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Understanding AI Adoption In Education: The Role of Readiness, Confidence, And Social Influence Among Pakistani Students

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Abstract: The purpose of this study is to explore the key factors influencing Artificial Intelligence (AI) adoption in education among Pakistani university students. Specifically, it examines how AI Readiness (AIRD), AI Confidence (AICF), and Social Influence (SI) affect students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), and how these perceptions shape their Attitudes toward AI (ATT). The study also investigates the mediating roles of PEOU and PU. A quantitative research design was adopted using survey data collected from Pakistani students. Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied through Smart PLS 4 to assess both the measurement and structural models. The results reveal that AIRD, AICF, and SI significantly influence students' perceptions of ease of use, while AIRD and SI also positively impact perceived usefulness. However, AI confidence does not appear to shape perceived usefulness. Notably, perceived ease of use plays a substantial role in forming positive attitudes toward AI, while perceived usefulness does not have a direct effect. Mediation analysis further confirms that PEOU mediates the relationship between AIRD, AICF, SI, and ATT, whereas PU does not. The findings underscore the critical importance of usability over perceived benefits in shaping students' acceptance of AI technologies. In contexts where AI adoption is still emerging, ease of use appears to be the dominant factor influencing attitudes. Educators and policymakers should focus on enhancing students' readiness and confidence in using AI, promoting user-friendly tools, and leveraging social influence to drive adoption. These insights are crucial for designing inclusive strategies that support effective AI integration into educational environments.

Keywords: Artificial Intelligence Adoption, Education Technology, Pakistani Students, Perceived Ease of Use, Attitude, AI Readiness and Confidence, Social Influence

1. Introduction

The 21st century has witnessed exponential technological advancement, with Artificial Intelligence (AI) emerging as a transformative force across various sectors, particularly in industry. The education sector is similarly poised for significant transformation through the integration of AI-based tools and techniques (Wong et al., 2024). Globally, AI holds the potential to revolutionize conventional educational theories and practices at all levels of the education system. Its applications range from traditional classroom instruction and self-directed learning to administrative operations and the enhancement of learning experiences through personalization and interactivity (Holmes, 2019; Zawacki-Richter et al., 2019). AI-driven innovations, such as intelligent tutoring systems, automated assessment tools, predictive analytics of student performance, and AI-powered chatbots, are rapidly reshaping educational landscapes (M. M. Hussain et al., 2025).

In the context of Pakistan, a country facing persistent educational challenges such as low enrolment rates, insufficient infrastructure, teacher shortages, and stark regional disparities in educational quality, AI offers a promising avenue for systemic reform (Crompton & Traxler, 2018). Its potential to address longstanding issues includes enabling personalized learning, identifying student learning gaps through diagnostic tools, facilitating remote education in underserved regions, and enhancing teacher training and professional development (Bhimavarapu et al., 2024; Khurshid et al., 2024). Despite this promise, the adoption of AI in Pakistan's education sector remains nascent and is constrained by several critical barriers.

First, infrastructural limitations continue to impede progress. Many Pakistani educational institutions lack stable internet connectivity, access to adequate hardware, and consistent electricity supply, all of which are prerequisites for deploying AI-based educational technologies (S. Hussain et al., 2025). Second, there is a significant digital literacy gap among both students and educators, preventing effective integration of AI tools into pedagogical practices (Al Yakin et al., 2024). Third, socio-cultural resistance to technological change persists. Traditional teaching approaches, skepticism toward digital innovations, and culturally rooted attitudes toward education

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often hinder the acceptance of AI (Abulkassova et al., 2025). Furthermore, financial constraints are a major impediment. Many under-resourced institutions lack the budget to procure AI technologies, build digital infrastructure, or fund training initiatives for educators (Aijaz et al., 2024). Lastly, a lack of awareness and understanding among policymakers, educators, and stakeholders about the benefits and implementation of AI in education results in weak institutional support and hesitance to invest in AI integration (Syed et al., 2025).

Addressing these challenges requires a multi-dimensional strategy that includes infrastructural investment, development of digital competencies, promotion of AI literacy, culturally sensitive policymaking, and financial support mechanisms. However, to design and implement effective interventions, it is crucial first to understand the underlying factors that facilitate or hinder AI adoption among students, particularly in developing countries such as Pakistan.

To fill this gap, the present study investigates the impact of AI Readiness (AIRD), AI Confidence (AICF), and Social Influence (SI) on Pakistani students' perceptions and attitudes toward AI in education. It posits that students' readiness (i.e., their preparedness to adopt AI), their self-efficacy regarding AI (i.e., confidence in their ability to use AI tools), and the influence of significant others (e.g., peers, teachers, family) shape their perceptions of AI's ease of use and usefulness. These perceptions, in turn, inform their attitudes toward adopting AI in educational contexts.

The central research question of this study is: *What impact do AI readiness, confidence, and social influence have on Pakistani students' adoption of AI in education?* This inquiry is further explored through four sub-questions:

- How does AI readiness affect students' perceptions of the ease of use and usefulness of AI in education?
- To what extent does AI confidence shape students' attitudes toward AI in educational settings?
- What role does social influence play in shaping perceptions and attitudes toward AI?
- Do perceived ease of use (PEOU) and perceived usefulness (PU) mediate the relationships between AI readiness, confidence, social influence, and attitudes toward AI?

Accordingly, this study pursues three core objectives. First, it examines how students' technological preparedness, AI-related confidence, and social context influence their perceptions of AI accessibility and readiness in Pakistan's educational environment. Second, it assesses how these perceptions, particularly of ease of use and usefulness, impact students' attitudes toward AI adoption. Third, it evaluates whether perceived ease of use and perceived usefulness serve as mediators in the relationships between AIRD, AICF, SI, and students' overall attitudes toward AI.

This study offers both theoretical and practical contributions. Theoretically, it extends existing models of technology acceptance by introducing two AI-specific constructs, AI Readiness and AI Confidence, into the UTAUT and TAM frameworks. Drawing from the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), Social Cognitive Theory (Bandura, 1986), and the Theory of Reasoned Action/Planned Behavior (Ajzen, 1980; 1991), the study provides a multi-theoretical perspective on how psychological, social, and contextual factors influence technology acceptance behaviors.

Practically, the findings will offer evidence-based recommendations for educators, technology developers, and policymakers aiming to enhance AI integration in Pakistani educational institutions. A nuanced understanding of students' acceptance mechanisms can help stakeholders design effective, equitable, and culturally sensitive strategies to foster AI adoption. These strategies may include the development of AI literacy programs for both students and teachers, investment in digital infrastructure, creation of locally relevant and linguistically inclusive AI content, awareness campaigns to improve perceptions of AI, and targeted funding to support AI-based education initiatives.

