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Factors influencing artificial intelligence tools integration in teaching by Pakistani university lecturers

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ABSTRACT

This study examines the underlying factors influencing artificial intelligence (AI) integration in teaching. It incorporates technological pedagogical content knowledge (TPACK), technology acceptance model (TAM), and perceived organizational support (POS) grounded in organizational support theory (OST). A quantitative, cross-sectional survey design is employed to test six hypotheses. A questionnaire was distributed online to all lecturers at two universities in Peshawar, Pakistan. Of the 317 questionnaires emailed, 192 valid responses were collected. The results were analyzed using partial least squares structural equation modeling (PLS-SEM). The results confirm that TPACK significantly influences lecturers' perceived usefulness (PU) (β=0.52) and perceived ease of use (PEU) of AI (β=0.47), which in turn predict their behavioral intention (BI) to adopt AI. BI positively influences actual use (AU) (β=0.45), with POS strengthening this relationship (β=0.21). The findings underscore the critical role of individual competencies and institutional support in driving sustainable AI integration, offering theoretical contributions to extended TAM models and practical insights for achieving inclusive and quality education sustainable development goal 4 (SDG 4). The findings suggest that Pakistani higher education institutions should prioritize TPACK-focused professional development and strengthen organizational support mechanisms to enhance effective and sustained AI adoption among lecturers.

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1. INTRODUCTION

Artificial intelligence (AI) adoption in education has increased in recent years, particularly through chatbots, intelligent tutoring systems (ITS), and adaptive learning platforms [1]. Chatbots enable students to access personalized learning support and real-time homework guidance, which reduces teachers' workload and enhances student engagement [2]. Over several years of educational research and development, ITS have become capable of diagnosing misconceptions, tracking students' progress, and generating tailored feedback, thereby positively impacting students' learning achievement [3], [4]. In addition, some learning platforms use real-time learner data to adjust the difficulty level of instructional materials and organize content according to individual needs, enabling a personalized learning progression [5]. As a result, AI tools have shifted education from rigid traditional methods toward more individualized, equitable, and student-centered practices.

In higher education, AI presents both opportunities and challenges. AI tools support personalized learning by adapting teaching methods, materials, and pace, thereby enhancing student engagement and learning outcomes [6]. Moreover, these tools provide instructors with analytical feedback on learners' engagement, performance, and emotional indicators. This enables instructors to adapt their teaching methods and intervene more effectively in the learning process [7]. In addition, AI reduces administrative workload by automating institutional tasks, supporting assessment design, and providing timely feedback to students [8]. Despite these benefits, AI integration faces challenges such as the digital divide, particularly in underdeveloped areas where unequal infrastructure and access hinder equitable use [9]. Likewise, ethical concerns such as algorithmic bias and data privacy have increased in higher education and are intensified by limited regulations and vague administrative policies [10]. Finally, many lecturers remain underprepared due to limited competence, insufficient training, and a lack of institutional support for AI integration [11].

Recent studies indicate that lecturers' success in applying AI in higher education is related to factors such as attitudes toward technology, confidence, and pedagogical preparedness. One study reported that 84% of university lecturers expressed willingness to integrate AI tools, with this willingness significantly predicted by perceived pedagogical advantage, institutional support, positive attitude, and perceived usability [12]. In addition, a survey of 208 lecturers in Mexico indicated that readiness to use AI in teaching directly influences the classroom implementation, with positive correlations observed among generative AI (GenAI) acceptance, actual AI use in text generation, and intention to use AI in teaching [13]. Another study from China further highlights that although lecturers report using GenAI for formative assessment and curriculum adaptation, many continue to struggle with ethical concerns, assessment transformation, and professional development gaps. This suggests that readiness is uneven and that effective curricular integration depends on strengthening pedagogical competence [14]. Taken together, these findings demonstrate that lecturers' readiness, which encompasses attitudes, confidence, and structured training, is integral to moving from AI awareness to effective, sustainable classroom practice.

AI integration in Pakistani higher education is gradually expanding, driven by both institutional initiatives and academic inquiry, although deeper insights into lecturers' direct experiences remain limited. A descriptive survey of 160 social science lecturers at public universities in Multan reported generally positive perceptions of AI. Respondents emphasized the need for AI-focused teacher training, improved access to AI tools, ethical guidelines, and pilot projects to support classroom innovation [3]. Complementing this, a recent national-level study examining lecturers' use of GenAI tools such as ChatGPT, Gemini, and Meta AI revealed that ChatGPT is the most widely adopted tool among educators. It is primarily used for content creation, personalized instruction, and administrative activities, highlighting both enthusiasm and variability in usage across Pakistani universities [15]. An ethnographic strengths, weaknesses, opportunities, and threats (SWOT) analysis conducted in Pakistani university libraries identified key implementation barriers, including limited IT infrastructure, budgetary constraints, and a shortage of skilled staff, while librarians simultaneously recognized the potential of AI to enhance service delivery [16]. Viewed together, these studies provide an overview of AI adoption. They underscore the need for further research on local lecturers' hands-on experiences, pedagogical preparedness, and perceptions in order to develop context-specific strategies for sustainable AI integration in Pakistani universities.

