students appreciate the ease and accessibility of AI tools, their deployment in many educational contexts lacks higher-order personalization learning features. The study found that a lack digital infrastructure, inadequate faculty skill training, and absence of policy frameworks regulating AI at the school and university level were barriers to utilization. Addressing these barriers will require the collaboration of the Higher Education Commission (HEC), university management, and faculty to provide resources, training and establish ethical frameworks for AI use. The study has an optimistic view of AI for personalizing learning in higher education institutions in Pakistan. It suggests that developing the appropriate institutional and technological infrastructure will assist in realizing that potential. The study supports future research on the drawbacks of AI in teaching and learning that is more representative and inclusive of urban and rural frameworks, and of diverse methodologies including the mixed-methods research approaches.

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