By empirically identifying the factors that drive AI adoption among Pakistani students, this study bridges an important knowledge gap and contributes to the design of informed and impactful educational technology policies. Ultimately, it seeks to support the equitable and successful integration of AI in education, empowering Pakistani students to thrive in an increasingly digital and AI-driven world.

2. Literature Review

The integration of Artificial Intelligence (AI) into educational settings has garnered increasing scholarly attention, particularly due to its transformative potential to reshape learning paradigms. While technological innovations have long impacted education, AI tools, such as intelligent tutoring systems, predictive analytics, and automated feedback mechanisms, represent a leap forward in both personalization and scalability (Zawacki-Richter et al., 2019; Wong et al., 2024). However, the successful adoption of AI technologies depends not only on their availability but also on how users perceive and engage with them. The Technology Acceptance Model (TAM) and its extensions, including the Unified Theory of Acceptance and Use of Technology (UTAUT), offer robust theoretical foundations to examine such dynamics (Davis, 1989; Venkatesh et al., 2003).

The Technology Acceptance Model posits that two core constructs, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), drive user attitudes and subsequent behavioral intentions toward technology adoption. This framework has been widely validated across domains, including educational contexts (Abdullah & Ward, 2016). However, in developing countries such as Pakistan, additional factors such as infrastructure, sociocultural norms, and digital literacy play significant roles in shaping these perceptions (Crompton & Traxler, 2018). To address these contextual variables, this study incorporates constructs from Social Cognitive Theory (SCT) and the Theory of Planned Behavior (TPB), which emphasize the role of self-efficacy, subjective norms, and behavioral control in shaping attitudes and intentions (Bandura, 1986; Ajzen, 1991).

Recent literature has introduced the concept of AI Readiness (AIRD) as a multidimensional construct encompassing psychological, cognitive, and resource preparedness to engage with AI technologies (Pillai & Ramakrishnan, 2024). Empirical studies have shown that individuals who perceive themselves as ready are more likely to view AI tools as accessible and beneficial, thereby enhancing both PEOU and PU (Soares et al., 2025). In the context of this study, AI Readiness is expected to serve as a critical antecedent to students' ease-of-use and usefulness perceptions. Therefore, the following hypotheses are proposed:

H1: *AI Readiness (AIRD) will positively influence the Perceived Ease of Use (PEOU) of AI in education.*
H2: *AI Readiness (AIRD) will positively influence the Perceived Usefulness (PU) of AI in education.*

Similarly, AI Confidence (AICF), defined as students' domain-specific self-efficacy related to the use of AI tools, has emerged as an important construct. Rooted in SCT, self-efficacy has long been associated with persistence, reduced anxiety, and improved performance in technology use (Compeau & Higgins, 1995). In educational contexts, students who believe in their ability to use AI are more likely to find such tools easy and useful (Abdullah & Ward, 2016). Consequently, the following hypotheses are formulated:

H3: *AI Confidence (AICF) will positively influence the Perceived Ease of Use (PEOU) of AI in education.*
H4: *AI Confidence (AICF) will positively influence the Perceived Usefulness (PU) of AI in education.*

Social Influence (SI), as conceptualized in UTAUT and TPB, captures the extent to which individuals believe that important others expect or encourage them to use a particular technology (Venkatesh et al., 2003; Ajzen, 1991). In collectivist cultures like Pakistan, social norms and expectations significantly affect technology adoption decisions (Al Yakin et al., 2024). When instructors, peers, or family members advocate for AI tools, students may be more inclined to perceive them as both easy to use and useful. Thus, the following hypotheses are suggested:

H5: *Social Influence (SI) will positively affect the Perceived Ease of Use (PEOU) of AI in education.*
H6: *Social Influence (SI) will positively affect the Perceived Usefulness (PU) of AI in education.*

The TAM further posits that PEOU and PU are the most proximal predictors of Attitude Toward Technology (ATT), which in turn influences actual behavior. When students perceive AI tools as user-friendly and beneficial, they are more likely to form favorable attitudes towards their integration into education (Davis, 1989; Zawacki-Richter et al., 2019). Therefore, the study posits:

H7: *Perceived Ease of Use (PEOU) will positively influence Attitude Toward AI in education.*
H8: *Perceived Usefulness (PU) will positively influence Attitude Toward AI in education.*

While numerous studies have validated the direct effects of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) on attitudes and behavioral intentions toward technology adoption, their mediating roles remain underexplored, especially in the context of AI adoption in developing countries. According to Davis (1989), these constructs are central to the Technology Acceptance Model (TAM), which posits that users' behavioral intentions are shaped by how useful and user-friendly they perceive a system to be. However, recent studies have shown that PEOU and PU may also function as psychological mechanisms that explain how distal antecedents, such as technological readiness, confidence in AI, and social influence, translate into favorable or unfavorable attitudes (Abdullah & Ward, 2016; Compeau & Higgins, 1995). Despite this theoretical potential, empirical evidence on their mediating roles remains fragmented, with most studies focusing on direct paths while neglecting the underlying cognitive processes. Moreover, there is a lack of research that integrates these mediators within multi-theory models, such as those combining TAM with UTAUT, Social Cognitive Theory (SCT), or the Theory of Planned Behavior (TPB), particularly within the sociocultural context of Pakistan. This omission limits our understanding of how students' perceptions of AI ease and usefulness are shaped by their personal efficacy, readiness, and external social pressures. Therefore, this study addresses this gap by explicitly testing the mediating effects of PEOU and PU in the relationships between AI Readiness (AIRD), AI Confidence (AICF), Social Influence (SI), and Attitude Towards AI, thereby advancing the literature on AI acceptance in underrepresented educational environments.