In contrast to global higher education systems where AI readiness is increasingly supported by stable infrastructure, clear institutional policies, and structured professional development, Pakistani universities continue to face constraints related to uneven technological infrastructure, limited policy guidance, and insufficient AI-focused training. Moreover, studies worldwide underscore that factors such as digital literacy, institutional support, professional development, and personal motivation shape educators' acceptance of digital tools [17], [18]. Zamir and Thomas [19] reported similar results in the Pakistani context; however, it particularly emphasized localized shortcomings such as inequitable access, infrastructural constraints, and limited digital learning programs. Warsi and Rani [20] underscored that although the majority of educators have positive attitudes toward technology adoption, their readiness is impeded by limitations in policy support and technology learning programs. Taken together, these findings indicate the necessity of targeted capacity-building and policy-level initiatives to bridge the technology-readiness gap and promote inclusive technological transformation in education. To comprehend how teachers can be effectively equipped for this technological transformation, it is necessary to investigate technological pedagogical content knowledge (TPACK), technology acceptance model (TAM), and organizational support theory (OST) frameworks together because they explore competencies, motivational enablers, and institutional factors that determine effective technology integration.

The TPACK model, developed by Mishra and Koehler [21], was grounded in Shulman's [22] concept of pedagogical content knowledge (PCK) and expanded to include technology in order to conceptualize the knowledge teachers are required to possess for teaching effectively with technology. TPACK consists of seven interrelated components: i) content knowledge (CK), referring to subject matter understanding; ii) pedagogical knowledge (PK), referring to mastery of teaching methods and classroom techniques; iii) technological knowledge (TK), referring to knowledge of technological tools and their utilization; and four integrative constructs: iv) PCK; v) technological content knowledge (TCK); vi) technological pedagogical knowledge (TPK); and vii) the central intersection, TPACK, which denotes the multifaceted interplay of these three knowledge domains. The application of the TPACK model in studies of AI integration in education is particularly relevant, as it enables the evaluation of whether educators possess the competencies required to integrate AI tools into instructional design, classroom practice, and learner engagement.

Recent empirical research has extensively used TPACK to evaluate educators' readiness to use AI in teaching in the Pakistani higher education context. For instance, Alwakid *et al.* [23] revealed that lecturers with strong TPACK competencies were more adept at utilizing AI tools for teaching and achievement-based assessment. Correspondingly, Sahito and Almani [24] reported that lecturers who displayed a deeper knowledge of pedagogical strategies coupled with technological competencies were more likely to apply AI efficiently and ethically in their instruction. Aslam *et al.* [25] further underscored that teachers with enhanced TPACK profiles demonstrate higher levels of self-efficacy and digital skills, attributes closely associated with their confidence and potential to integrate AI tools into classroom practice. Taken together, these findings highlight the importance of TPACK in equipping educators with integrated knowledge required for effective AI-integrated pedagogy.

Subsequently, the TAM model conceptualized by Davis [26] complements the TPACK framework, as it addresses the role of psychological and behavioral aspects of technology adoption. TAM proposes that perceived usefulness (PU) and perceived ease of use (PEU), as its two core constructs, predict attitudes toward technology, which consequently impact the behavioral intention (BI) of technology adoption. Within educational contexts, TAM explains why certain lecturers use AI tools efficiently while others remain reluctant. Current studies have attempted to integrate TPACK and TAM to demonstrate that pedagogical and technological competencies shape the PU and PEU of users. As an example, Bervell *et al.* [27] explored a flipped classroom implementation in the Ghanaian higher education context and found that lecturers equipped with robust TPACK had higher PU and PEU regarding digital platforms, which subsequently led to positive BI to adopt teaching technologies. Likewise, Batool *et al.* [28] demonstrated that TPK—a subdomain of TPACK—significantly predicted both PU and PEU, validating the view that TPACK can act as a precursor to TAM variables. This integration offers a more holistic understanding of how educators' knowledge, perceptions, and attitudes converge to influence their actual technology integration practices.

While the integration of TPACK and TAM can enhance teachers' readiness to use AI in teaching, institutional support has been neglected as a critical mediating factor that determines whether this readiness translates into actual classroom implementation. For instance, OST, introduced by Eisenberger *et al.* [29], posits that when employees perceive that their organization values their contributions and cares about their well-being—a construct referred to as perceived organizational support (POS)—they develop a greater sense of obligation, commitment, and motivation toward organizational goals. POS encompasses several dimensions, including emotional support (feeling respected and valued), instrumental support (the provision of tools and resources), and informational support (communication and guidance), all of which shape how employees interpret their organizational environment.

