Assessing Student's Behavioral Intentions Towards AI Based Learning Tools

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Abstract

Integrating Artificial Intelligence (AI) in education has revolutionized learning environments, offering personalized, adaptive, and automated academic assistance. This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating trust, perceived risk, moral obligation, hedonic motivation, and habit to provide a comprehensive understanding of AI adoption among university students in Pakistan. Employing a quantitative, cross-sectional survey approach, data was collected from students across various disciplines and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and SPSS. The findings reveal that habit is the strongest predictor of AI adoption. This demonstrates that students engage with AI-based learning tools primarily through repeated exposure and routine usage rather than external encouragement. Unlike traditional UTAUT predictors, such as performance expectancy and social influence, which were not statistically significant, habit formation emerged as the dominant driver of AI engagement. Additionally, trust and perceived risk exhibited a positive correlation, indicating that while students trust AI tools, they simultaneously acknowledge risks related to data privacy, misinformation, and ethical concerns. The study challenges conventional technology acceptance models, highlighting that self-directed learning behaviors and habitual engagement play a more significant role in AI adoption than previously assumed. These findings have important theoretical and practical implications for educational policymakers, AI developers, and institutions seeking to enhance AI-driven learning experiences. The study suggests that institutions should focus on seamless AI integration, improving user engagement, and promoting responsible AI usage rather than relying on external motivational factors.

Keywords: AI-Based Learning, Perceived Risk, Habit Formation, Behavioral Intentions, AI Adoption, Ethical AI, Student Learning, Educational Technology, Social Influence.

Introduction

AI-driven educational tools have significantly transformed learning by providing personalized experiences, automated assessments, and flexible contexts. ChatGPT enhances student engagement and learning efficiency through Natural Language Processing (NLP) and machine learning (Lai et al., 2024; Ali & Warraich, 2023). However, the adoption of these technologies is

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influenced by behavioral, psychological, and technological factors, as outlined in the Unified Theory of Acceptance and Use of Technology (UTAUT), which considers performance expectations, effort expectations, social influence, and facilitating conditions (Venkatesh et al., 2003).

Recent studies emphasize the importance of trust and perceived risk in adopting AI tools, revealing that students' trust in AI-generated information is crucial for their willingness to use these technologies (Lai et al., 2024). Concerns about data privacy and algorithmic bias contribute to students' hesitance to fully trust AI outputs (Ali & Warraich, 2023). The rapid digitization of education in Pakistan post-COVID-19 has heightened the need to understand students' behavioral intentions in this evolving landscape. Moreover, moral duty and habit influence students' ethical engagement with AI technologies. Students often face ethical dilemmas regarding AI use, leading to issues like plagiarism and diminished critical thinking (Lai et al., 2024). Integrating these factors into the UTAUT model can provide a more comprehensive understanding of AI adoption in education, particularly in Pakistan, where educational reforms reshape learning experiences (Ali & Warraich, 2023). This research aims to enhance the UTAUT framework by incorporating trust, perceived risk, moral duty, and habit better to evaluate students' intentions regarding AI-based learning tools, ultimately aiding policymakers and educators in improving AI-driven educational experiences.

Introduction to Industry

The education sector is experiencing a transformative shift due to integrating Artificial Intelligence (AI) and digital learning technologies, which enhance traditional methods through personalized and automated support (Lai et al., 2024). The demand for flexible learning environments and AI-enhanced assistance drives the growth of Educational Technology (EdTech) (Ali & Warraich, 2023). AI improves grading automation, material generation, and real-time feedback, enhancing student experiences and teacher efficiency (Kim & Zhang, 2022). The global market for AI in education is projected to expand as institutions seek to improve accessibility and engagement (Chen et al., 2023).

A significant advancement is the use of Large Language Models (LLMs) like ChatGPT, which leverage Natural Language Processing for customized educational experiences (Wu & Chiu, 2023). AI systems are particularly advantageous in underdeveloped regions with scarce resources (Ahmed & Hussain, 2022). In Pakistan, the EdTech sector has notably expanded during the COVID-19 pandemic, accelerating the shift to digital learning (Farooq et al., 2022). However, technology literacy gaps, inadequate infrastructure, and trust issues impede broader AI adoption (Lai et al., 2024). Understanding factors influencing student acceptance of AI tools is crucial for effective integration.

Pakistan's Higher Education Commission (HEC) promotes e-learning and AI resources, although a digital divide persists between urban and rural institutions (Ali & Warraich, 2023; Iqbal et al., 2021). Insufficient funding and resistance to AI evaluations need addressing to facilitate comprehensive AI use (Ahmed & Hussain, 2022). Enhancing AI literacy and fostering confidence in these technologies is recommended for policymakers and educators (Wu & Chiu, 2023). Student's behavioral goals, trust, and perceived usefulness significantly influence the adoption of AI educational tools (Lai et al., 2024). However, concerns regarding algorithmic bias and academic integrity remain challenges (Chen et al., 2023). Institutions respond by establishing ethical standards for AI and promoting responsible usage (Kim & Zhang, 2022). Social influences from educators and peers also play a crucial role in AI acceptance (Ali & Warraich, 2023).