In addition to these direct effects, PEOU and PU are also expected to mediate the relationships between AIRD, AICF, SI, and ATT. These mediating effects are crucial for understanding the underlying mechanisms through which individual readiness, confidence, and social context influence attitudes. Accordingly, the following mediation hypotheses are proposed:

H9: *Perceived Ease of Use (PEOU) will mediate the relationship between AI Readiness (AIRD) and Attitude Toward AI.*

H10: *Perceived Usefulness (PU) will mediate the relationship between AI Readiness (AIRD) and Attitude Toward AI.*

H11: *Perceived Ease of Use (PEOU) will mediate the relationship between AI Confidence (AICF) and Attitude Toward AI.*

H12: *Perceived Usefulness (PU) will mediate the relationship between AI Confidence (AICF) and Attitude Toward AI.*

H13: *Perceived Ease of Use (PEOU) will mediate the relationship between Social Influence (SI) and Attitude Toward AI.*

H14: *Perceived Usefulness (PU) will mediate the relationship between Social Influence (SI) and Attitude Toward AI.*

This integrated model, grounded in TAM, UTAUT, SCT, and TPB, thus provides a comprehensive framework for exploring AI adoption in education within the Pakistani context. It also addresses the gap in existing literature by focusing on students' attitudinal pathways to AI adoption, incorporating both internal and external influencing factors.

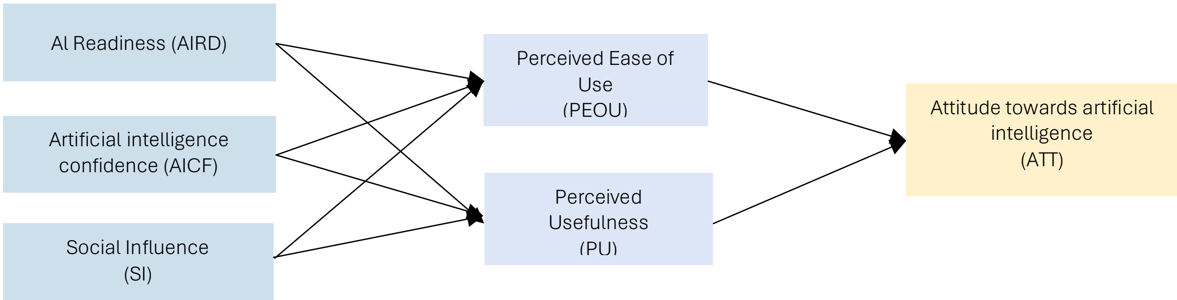

Figure 1: Research Model

3. Research Methodology

This study adopts a quantitative research design to empirically examine the theoretical relationships proposed in the integrated conceptual model. Data were collected from university students in Pakistan through a structured, self-administered questionnaire. The quantitative approach was chosen due to its suitability in testing causal relationships, quantifying associations between latent constructs, and enabling statistical generalization across a relevant population subset.

The target population comprised undergraduate and postgraduate students enrolled in various public and private universities across Pakistan. A non-probability purposive sampling technique was employed, focusing on students who were enrolled in technology-integrated academic programs and were presumed to have some familiarity with AI-based tools. This sampling strategy ensured the relevance and reliability of responses. A total of 402 valid responses were retained after data screening. The final sample included a diverse demographic composition: approximately 57% male and 43% female respondents, with the majority aged between 18 and 26 years. Most students were pursuing undergraduate degrees (66%), while the rest were enrolled in postgraduate programs.

The measurement instrument was adapted from previously validated scales to ensure construct validity and alignment with the study's conceptual model. All items were measured using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The constructs included AI Readiness (AIRD), AI Confidence (AICF), Social Influence (SI), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Attitude Toward AI (ATT). The AIRD items were derived from the multidimensional AI readiness framework proposed by Pillai and Ramakrishnan (2024), while AICF was measured using a domain-specific self-efficacy scale adapted from Compeau and Higgins (1995). The measures for PEOU and PU were adapted from the original TAM model (Davis, 1989), and SI was operationalized based on the constructs used in UTAUT (Venkatesh et al., 2003). ATT was assessed using items reflecting both cognitive and affective dimensions of attitude, as suggested in the technology acceptance literature (Ajzen, 1991; Abdullah & Ward, 2016).

To ensure content validity, the questionnaire was reviewed by three academic experts in educational technology and pilot-tested with 30 students. Minor revisions were made to improve clarity and contextual appropriateness before the final version was distributed. Ethical considerations, including informed consent and voluntary participation, were strictly observed throughout the data collection process.

In the initial phase of data analysis, IBM SPSS Statistics was employed to conduct descriptive statistics, assess internal consistency, and compute bivariate correlations. These preliminary analyses verified the data's reliability, distribution, and suitability for structural modeling.

To examine the hypothesized relationships among constructs and to evaluate mediating effects, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed using SmartPLS 4. PLS-SEM was chosen for its capacity to estimate complex models with multiple latent variables, its suitability for smaller sample sizes, and its robustness in handling non-normal data distributions. Moreover, PLS-SEM supports exploratory research and theory development, aligning with the objective of this study to extend and validate technology acceptance frameworks within the under-researched context of Pakistani higher education.

The study employed a purposive sampling strategy to recruit participants with a foundational understanding of Artificial Intelligence applications in education, thereby ensuring the relevance and validity of their responses. Data were collected from 426 university students across various higher education institutions in Pakistan, representing diverse academic backgrounds. The sample size was determined using G*Power 3.1 software, assuming a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power = 0.80, with a maximum of three predictors per endogenous construct, yielding a minimum requirement of 77 participants. Furthermore, this sample exceeds PLS-SEM guidelines, which recommend 200–300 participants for moderately complex models (Hair et al., 2021), thereby ensuring sufficient statistical power and generalizability.

3.1. Demographic Profile Of Respondents

The demographic characteristics of the 426 respondents are presented in Table 1. The sample consisted of students from diverse backgrounds in terms of gender, academic discipline, and level of study, which supports the generalizability of the findings within the Pakistani higher education context. Among the participants, 56.3% were male and 43.7% were female, indicating a relatively balanced gender distribution. The majority of respondents were undergraduate students (68.5%), followed by postgraduates (31.5%). Students came from various academic fields, with computer science (32.4%), engineering (27.9%), business studies (18.8%), and social sciences (20.9%) represented. Most participants were aged between 18 and 25 years (84.3%), suggesting that the sample predominantly consisted of young adult learners typically engaged in higher education. These demographic distributions reflect the diversity necessary for examining attitudes toward AI in education.

Table 1: Demographic Profile of the Respondents (N = 426)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	240	56.3%
	Female	186	43.7%
Age Group	18–20	168	39.4%
	21–25	191	44.9%
	Above 25	67	15.7%
Level of Study	Undergraduate	292	68.5%
	Postgraduate	134	31.5%
Field of Study	Computer Science	138	32.4%
	Engineering	119	27.9%
	Business Studies	80	18.8%
	Social Sciences	89	20.9%

Source: Calculated by the author

4. Results and Analysis

The empirical analysis in this study was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4 software (Sarstedt et al., 2022), following a two-step analytical approach. The first stage involved evaluating the measurement model to ensure the reliability and validity of the constructs, followed by an assessment of the structural model to test the hypothesized relationships. The data were collected from Pakistani university students to explore the factors influencing their attitudes toward the adoption of Artificial Intelligence (AI) in education.