In the context of education, POS becomes critical in shaping how teachers and lecturers adopt new technologies, including AI. For instance, Molefi *et al.* [30] emphasized the critical mediating role of school support and resources (SSR) in translating teachers' PU and PEU of AI into genuine BI to adopt it. Their study in Lesotho found that even when teachers valued AI, its adoption was contingent upon access to adequate infrastructure, training, and administrative backing. Similarly, Bakhadirov *et al.* [31] identified institutional policy and peer usage as key predictors of AI adoption in private schools, revealing that clear administrative frameworks and visible leadership support substantially boosted teacher uptake of AI tools. They argue that without such institutional backing, even technologically proficient or innovative educators may hesitate to integrate AI due to perceived risk or misalignment with school goals. In a comprehensive review, Celik [32] further reinforced this view by demonstrating that teachers often serve as both users and contributors in AI integration but struggle with adoption when institutional systems fail to provide adequate training, technical infrastructure, or involvement in AI tool development. Moreover, academic quality—linked to strong teaching practices, qualified staff, and sufficient resources—reflects an environment where lecturers are supported to innovate [33]. This aligns with OST, since strong academic culture fosters experimentation with new pedagogical tools such as AI. Together, these studies illustrate that institutional support—via policy, professional development, peer engagement, and resource provisioning—functions as an enabler or mediator for teachers' effective and sustained use of AI technologies.

While global research has acknowledged the significance of digital readiness, pedagogical competence, and institutional backing in AI adoption, few studies have examined these factors within a unified framework that captures both the cognitive (TPACK, TAM) and contextual (OST) determinants of AI integration in teaching, particularly in contexts such as Pakistan. Moreover, existing Pakistani studies primarily offer descriptive insights into general perceptions and usage trends, while lacking a robust structural model that explains how and why these factors interact to influence actual AI implementation in the classroom. Therefore, this study addresses this gap in the literature by providing a systematic and theory-grounded analysis based on context-specific data, contributing to the theoretical and practical development of higher education strategies for using sustainable AI. Additionally, by integrating TPACK, TAM, and OST, this study contributes significance to the field of education by offering a comprehensive and localized analysis into Pakistani university lecturers' AI adoption in their instructional practices. Given the rapid transformation of global education driven by AI, understanding the relationship between teachers' digital acceptance, capabilities, and institutional support becomes important, particularly in countries with infrastructural and training limitations. By offering empirical insights through a structural model, the study informs targeted interventions, professional development strategies, and policy decisions to enhance AI integration in higher education, directly supporting the goals of digital equity and quality education sustainable development goal 4 (SDG 4).

Based on the identified research gap and the significance of the study, the following research objectives have been formulated to examine the key factors influencing the integration of AI tools in teaching among Pakistani university lecturers:

- To examine the influence of lecturers' TPACK on their PU of AI in teaching.
- To examine the influence of lecturers' TPACK on their PEU of AI in teaching.
- To investigate the effect of PU of AI in teaching on lecturers' BI to use AI in teaching.
- To investigate the effect of PEU of AI in teaching on lecturers' BI to use AI in teaching.
- To examine the effect of lecturers' BI to use AI in teaching on their actual use (AU) of AI in teaching.
- To analyze the mediating role of POS in the relationship between lecturers' BI and their AU of AI in teaching.

In this study, the conceptual model integrating TPACK and TAM frameworks is well supported by empirical literature. Previous studies [34], [35] confirm that TPACK significantly influences both PU and PEU—key constructs of the TAM—by providing educators with the technological and pedagogical competencies necessary to perceive technology as both useful and manageable. These beliefs, in turn, strongly predict BI to use technology, as established by the original TAM proposed by Davis and further validated by [36], [37]. BI consistently precedes AU of AI in teaching, a relationship affirmed by numerous TAM-based studies [38]. Meanwhile, POS independently influences BI to use AI by shaping users' motivational context, and functions as a contextual enabler that complements the cognitive evaluation mechanisms of TAM [39]. Furthermore, the mediating role of BI in the relationship between POS and AU is conceptually aligned with organizational behavior theory, suggesting that when users feel institutionally supported, their motivational drive translates into action through intentional commitment [40]. This integrated framework synthesizes cognitive, motivational, and organizational perspectives, yielding a robust explanation of technology and AI adoption. Figure 1 depicts the conceptual model of the study, illustrating the relationship between different latent variables and their related hypotheses.

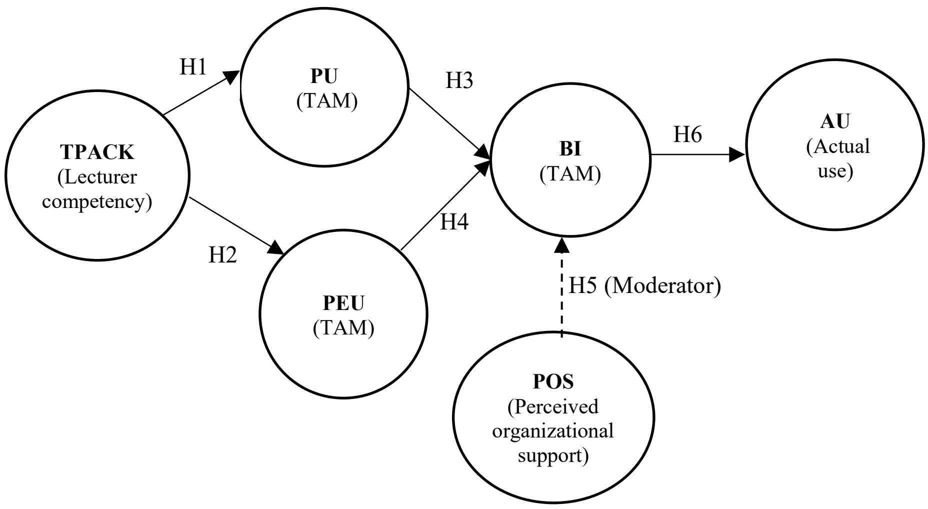

Figure 1. Conceptual model of the study

Based on the conceptual model, this study aims to test the following hypotheses:

- H1: TPACK positively predicts PU of AI in teaching among university lecturers.
- H2: TPACK positively predicts PEU of AI in teaching among university lecturers.
- H3: PU of AI in teaching positively predicts lecturers' BI to use AI in teaching.
- H4: PEU of AI in teaching positively predicts lecturers' BI to use AI in teaching.
- H5: Lecturers' BI to use AI in teaching positively predicts their AU in teaching.
- H6: POS mediates the relationship between lecturers' BI to use AI and their AU of AI in teaching.

2. METHOD

This study adopted a quantitative, cross-sectional survey design, collecting data from lecturers in two higher education institutions in Peshawar, Pakistan, at a single point in time. The two universities in Peshawar were selected based on accessibility and feasibility. Official permission was granted by the university administrations, enabling ethical and efficient access to lecturers for data collection. A cross-sectional design is widely recognized for allowing effective analysis of relationships among different variables in educational studies and enabling robust interpretation of survey data [41]. The total population (N=317) comprises 97 lecturers from University A and 220 from University B. Upon receiving formal approval letters from the universities' administrations, an online questionnaire with an informed consent form was distributed to their institutional emails, excluding the 12 participants involved in the pilot test. Over the course of three weeks, 204 responses were collected. However, after data screening, 192 valid responses were included in the analysis. The questionnaire comprised demographic information and four sections on a 7-point Likert scale to capture lecturers' TPACK, TAM, POS, and AU of AI in teaching.

To measure the lecturers' TPACK, an Intelligent-TPACK subscale developed by Celik [32] was adopted, comprising seven items that assess lecturers' integrated knowledge of using AI-driven tools effectively across pedagogical and subject-specific contexts. Celik's model [32] extends the traditional TPACK model developed by Mishra and Koehler [21] by adding AI-driven pedagogical applications and ethical considerations to offer a more contextualized and contemporary framework. Since the aim of this study is to examine the impact of TPACK on PU and PEU within the TAM framework, the Intelligent-TPACK construct is appropriate for representing TPACK within an AI-driven instructional context.

Moreover, the TAM construct, comprising 12 items, was adapted from the questionnaire developed by Montes and Elizondo-Garcia [13]. However, the Attitude and Subjective Norm variables were excluded. This decision is supported by prior research indicating that these variables do not always contribute significantly to the explanatory power of the model. For instance, Kemp *et al.* [42] suggested that Attitude may be omitted when PU and PEU sufficiently predict BI. Similarly, previous studies [43], [44] demonstrated that subjective norm often has a weak or inconsistent influence on technology adoption, particularly in voluntary settings. Therefore, their exclusion allows for a more parsimonious and focused model without compromising theoretical rigor. In addition, the questionnaire used to assess POS in this study was adapted from the validated scale developed by Eisenberger *et al.* [45]. It consists of 10 items designed to capture lecturers' perceptions of how much their universities value their contributions and care about integrating AI in their teaching purposes. Lastly, this study adapts the DigCompEdu check-in instrument (originally comprising 22 self-assessment items across six competence areas) into a tailored questionnaire focused on AU of AI by university lecturers in Pakistan. Cabero-Almenara *et al.* [46] confirms that the DigCompEdu check-in questionnaire is a valid and reliable instrument for assessing university lecturers' digital competence. In this study, 11 items were selected from the original framework, excluding 11 items that did not pertain to real in-class application of technology. Furthermore, the remaining items were revised to reflect AI integration, reworded to suit the pedagogical context of Pakistani university lecturers. For example, a generic DigCompEdu item such as "I use digital technologies to design assessments" was adapted to "I use AI tools to design or support student assessments." Similarly, an item originally phrased as "I use digital technologies to provide feedback to students" was revised to "I use AI-based tools to generate, support, or enhance feedback for students." The AU construct comprises the following dimensions: teaching and learning with AI, AI-supported assessment, empowering learners through AI, and supporting students' AI and digital literacy.

Afterward, the reliability and validity of the questionnaire were ensured through careful design and evaluation. Content validity was established by aligning the items with relevant theoretical frameworks and through an expert review process conducted prior to the pilot study. A panel of five experts participated in this review, including two senior academics in educational technology, two experts in educational psychology and research methodology, and one specialist in AI-supported pedagogy. All experts held doctoral degrees and had prior experience in technology-enhanced teaching and survey instrument development. The experts were asked to evaluate each item based on three criteria: i) relevance to the intended construct; ii) clarity and appropriateness of wording; and iii) alignment with the theoretical frameworks underpinning the study (TPACK, TAM, and POS). Items rated as unclear, redundant, or insufficiently representative were revised or removed based on consensus feedback. Minor wording adjustments were made to improve clarity and ensure contextual alignment with AI-integrated teaching practices. Reliability was assessed using Cronbach's alpha, with the pilot test results showing that all constructs achieved values above the acceptable threshold of 0.70, indicating internal consistency. The results confirmed that the questionnaire items were clear, consistent, and effective in capturing the intended constructs.