4.1. Measurement Model Assessment

To evaluate the adequacy of the measurement model, the constructs were tested for internal consistency reliability, convergent validity, and discriminant validity. Internal consistency was assessed using Cronbach's alpha and composite reliability indices (ρ_a and ρ_c). Convergent validity was examined through the Average Variance Extracted (AVE) scores.

As presented in Table 2, all constructs demonstrated acceptable levels of reliability. Cronbach's alpha coefficients ranged from 0.747 (AI Readiness) to 0.878 (Social Influence), exceeding the minimum threshold of 0.70 recommended for exploratory research. Similarly, the composite reliability (ρ_c) values for all constructs ranged from 0.832 to 0.904, further confirming internal consistency. The AVE values for most constructs exceeded the conventional threshold of 0.50, ranging from 0.575 (AI Confidence) to 0.747 (Perceived Ease of Use). Although the AVE for AI Readiness was slightly below the cutoff (0.4989), its strong composite reliability supports its inclusion as a valid construct in the model (Hair Jr. et al., 2017).

Therefore, the findings from the measurement model assessment confirm that the items exhibit satisfactory reliability and convergent validity, providing a robust foundation for the subsequent structural model analysis.

Table 2: Construct Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
AI Readiness	0.7467	0.7603	0.8316	0.4989
AI confidence	0.8163	0.8295	0.8710	0.5754
Attitude towards AI	0.8290	0.8390	0.8976	0.7454
Perceived Ease of Use	0.8310	0.8357	0.8986	0.7471
Perceived Usefulness	0.7760	0.7799	0.8694	0.6894
Social Influence	0.8784	0.8855	0.9043	0.5437

Source: Calculated by the author

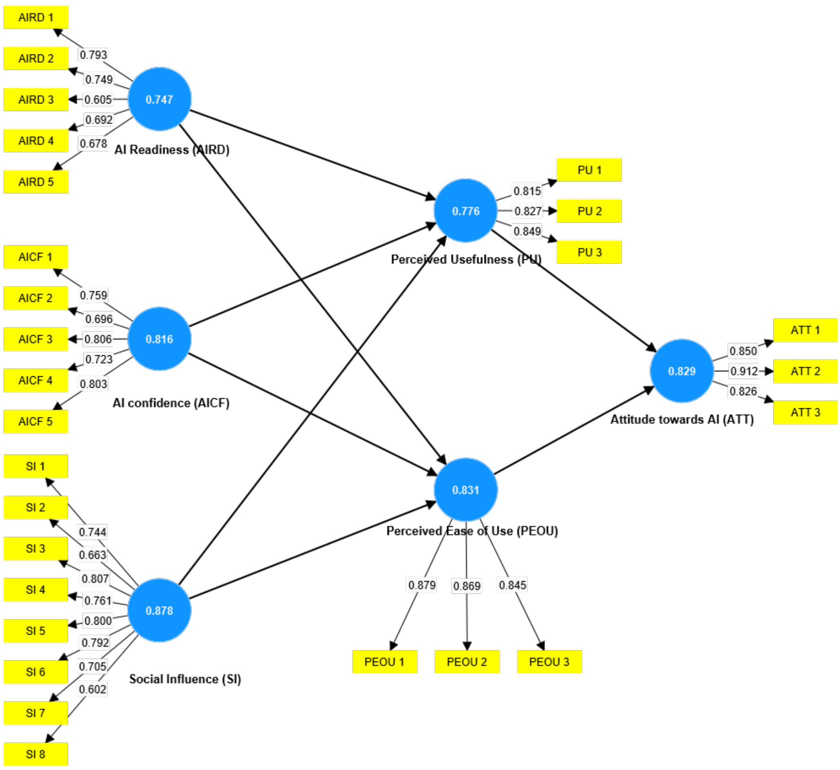

Figure 2: Structural equational model

4.2. Factor Loadings And Multicollinearity (VIF)

The factor loadings for all measurement items were assessed to ensure their adequacy in representing the respective latent constructs. According to the SmartPLS output, all observed variables loaded significantly on their respective constructs, with loadings exceeding the recommended threshold of 0.60. In most cases, loadings were above 0.70, indicating strong item reliability. For example, items measuring Attitude Toward AI (ATT1 = 0.850; ATT2 = 0.912; ATT3 = 0.826) and Perceived Ease of Use (PEOU1 = 0.879; PEOU2 = 0.869; PEOU3 = 0.845) exhibited particularly robust factor loadings, affirming the reliability and validity of the measurement model.

Multicollinearity was assessed using the Variance Inflation Factor (VIF) to ensure that there were no collinearity issues that could distort path estimates. In the outer model, all VIF values ranged between 1.229 and 2.493, well below the conservative threshold of 5.0. Similarly, VIF values for the inner (structural) model were also within acceptable limits, ranging from 1.677 to 2.993. These results confirm the absence of significant multicollinearity among the indicators and latent constructs, supporting the robustness of the model.

4.3. Discriminant Validity

To evaluate discriminant validity, the study employed two widely accepted methods: the Fornell–Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. According to the Fornell–Larcker criterion, the square root of the Average Variance Extracted (AVE) for each construct should exceed its correlations with other constructs. As shown in Table 3, this criterion was met for all constructs, confirming that each latent variable shares more variance with its own indicators than with those of other constructs.

The HTMT ratio was also examined to assess the degree of similarity between constructs. All HTMT values fell below the more liberal threshold of 0.90, and most were also below the more conservative threshold of 0.85, supporting discriminant validity. Although two relationships, AI Readiness and Perceived Usefulness (HTMT = 0.946) and AI Readiness and Social Influence (HTMT = 0.918), exceeded the 0.85 mark, these constructs remain conceptually distinct, and their discriminant validity is supported by the Fornell–Larcker results. This outcome is acceptable within the PLS-SEM framework, particularly when constructs are theoretically related (Hair Jr. et al., 2017).