This study applies partial least squares structural equation modeling (PLS-SEM) to analyze the data and investigate the relationships among latent constructs. PLS-SEM is a component-based, predictive technique well-suited for estimating complex causal relationships with small to moderate sample sizes. Under such conditions, covariance-based SEM (CB-SEM) often encounters convergence issues or distributional assumptions [47]. Unlike CB-SEM, PLS-SEM does not require normally distributed data, handles both formative and reflective measurement models, and excels at estimating structurally complex models that would otherwise be untenable with smaller samples [48]. Moreover, recent educational technology studies have similarly used PLS-SEM to examine AI and technology adoption processes in authentic educational settings. For example, López-Costa *et al.* [49] used PLS-SEM to investigate factors predicting teachers' AI adoption in secondary education, demonstrating the method's appropriateness for modeling educator-level adoption mechanisms. In addition, a recent systematic review of educational technology research confirms the growing and methodologically accepted use of PLS-SEM in the field for evaluating structural relations among technology-related constructs [50].

According to Chin's "10 times rule" [51], the minimum required sample size should be 10 times the maximum number of predictors pointing to any latent variable. In this study, the BI to use AI construct has seven predictors, and the AU of AI construct includes 11 indicators, suggesting a minimum of 110 respondents [52]. Furthermore, the inverse square-root method proposed by Kock and Hadaya [53], assuming a minimum expected path coefficient of approximately 0.20 with 80% power and $\alpha = 0.05$, indicates a required sample size of around 155. Our actual sample of university lecturers exceeds both heuristic thresholds, thereby providing sufficient statistical power, stable estimates, and reliable model inference.

3. RESULTS AND DISCUSSION

In this section, the analysis of the data for each hypothesis is presented, followed by a discussion of the findings. As mentioned earlier, the sample size of the study consists of 192 university lecturers. Descriptive statistics were conducted using IBM SPSS Statistics version 26.0 (IBM Corp., USA) to examine the frequency distribution of sample data. Table 1 presents this frequency distribution. The sample reflects a diverse academic workforce, with variation in gender, age, experience, and qualifications. Moreover, the sample includes lecturers from diverse fields, including accounting, computer science, economics, English, hospitality management, IT, law, management, mathematics, Pakistani studies, physics, psychology, and Urdu language; however, Table 1 presents only the most frequently represented fields.

Table 1. Frequency distribution of sample characteristics

Gender	Age	Experience	Academic disciplines	Qualifications	Institutional affiliation
Male: 63.54% Female: 36.46%	Range: 26–57 Mean: 39.72	Range: 0.5–30 years Mean: 12.46 years	Psychology (10.94%), IT (9.90%), Economics (8.85%), Computer Science (8.85%), Law (4.69%)	Master's (58.85%), PhD (41.15%)	University A (35.94%), University B (64.06%)

3.1. Measurement model assessment

The current study employed a measurement model comprising TPACK, PEU, PU, BI, POS, and AU. The measurement model in PLS-SEM is fundamental for assessing the validity and reliability of the constructs under examination. This assessment involves several key measures, which are explained and examined in the following paragraphs. These analyzes collectively establish convergent validity, discriminant validity using the HTMT ratio, and the predictive relevance of the measurement model [54].

3.1.1. Indicator reliability

Individual indicator reliability was the primary criterion assessed in the measurement model evaluation. It is examined by analyzing the factor loadings (FL) of the indicators, which represent the strength of the relationship between the constructs and their indicators. Hair *et al.* [54] states that FL greater than 0.50 indicate acceptable reliability. As shown in Figure 2, all indicator loadings in this study exceeded 0.70, indicating strong reliability.