Table 3: Fornell-Larcker Criterion

Construct	AI Readiness	AI confidence	Attitude towards AI	Perceived Ease of Use	Perceived Usefulness	Social Influence
AI Readiness	**0.706**					
AI confidence	0.596	**0.759**				
Attitude towards AI	0.474	0.396	**0.863**			
Perceived Ease of Use	0.630	0.618	0.616	**0.864**		
Perceived Usefulness	0.725	0.564	0.438	0.635	**0.830**	
Social Influence	0.757	0.695	0.559	0.713	0.728	**0.737**

Source: Calculated by the author. Note: Diagonal values (bold) represent the square root of AVE.

Table 4: Heterotrait Monotrait Ratio (HTMT)

Construct	AI Readiness	AI confidence	Attitude towards AI	Perceived Ease of Use	Perceived Usefulness	Social Influence
AI Readiness						
AI confidence	0.738					
Attitude towards AI	0.591	0.460				
Perceived Ease of Use	0.790	0.741	0.736			
Perceived Usefulness	0.946	0.678	0.532	0.780		
Social Influence	0.918	0.809	0.650	0.828	0.864	

Source: Calculated by the author

4.4. Measurement of Structural Model

Following validation of the measurement model, the structural model was examined to evaluate the hypothesized relationships. This phase involved analyzing path coefficients, the coefficient of determination (R^2), effect sizes (f^2), and model fit indices.

Table 5: Path Coefficients (Direct Effects)

H	Path	Original Sample (O)	T-Stat	P-Values	Supported?
H1	AI Readiness (AIRD) -> Perceived Ease of Use (PEOU)	0.177	2.82	0.005	Yes
H2	AI Readiness (AIRD) -> Perceived Usefulness (PU)	0.397	6.736	<0.001	Yes
H3	AI confidence (AICF) -> Perceived Ease of Use (PEOU)	0.212	4.048	<0.001	Yes
H4	AI confidence (AICF) -> Perceived Usefulness (PU)	0.058	1.053	0.293	No
H5	Social Influence (SI) -> Perceived Ease of Use (PEOU)	0.432	6.832	<0.001	Yes
H6	(SI)Social influence -> Perceived Usefulness (PU)	0.388	6.562	<0.001	Yes
H7	Perceived Ease of Use (PEOU) -> Attitude towards AI (ATT)	0.567	9.562	<0.001	Yes
H8	Perceived Usefulness (PU) -> Attitude towards AI (ATT)	0.077	1.164	0.245	No

Source: Calculated by the author

Table 5 presents the direct path coefficients along with their corresponding T-values and p-values, using a significance threshold of $p < 0.05$. The results indicate support for the majority of the hypothesized relationships. As shown in Figure 3 (not included here), the structural model provides an informative representation of the directional associations among the key constructs influencing attitudes toward AI in Pakistani higher education.

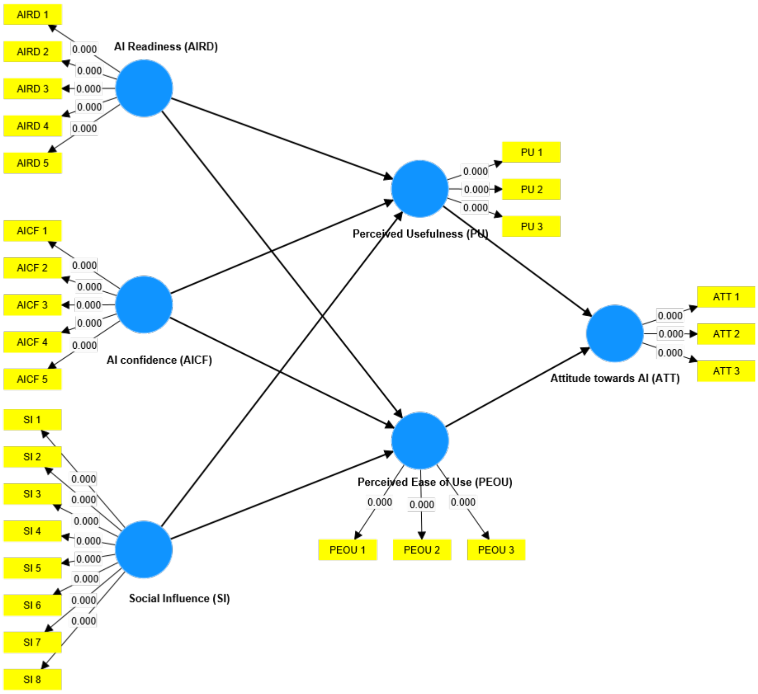

Figure 3: Bootstrap Modal

5.5. Hypothesis Testing Results

AI Readiness (AIRD) was found to have a statistically significant positive effect on Perceived Ease of Use (PEOU) ($\beta = 0.177$, $p = 0.005$). This implies that students who are more prepared to engage with AI technologies tend to perceive them as easier to use. Therefore, H1 is supported.

AI Readiness (AIRD) also demonstrated a strong and significant influence on Perceived Usefulness (PU) ($\beta = 0.397$, $p < 0.001$). This suggests that students with higher AI preparedness perceive AI as offering meaningful benefits to their educational experience. Therefore, H2 is supported.

Artificial Intelligence Confidence (AICF) had a significant positive impact on Perceived Ease of Use (PEOU) ($\beta = 0.212$, $p < 0.001$). Students who feel confident in their ability to work with AI technologies are more likely to find them easy to operate, highlighting the role of psychological assurance in user experience. Therefore, H3 is supported.

On the other hand, Artificial Intelligence Confidence (AICF) did not show a significant effect on Perceived Usefulness (PU) ($\beta = 0.058$, $p = 0.293$). Although students may feel capable of using AI, this confidence does not necessarily translate into perceiving AI as academically beneficial. Therefore, H4 is not supported.

Social Influence (SI) was shown to have a strong and significant effect on Perceived Ease of Use (PEOU) ($\beta = 0.432$, $p < 0.001$). This finding reflects that students' perceptions of AI usability are significantly shaped by the opinions and behaviors of peers, instructors, and social networks. Therefore, H5 is supported.

Furthermore, Social Influence (SI) also positively and significantly influenced Perceived Usefulness (PU) ($\beta = 0.388$, $p < 0.001$). Students appear to regard AI as more beneficial when its adoption is endorsed by their academic or social environment. Therefore, H6 is supported.

Perceived Ease of Use (PEOU) had a robust and statistically significant effect on students' Attitudes Toward AI (ATT) ($\beta = 0.567$, $p < 0.001$). This indicates that students who find AI systems accessible and manageable are more inclined to hold favorable attitudes toward their implementation in education. Therefore, H7 is supported.