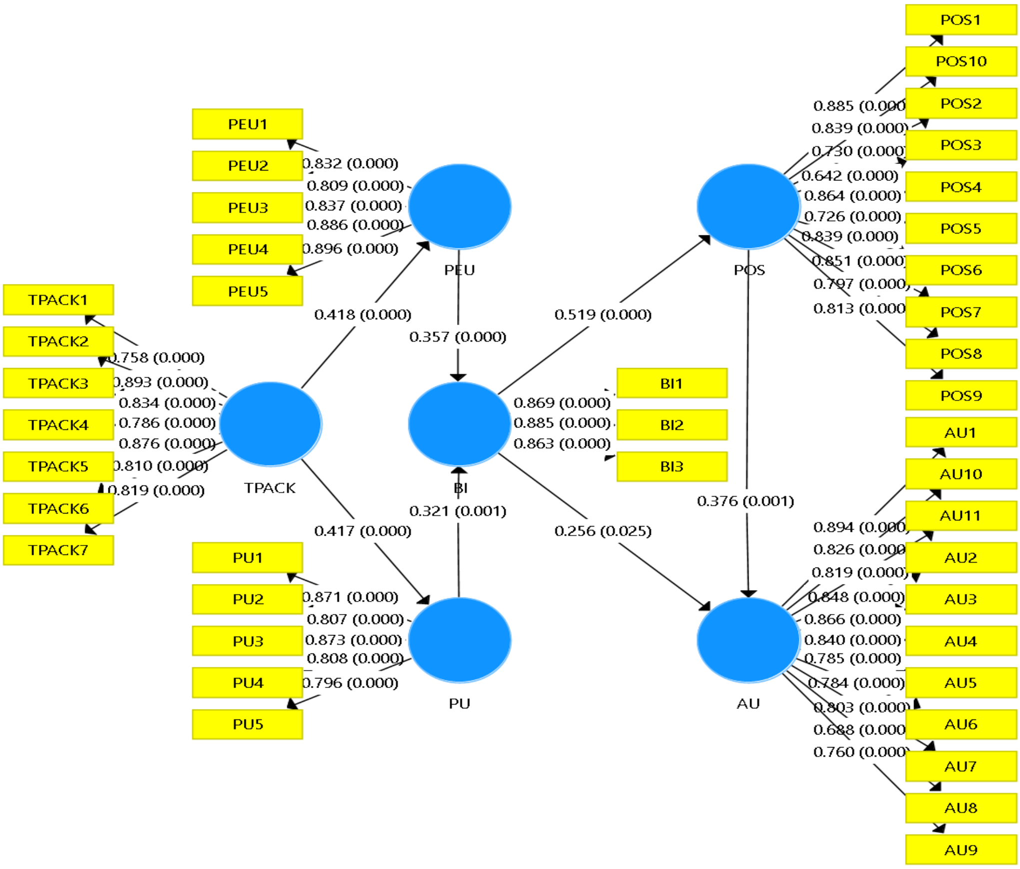

Figure 2. Statistical model of the study

3.1.2. Internal consistency

Internal consistency reliability represents the second criterion in the measurement model assessment. Cronbach's alpha is applied to evaluate the internal consistency of a measurement scale, referring to the extent to which a set of items are closely related as a group. Hair *et al.* [54] states that a Cronbach's alpha value greater than 0.70 indicates acceptable reliability. Our results meet this criterion for all constructs in the study, as seen in Table 2.

3.1.3. Composite reliability

Composite reliability (CR) represents the third criterion used to assess the internal consistency and stability of the constructs. For this reason, Cronbach's alpha alone is considered insufficient, and CR provides a more accurate estimation of true reliability [55]. For confirmatory purposes, the measurement model achieved CR values above the recommended threshold of 0.70, as presented in Table 2 [54].

Table 2. The measurement model validity, reliability and quality

Variable	CA	CR	AVE	H^2	HTMT					
					AU	BI	PEU	POS	PU	TPACK
AU	0.95	0.95	0.66	0.58						
BI	0.84	0.91	0.76	0.50	0.50					
PEU	0.91	0.93	0.73	0.58	0.65	0.64				
POS	0.94	0.95	0.64	0.56	0.53	0.57	0.63			
PU	0.89	0.92	0.69	0.53	0.58	0.63	0.71	0.55		
TPACK	0.92	0.94	0.68	0.57	0.43	0.54	0.45	0.36	0.46	

3.1.4. Convergent validity

Convergent validity, as the fourth criterion of the measurement model, refers to the extent to which items of the same construct are related to each other. It reflects the degree to which indicators of a construct are positively associated. To assess convergent validity, average variance extracted (AVE) is employed. Hair *et al.* [54] states that AVE values should exceed 0.50 to indicate adequate convergent validity. Table 2 shows that all AVE values are well above this threshold, thereby confirming the convergent validity of the constructs.

3.1.5. Discriminant validity

Discriminant validity refers to the extent to which a latent construct is distinct from other constructs in the measurement model [56]. As presented in Table 2, all HTMT values are below the recommended threshold of 0.85 [54]; therefore, it can be concluded that the constructs demonstrate adequate discriminant validity.

3.1.6. Predictive relevance (H^2)

Predictive relevance in this study is assessed through the measurement model by examining its predictive validity. Predictive validity refers to the model's ability to accurately predict future outcomes or behaviors based on the measured variables. It reflects the model's effectiveness in generating reliable predictions. The positive H^2 values (Table 2) for all constructs indicate the predictive relevance of the measurement model. This finding suggests that the indicators within each construct make a meaningful contribution to predicting their respective latent variables [57].

3.2. Structural model assessment

Upon completion of the assessment of validity and reliability in the measurement model, the structural model (inner model) was evaluated. This step aims to examine the relationships among endogenous and exogenous constructs within the PLS-SEM framework. Hypothesis testing was conducted using a bootstrapping technique with 2,000 subsamples. The results were evaluated based on path coefficients, t-statistics, and p-values.

H1: TPACK positively predicts PU of AI in teaching among university lecturers. As shown in Table 3, TPACK has a positive and significant effect on PU (β=.417, t=4.927, p<.001), with a moderate effect size (f^2=.211; [58]). Therefore, H1 is supported (Figure 2).

H2: TPACK positively predicts PEU of AI in teaching among university lecturers. Similarly, TPACK has a positive and significant effect on PEU (β=.418, t=4.332, p<.001), with a moderate effect size (f^2=.212). Therefore, H2 is also supported.