In contrast, Perceived Usefulness (PU) did not have a statistically significant effect on Attitude Toward AI (ATT) ($\beta = 0.077$, $p = 0.245$). Despite theoretical expectations, students' beliefs about the benefits of AI do not directly translate into positive attitudes unless moderated or complemented by other variables. Therefore, H8 is not supported.

4.5. R-Squared Values

Table 6 presents the R-squared values for the endogenous constructs, which reflect the model's explanatory power. Specifically, the R-squared values indicate the proportion of variance in each dependent variable that is accounted for by its respective predictors. These values are crucial for evaluating how well the theoretical framework explains the targeted behavioral outcomes related to AI adoption in education.

The results show that AI Readiness, AI Confidence, and Social Influence collectively explain 55.1% of the variance in Perceived Ease of Use (PEOU), as indicated by an R^2 value of 0.551. This represents a substantial level of explanatory power, suggesting that these predictors are significant contributors to students' perceptions of ease in using AI technologies.

Similarly, the same three antecedents account for 60.3% of the variance in Perceived Usefulness (PU) (R^2 = 0.603). This high R-squared value demonstrates that the model effectively captures the determinants of how useful students perceive AI tools to be within their academic environment.

In contrast, the attitude toward AI (ATT), which is predicted by Perceived Ease of Use and Perceived Usefulness, exhibits an R-squared value of 0.383. This implies that 38.3% of the variance in students' attitudes can be attributed to these two constructs. While not as high as the values for PEOU or PU, this level of explained variance still represents meaningful predictive power in the context of attitudinal research.

To complement the R-squared values, effect size (f^2) was assessed to evaluate the relative impact of each independent variable on its respective dependent variable. According to Cohen's (1988) guidelines, f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effect sizes, respectively. These values help to determine the strength of each predictor within the structural model beyond what is indicated by significance testing alone. Table 6 reports the f^2 statistics, which are further discussed in the following section.

Table 6: R-squared Values

Endogenous Construct	R-squared	R-squared Adjusted
Attitude towards AI (ATT)	0.383	0.379
Perceived Ease of Use (PEOU)	0.551	0.547
Perceived Usefulness (PU)	0.603	0.599

Source: Calculated by the author

Table 7 presents the f-squared (f^2) statistics, which estimate the magnitude of the effect that each exogenous variable has on the corresponding endogenous constructs. According to Cohen's (1988) thresholds, effect sizes can be categorized as small ($f^2 \geq 0.02$), medium ($f^2 \geq 0.15$), or large ($f^2 \geq 0.35$). These values provide an indication of each predictor's substantive impact beyond statistical significance. The analysis reveals that Perceived Ease of Use (PEOU) had a large effect on Attitude toward AI (ATT), with an f^2 value of 0.310. This suggests that students' perceptions of the ease of using AI technologies strongly shape their overall attitudes toward adopting AI in education.

AI Readiness (AIRD) exhibited a medium effect on Perceived Usefulness (PU) (f^2 = 0.165), indicating that students' preparedness and familiarity with AI tools considerably enhance their perception of AI's usefulness in academic settings. Meanwhile, the effect of Social Influence (SI) on both PEOU (f^2 = 0.139) and PU (f^2 = 0.126) was also in the medium range, underscoring the importance of peer, social, and institutional endorsement in shaping students' ease-of-use judgments and perceived value of AI. In contrast, AIRD and AI Confidence (AICF) exerted small effects on PEOU (f^2 = 0.029 and 0.051, respectively), suggesting that while these predictors are statistically significant, their practical impact on students' perceived ease of AI use is modest.

Furthermore, the influence of AICF on PU (f^2 = 0.004) and PU on ATT (f^2 = 0.006) was found to be negligible, which is consistent with the earlier hypothesis testing results where these paths were not statistically significant. These findings imply that confidence in AI skills alone may not be sufficient to enhance perceptions of usefulness, nor does usefulness alone appear to strongly alter attitudes toward AI without the mediating role of ease of use. Overall, the effect size analysis provides nuanced insights into the structural model by highlighting which constructs have the greatest substantive impact on AI adoption attitudes among Pakistani university students.

Table 7: f-squared (Effect Size)

Path	f-squared	Effect Size
AI Readiness (AIRD) -> Perceived Ease of Use (PEOU)	0.029	Small
AI Readiness (AIRD) -> Perceived Usefulness (PU)	0.165	Medium
AI confidence (AICF) -> Perceived Ease of Use (PEOU)	0.051	Small
AI confidence (AICF) -> Perceived Usefulness (PU)	0.004	No effect
Perceived Ease of Use (PEOU) -> Attitude towards AI (ATT)	0.310	Large
Perceived Usefulness (PU) -> Attitude towards AI (ATT)	0.006	No effect
Social Influence (SI) -> Perceived Ease of Use (PEOU)	0.139	Medium
Social Influence (SI) -> Perceived Usefulness (PU)	0.126	Medium

Source: Calculated by the author

4.7. Mediation Analysis (Indirect Effects)

Table 8 presents the specific indirect effects evaluated through mediation hypotheses H9 to H14. These indirect paths assess whether Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) act as mediating variables between the exogenous constructs, AI Readiness (AIRD), AI Confidence (AICF), and Social Influence (SI), and the endogenous outcome, Attitude toward AI (ATT).

Table 8: Specific Indirect Effects

Hypothesis	Path	Original Sample (O)	T Statistics	P Values	Supported?
H9	AI Readiness (AIRD) → PEOU → Attitude towards AI (ATT)	0.100	2.717	0.007	Yes
H10	AI Readiness (AIRD) → PU → Attitude towards AI (ATT)	0.031	1.113	0.266	No
H11	AI Confidence (AICF) → PEOU → Attitude towards AI (ATT)	0.120	3.636	<0.001	Yes
H12	AI Confidence (AICF) → PU → Attitude towards AI (ATT)	0.004	0.657	0.511	No
H13	Social Influence (SI) → PEOU → Attitude towards AI (ATT)	0.245	5.251	<0.001	Yes
H14	Social Influence (SI) → PU → Attitude towards AI (ATT)	0.030	1.131	0.258	No

Source: Calculated by the author

4.8. Interpretation Of Mediation Results

AI Readiness (AIRD) demonstrated a significant indirect effect on Attitude toward AI through Perceived Ease of Use ($\beta = 0.100$, $p = 0.007$), thereby supporting H9. This suggests that students who are more familiar and prepared to use AI technologies tend to develop more favorable attitudes, primarily because they perceive these tools as easier to use. However, when Perceived Usefulness served as the mediating variable (H10), the indirect effect was not statistically significant ($\beta = 0.031$, $p = 0.266$), indicating that usefulness alone does not mediate the AIRD–ATT relationship.

Similarly, AI Confidence (AICF) had a significant mediated effect through Perceived Ease of Use ($\beta = 0.120$, $p < 0.001$), confirming H11. This implies that students confident in their AI-related abilities develop favorable attitudes because they find such tools easier to navigate. However, the mediation through Perceived Usefulness (H12) was not significant ($\beta = 0.004$, $p = 0.511$), further reinforcing that usefulness does not play a mediating role in this path.

In the case of Social Influence (SI), the mediation effect via Perceived Ease of Use was highly significant ($\beta = 0.245$, $p < 0.001$), validating H13. This underscores the critical role of peer and institutional encouragement in making AI tools seem more accessible, which in turn strengthens students' attitudes toward adopting them. In contrast, the indirect effect through Perceived Usefulness (H14) was not supported ($\beta = 0.030$, $p = 0.258$).

Taken together, these findings highlight an important distinction: although Perceived Usefulness is directly influenced by AIRD, AICF, and SI (as shown in the structural model results), it does not significantly mediate their effects on Attitude toward AI. This is consistent with the earlier finding that the direct path from PU to ATT was also not significant. In contrast, Perceived Ease of Use consistently and significantly mediates the relationships between all three antecedent variables and students' attitudes toward AI.

Therefore, these results suggest that students' attitudes are more strongly shaped by how user-friendly they perceive AI to be, rather than by how useful they believe it is. The ease with which students can interact with AI technologies appears to be the most influential mechanism through which readiness, confidence, and social encouragement translate into favorable attitudes toward educational AI.

4.9. Total Effects

Table 9 presents the total effects of the exogenous constructs on the endogenous constructs. These total effects reflect the combined impact of both direct and indirect pathways, thereby offering a comprehensive understanding of each construct's overall influence within the structural model.

The total effects analysis underscores the centrality of Social Influence and AI Readiness in shaping students' perceptions and attitudes toward AI. Specifically, Social Influence exerted a strong cumulative effect on Attitude toward AI ($\beta = 0.275$, $p < 0.001$), mediated primarily through Perceived Ease of Use and Perceived Usefulness. Similarly, AI Readiness exhibited a total effect of $\beta = 0.131$ ($p = 0.002$) on Attitude toward AI, further reinforcing its role as a foundational factor in students' acceptance and evaluation of AI tools.

AI Confidence also emerged as a meaningful predictor, with a significant total effect on Attitude toward AI ($\beta = 0.125$, $p < 0.001$), despite its non-significant relationship with Perceived Usefulness in the direct and indirect models. Among the mediators, Perceived Ease of Use stood out with the highest total effect on Attitude toward AI ($\beta = 0.567$, $p < 0.001$), while Perceived Usefulness, though theoretically relevant, showed no statistically significant total effect on attitudes ($\beta = 0.077$, $p = 0.245$). This again confirms the earlier finding that perceived ease is a more dominant driver of students' positive evaluation of AI in education than perceived usefulness.

Table 9: Total Effects

Path	Original Sample (O)	T Statistics	P Values
AI Readiness (AIRD) → Attitude towards AI (ATT)	0.131	3.167	0.002
AI Readiness (AIRD) → Perceived Ease of Use (PEOU)	0.177	2.820	0.005
AI Readiness (AIRD) → Perceived Usefulness (PU)	0.397	6.736	<0.001
AI Confidence (AICF) → Attitude towards AI (ATT)	0.125	3.819	<0.001
AI Confidence (AICF) → Perceived Ease of Use (PEOU)	0.212	4.048	<0.001
AI Confidence (AICF) → Perceived Usefulness (PU)	0.058	1.053	0.293
Perceived Ease of Use (PEOU) → Attitude towards AI (ATT)	0.567	9.562	<0.001
Perceived Usefulness (PU) → Attitude towards AI (ATT)	0.077	1.164	0.245
Social Influence (SI) → Attitude towards AI (ATT)	0.275	6.263	<0.001
Social Influence (SI) → Perceived Ease of Use (PEOU)	0.432	6.832	<0.001
Social Influence (SI) → Perceived Usefulness (PU)	0.388	6.562	<0.001

Source: Calculated by the author

4.10. Model Fit

To assess the overall fit of the structural model, the Standardized Root Mean Square Residual (SRMR) was used as the key indicator. The SRMR value was 0.0711, which falls below the recommended cut-off threshold of 0.08 (Hu & Bentler, 1999). This value indicates an acceptable level of discrepancy between the observed and predicted correlations, thus confirming that the model demonstrates a satisfactory fit with the empirical data obtained from Pakistani university students.

The good model fit, combined with the significant total and indirect effects discussed above, lends strong support to the robustness of the proposed conceptual framework. It affirms the validity of the underlying theoretical structure and its applicability in examining AI adoption within the educational context of a developing country.

5. Discussion

This study aimed to examine how AI Readiness (AIRD), AI Confidence (AICF), and Social Influence (SI) shape university students' perceptions of AI technologies in education through the mediating roles of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), ultimately influencing Attitude towards AI (ATT). The findings provide important insights into the cognitive and social mechanisms through which emerging technologies, particularly artificial intelligence, are adopted in the educational context of Pakistani universities.

With respect to AI Readiness, both hypotheses (H1 and H2) were supported. AIRD emerged as a significant determinant of both PEOU and PU. Students who perceived themselves as adequately prepared in AI-related skills were more likely to report that AI tools were easy to use and beneficial for their learning. This supports previous assertions that foundational digital literacy is critical for technology adoption (Cao et al., 2025). Moreover, the medium effect size observed between AIRD and PU indicates that increasing students' readiness can substantially enhance their perceived value of AI in education, reinforcing the importance of early-stage AI training and exposure.

The analysis of AI Confidence (AICF) yielded a more nuanced interpretation. While AICF significantly influenced PEOU (H3 supported), it did not significantly affect PU (H4 not supported). This suggests that students with higher confidence in their AI capabilities find the tools easier to use, which aligns with self-efficacy theory in Social Cognitive Theory (Bandura, 1986). However, confidence alone does not necessarily lead students to view AI as useful. This highlights a critical gap: even if students feel technically capable, they may not recognize the educational value of AI unless its usefulness is explicitly demonstrated through meaningful applications or measurable learning outcomes.