H3: PU of AI in teaching positively predicts lecturers' BI to use AI in teaching. PU has a positive and significant effect on BI (β=.321, t=3.195, p=.001), with a small effect size (f^2=.098; [58]). Therefore, H3 is also supported.

H4: PEU of AI in teaching positively predicts lecturers' BI to use AI in teaching. Likewise, PEU also has a positive and significant effect on BI (β=.357, t=4.471, p<.001), with a small effect size (f^2=.120), confirming that H4 is also supported.

H5: Lecturers' BI to use AI in teaching positively predicts their AU of AI in teaching. BI has a positive and significant effect size on AU (β=.256, t=2.245, p=.025), which means that H5 also receives obvious support.

H6: POS mediates the relationship between lecturers' BI to use AI and their AU of AI in teaching. BI also had a positive and significant effect on AU via POS (β=.195, t=3.089, p=.002), which meant that mediation by POS occurred. Therefore, H6 also receives obvious support.

Table 3. Path coefficients

Path	Estimate	T Statistics	P Values	f^2	Status
TPACK → PU	0.417	4.927	0.000	0.211	H1: Supported
TPACK → PEU	0.418	4.332	0.000	0.212	H2: Supported
PU → BI	0.321	3.195	0.001	0.098	H3: Supported
PEU → BI	0.357	4.471	0.000	0.120	H4: Supported
BI → AU	0.256	2.245	0.025	0.069	H5: Supported
BI → POS → AU	0.195	3.089	0.002	-	H6: Supported

3.3. Quality features of structural model

The coefficient of determination (R2) was used to evaluate the predictive precision of the structural model. R2 provides an estimate of the proportion of variance in the endogenous variables that can be explained by the exogenous variables. In the structural model, R2 values show the degree to which the exogenous variables together contribute to the variation in the endogenous constructs [54]. Greater R2 values indicate stronger explanatory power of the exogenous variables on the endogenous constructs [54]. As shown in Table 4, TPACK explained a variance of 17.5% in PEU and 17.4% in PU. BI explained 27% of the variance in POS, while BI and POS together explained 30.7% of the variance in AU.

By executing the blindfolding technique, cross-validated redundancy Q2 values were obtained for all endogenous variables. In this procedure, an omission interval of 7 was employed, signifying that every seventh data point was temporarily excluded from the analytical process. The Q2 value functions as a metric for assessing the predictive capacity of the structural model. It indicates the degree to which the model can estimate the endogenous variables based on the exogenous variables [59]. A positive Q2 value indicates that the model possesses predictive relevance and can precisely estimate the outcomes of interest, which was the case for this study as all Q2 values for the outcome variables were indeed positive (Table 4), implying small to moderate predictive relevance.

To further assess the robustness of the structural model, variance inflation factor (VIF) values were examined to detect potential collinearity issues, as high VIF values may indicate multicollinearity concerns [60]. The VIF values were all below the recommended threshold of 3.3 (Table 4), indicating the absence of collinearity issues. This confirms that the model is free from collinearity bias and demonstrates adequate structural validity.

Table 4. Quality features of the structural model

Outcome variable	R square	Q^2	VIF
AU	0.307	0.199	1.370
BI	0.378	0.273	1.704
PEU	0.175	0.121	1.000
POS	0.270	0.160	1.000
PU	0.174	0.111	1.000

3.4. Discussion

The main objective of this study is to examine the factors influencing AU of AI in teaching among Pakistani university lecturers using a PLS-SEM approach. The research model tested the relationship among TPACK, PU and PEU, BI to use AI, POS, and AU of AI in teaching. In this section, the findings are discussed in relation to previous studies. Additionally, this section underscores the unique contributions of this study to the Pakistani higher education context.

First, this research found that TPACK positively predicts PU (H1) and PEU (H2), consistent with prior research [34], [35]. TPACK, particularly "intelligent TPACK" when applied to AI tools, plays a key role in shaping university lecturers' views on AI in teaching. When lecturers possess a well-developed intelligent TPACK, reflecting their ability to integrate technology, pedagogy, and content with AI, they are more likely to perceive AI tools as both useful and easy to use. A strong foundation in intelligent TPACK enhances the perceived accessibility and usability of AI tools, thereby increasing PEU, while also enabling lecturers to recognize their potential to improve learning outcomes, thus enhancing PU. Consequently, lecturers with higher levels of intelligent TPACK are more likely to perceive AI tools as both intuitive to use and valuable for improving teaching practices.

Second, it was discovered that both PU (H3) and PEU (H4) positively predict BI to use AI in teaching separately. These two proven hypotheses are consistent with the studies by [36], [37]. According to Davis [26], PU, defined as the extent to which an individual believes that using a system enhances job performance, is a key determinant of BI to adopt technology. Lecturers who believe that AI can improve teaching effectiveness, streamline tasks, or enhance student engagement are more likely to demonstrate a stronger intention to use it. Similarly, based on Davis [26], PEU, defined as the extent to which a system is perceived as effortless to use, is a fundamental driver of BI. In university settings, lecturers who perceive AI tools as easy to understand and operate tend to exhibit stronger positive attitudes and a greater sense of control over their use, which in turn increases their intention to integrate AI into teaching. Consistent with the TAM, when university lecturers believe AI tools are both valuable in enhancing teaching effectiveness (PU) and easy to use (PEU), their intention to adopt these tools in their instruction is significantly strengthened. While these relationships are well-established in TAM literature, the present study extends them by demonstrating their relevance in the context of AI adoption in Pakistani higher education. Importantly, our findings suggest that for lecturers, perceiving AI as both practical (PU) and manageable (PEU) creates a strong motivational foundation for future adoption.

Third, the findings robustly support both H5 and H6. Lecturers' BI to use AI has a strong and positive effect on their AU of AI in teaching. This relationship is further strengthened by POS, which acts as a mediator that facilitates the translation of intention into AU. These findings are consistent with several studies [26], [38], which indicate that BI leads to the AU of AI, as well as Huang and Teo [39], which shows that POS influences the intention to use AI. Based on OST [29], when employees perceive that their organization values their contributions and cares about their well-being, they develop stronger commitment and motivation toward organizational goals. In this context, lecturers' BI to use AI predicts their AU, and this relationship is strengthened when institutions provide adequate support. This finding highlights the mediating role of POS in converting intention into actual implementation of AI in teaching. It also provides an important contribution to the literature. While the TAM explains intention, the present study demonstrates that POS functions as a critical enabling mechanism that transforms intention into actual adoption. In the Pakistani higher education context, where institutional readiness varies, the mediating role of POS is particularly significant.

3.5. Implications

3.5.1. Policy implications

The findings indicate that effective AI integration in higher education requires more than individual lecturer readiness. Policymakers and university leaders should establish clear institutional policies, ethical guidelines, and funding mechanisms to support AI use in teaching. Aligning AI integration strategies with national higher education priorities and SDG 4 can help ensure equitable and sustainable adoption across institutions.

3.5.2. Practical implications

Universities should implement structured professional development programs that strengthen lecturers' AI-related TPACK, as this directly enhances PU, PEU, and BI. In addition, providing strong POS, such as access to AI tools, technical assistance, and pedagogical guidance, is essential for translating lecturers' intentions into actual classroom use.

3.5.3. Implications for future research

Future studies should employ longitudinal or mixed-methods designs to examine changes in AI adoption over time and explore additional factors, such as digital self-efficacy, teaching experience, and disciplinary differences. Expanding the model to other institutional and national contexts would further enhance the generalizability of the findings.

3.6. Research limitations and recommendations

In this study, PLS-SEM provides a robust analysis of the data; however, it is limited to self-reported data collected through questionnaires, which may introduce bias due to participants' responses. Another limitation is the cross-sectional design, which restricts the ability to collect data from the same sample over time and to better understand changes in AI adoption in teaching. In addition, as the data were collected from a specific context (Peshawar), this may limit the generalizability of the findings to other contexts. Therefore, future studies are encouraged to incorporate observational methods or adopt experimental designs to avoid reliance solely on self-reported data. Furthermore, longitudinal designs are recommended to capture changes in lecturers' use of AI in teaching over time, along with including samples from other institutions or contexts. Finally, examining additional influencing factors, such as personality traits, teaching experience, and age, may enhance the model's comprehensiveness and applicability.

4. CONCLUSION

The PLS-SEM analysis robustly validates the measurement and structural models for AI integration in higher education teaching. The measurement model demonstrates strong reliability and validity, with FL>0.70, Cronbach's alpha and CR>0.7, AVE>0.5, HTMT ratios<0.85, and positive H2 values, confirming convergent, discriminant, and predictive validity. The structural model explains 17.4%–17.5% of the variance in PU and PEU, 27% of the variance in POS, and 30.7% of the variance in AU, with positive Q^2 values and VIF<3.3 indicating predictive relevance and no collinearity. Path coefficients (β=0.195–0.418, p<.05) support all hypotheses (H1–H6), with TPACK significantly predicting PU and PEU, which drive BI, and BI influencing AU directly and via POS mediation. These findings establish a statistically sound framework for understanding AI adoption in pedagogy.

This study provides empirical evidence supporting the extended TAM framework in the context of AI integration in higher education teaching. The findings demonstrate that intelligent TPACK significantly enhances lecturers' PU and PEU of AI tools, which in turn positively influence their BI to adopt AI.

In addition, BI directly influences lecturers' AU across teaching and learning, assessment, empowering students, and supporting their technological skills, with POS acting as a mediator in this relationship.

The findings have important implications for promoting AI integration in higher education. The strong influence of TPACK on PU and PEU, together with their effects on BI and AU, mediated by POS, highlights the need for targeted lecturer development programs to enhance TPACK, as well as institutional strategies to provide effective support systems. With the model explaining 30.7% of the variance in AU and demonstrating predictive relevance (positive Q^2 values), universities should prioritize training lecturers in AI-driven pedagogical skills and ensure that organizational resources, policies, and infrastructure support AI adoption. This approach can help bridge the gap between intention and AU, thereby enhancing teaching effectiveness and student outcomes in AI-integrated learning environments. In the Pakistani higher education context, these findings suggest that universities should strengthen institutional policies, infrastructure, and support systems to ensure that lecturers' intentions are effectively translated into actual AI use.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [US]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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