Regarding Social Influence, both hypotheses (H5 and H6) were supported. Students who perceived that their peers, instructors, or social networks endorsed the use of AI were more likely to find AI tools both easy to use and useful. This finding emphasizes the strong role of normative and informational influence in shaping perceptions of educational technology, consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT) and Theory of Planned Behavior (Ajzen, 1991; Venkatesh et al., 2003).

Interestingly, only PEOU (H7) had a statistically significant effect on ATT, whereas PU (H8) did not. This deviates from the traditional Technology Acceptance Model (TAM) which positions both constructs as key antecedents of attitude (Davis, 1989). Several possible explanations arise. First, in resource-constrained environments such as Pakistan, students may prioritize usability over perceived long-term benefits due to practical limitations. Second, as AI is still relatively novel in educational settings, students may focus more on immediate usability before appreciating its broader educational utility. Third, the operationalization of PU in the questionnaire may have been less sensitive in capturing its intended constructs compared to PEOU. This divergence also contrasts with findings from Geddam et al. (2024), who reported significant effects for both PU and PEOU on behavioral intention to use AI tools.

Mediation analysis further confirmed the centrality of PEOU in shaping attitudes. Specifically, AIRD, AICF, and SI all demonstrated significant indirect effects on ATT through PEOU (supporting H9, H11, and H13). This indicates that readiness, confidence, and peer influence improve students' attitudes primarily by enhancing their perception of AI's ease of use. In contrast, PU did not serve as a significant mediator in any of the tested pathways (H10, H12, and H14 not supported). This pattern suggests that although students may recognize AI's usefulness, it is the perception of simplicity and usability that ultimately drives their attitudinal acceptance.

The structural model explained a substantial proportion of variance in PEOU (55.1%) and PU (60.3%), but only a moderate portion in ATT (38.3%). This implies that while AIRD, AICF, and SI are effective in explaining students' perceptions of usability and usefulness, other variables, such as emotional readiness, institutional support, or prior experience, may also influence overall attitudes toward AI and should be considered in future research.

Overall, these findings partially align with the extant literature on technology adoption, particularly TAM and UTAUT models, which underscore the dual importance of PU and PEOU. However, the stronger influence of PEOU observed here may reflect contextual realities in developing countries, where basic access and functional ease are prioritized over potential utility. Similar patterns have been documented in other low-resource settings such as Bangladesh, where studies have highlighted the primacy of usability and attitude in shaping technology adoption among students.

Furthermore, this study reinforces the relevance of social influence as a determinant of educational technology adoption. The results suggest that interventions aimed at increasing AI acceptance in higher education should focus not only on building technical competence and demonstrating usefulness but also on enhancing peer and institutional encouragement while simplifying user experience. As AI continues to evolve in the educational landscape, user-centered design, peer support mechanisms, and foundational training will likely be key levers in accelerating adoption among students in emerging economies.

6. Implications

Theoretically, this study contributes to the literature on educational technology adoption by refining the understanding of mediating mechanisms within the TAM framework. Specifically, it underscores the dominant role of PEOU over PU in early-stage adoption of AI in low-resource contexts. The differentiation between AI readiness and AI confidence also adds granularity to existing models, suggesting that preparedness and self-efficacy, though related, have distinct pathways in shaping user perceptions.

From a practical standpoint, the findings highlight several areas for strategic intervention. First, universities and educational policymakers should invest in foundational AI training programs that enhance students' readiness and self-confidence. Interactive workshops, simulation-based learning, and integration of AI tools in existing coursework can serve as effective approaches to foster preparedness.

Second, the role of social influence suggests that peer-led awareness campaigns, faculty endorsement, and AI ambassador programs may be effective in shaping positive student perceptions. Encouraging student-to-student advocacy can accelerate cultural acceptance of AI technologies in academic settings.

Third, given the centrality of perceived ease of use, technology developers and platform designers must prioritize intuitive interfaces and accessible design. Tools that are overly complex or require advanced technical knowledge are less likely to gain traction, especially in environments with limited digital infrastructure.

Finally, to strengthen future adoption pathways, it is recommended that institutions evaluate students' evolving attitudes through longitudinal assessments and incorporate feedback loops into AI integration strategies. These insights can guide more adaptive and responsive policy and design decisions that align with student needs.

Together, these implications support the creation of an inclusive, supportive ecosystem for AI integration in education, one that is not only technologically equipped but also pedagogically and socially aligned with student realities in developing contexts.

7. Conclusion

This study investigated the role of AI Readiness (AIRD), AI Confidence (AICF), and Social Influence (SI) in shaping students' attitudes toward Artificial Intelligence (AI) in education, using Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) as mediating variables. Drawing on an integrated theoretical framework rooted in TAM, UTAUT, and SCT, the findings reveal that AIRD and SI significantly influence both PEOU and PU, whereas AICF primarily affects PEOU. Notably, PEOU emerged as a stronger predictor of students' attitudes toward AI than PU, which did not show a direct significant relationship with attitude.

Moreover, the mediation analysis highlighted that PEOU served as a consistent mediator between the antecedent variables (AIRD, AICF, SI) and attitude, while PU failed to demonstrate a significant mediating effect. This suggests that, in the context of Pakistani higher education, ease of use is more immediately influential than perceived usefulness in shaping favorable attitudes toward AI adoption.

The overall model explained substantial variance in PEOU (55.1%) and PU (60.3%), though the explained variance in attitude (38.3%) indicates that additional factors may also influence students' overall disposition toward AI. These findings emphasize the need to better understand user-centric and context-specific elements when introducing emerging technologies in developing educational systems.

8. Limitations and Future Research Directions

This study is subject to several limitations that should guide the interpretation and generalizability of its findings. First, the cross-sectional design limits causal inference; future longitudinal research is needed to assess changes in AI adoption over time. Second, the use of self-reported data may introduce bias, which could be mitigated by incorporating objective behavioral or performance-based metrics in future studies. Third, the sample was restricted to Pakistani university students, limiting generalizability to other cultural or educational contexts. Finally, while the measurement model demonstrated acceptable reliability, further refinement of scales through broader validation is recommended.

Future research should explore these relationships across diverse populations using comparative and longitudinal designs. Qualitative methods can provide deeper insights into students' lived experiences with AI. Additionally, future studies could examine the effects of institutional support, curriculum integration, and specific AI tools on adoption outcomes. Moderating variables such as gender, academic discipline, and digital literacy should also be investigated to capture nuanced adoption patterns. These efforts will help develop more inclusive and contextually grounded strategies for effective AI integration in education.

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