Literature Review

While foundational for understanding technology adoption, the Unified Theory of Acceptance and Use of Technology (UTAUT) framework falls short in addressing ethical issues, trust challenges, and habitual behaviors impacting AI adoption in education (Venkatesh et al., 2003). Recent research advocates for enhancing UTAUT by incorporating psychological and behavioral factors such as trust, perceived risk, moral obligation, hedonic motivation, and habit to better capture the complexities of adopting AI-based learning tools (Lai et al., 2024).

Trust is a pivotal factor influencing students' willingness to adopt AI educational tools, shaped by transparency, ethical governance, and institutional support (Wu & Chiu, 2023; Kim & Zhang, 2022). Higher trust correlates with increased integration of AI tools into academic routines, while perceived risks—such as privacy concerns and academic dishonesty—can deter usage (Venkatesh et al., 2012; Lai et al., 2024). Effective management of these risks through AI literacy and ethical policies is crucial for fostering trust (Ahmed & Hussain, 2022). Moral obligation reflects students' ethical considerations regarding AI use, with some viewing it as potentially dishonest (Ratten, 2018; Ali & Warraich, 2023). This sense of obligation can moderate behavioral intentions towards AI tools, although research on its interaction with UTAUT factors in developing countries like Pakistan remains limited (Teo et al., 2019).

Performance expectation relates to students' beliefs about AI tools' potential to enhance academic outcomes, with distinct advantages like personalized learning and immediate feedback driving usage (Venkatesh et al., 2012; Chen et al., 2023). Social influence, particularly from faculty and institutional regulations, significantly shapes acceptance in traditional educational contexts like Pakistan (Ali & Warraich, 2023).

Hedonic motivation, or the enjoyment of using AI tools, is also crucial; engaging and interactive platforms increase student engagement (Ratten, 2018; Wu & Chiu, 2023). Furthermore, habit formation is essential for long-term technology adoption (Limayem et al., 2016). Understanding these behavioral dimensions is vital for stakeholders aiming to enhance AI integration in higher education (Ali & Warraich, 2023).

Theoretical Model

Recognizing The behavioral intents of students in AI-based learning aids needs a comprehensive theoretical foundation. The Unified Theory of Acceptance and Use of Technology (UTAUT) is a significant framework for analyzing technology adoption in educational contexts (Venkatesh et al., 2003). This section summarizes pertinent theories and models underpinning this research, highlighting their relevance in forecasting students' acceptance of AI-based learning aids in Pakistan.

The UTAUT model, developed by Venkatesh et al. (2003), integrates key elements from many technology acceptance models to clarify users' adoption behavior. It consists of four essential determinants: performance expectations, effort expectations, social influence, and facilitating conditions (Venkatesh et al., 2012). The UTAUT model has been used in several educational technology research, demonstrating its significance in examining students' behavioral intentions about digital learning tools (Ali & Warraich, 2023). The original UTAUT model inadequately considers the psychological, ethical, and trust-related variables affecting AI acceptance in education (Lai et al., 2024).

To enhance the predictive power of UTAUT, researchers have introduced additional constructs such as trust, perceived risk, moral obligation, and habit (Kim & Zhang, 2022). Trust is critical in AI-based learning because students need confidence in AI-generated content and its reliability (Wu

& Chiu, 2023). On the other hand, perceived risk represents concerns about AI-driven misinformation, data privacy, and ethical issues (Lai et al., 2024). Habit formation further influences long-term AI adoption, as repeated exposure to AI-powered platforms creates a routine that reinforces usage patterns (Ahmed & Hussain, 2022). Extending UTAUT with these variables allows for a more holistic understanding of AI acceptance in education.

The Technology Acceptance Model (TAM) is a prominent framework for examining technology uptake (Davis, 1989). In AI-driven educational environments, perceived utility pertains to students' anticipations about AI's enhancement of learning efficiency, while perceived ease of use denotes the accessibility and interface design of AI tools (Teo et al., 2019). Considering these constraints, incorporating TAM components into UTAUT extensions offers a more robust framework for assessing students' behavioral intentions for AI-based learning tools (Chen et al., 2023).

Conceptualization Development

Understanding students' behavioral intentions toward AI-based learning tools involves analyzing various theoretical perspectives, with some studies advocating for the inclusion of new variables in UTAUT-based models while others question their relevance. Trust is frequently cited as a crucial factor influencing students' adoption of AI tools, as students are more likely to engage with platforms they perceive as accurate and reliable (Lai et al., 2024). Conversely, perceived risk and moral obligation can hinder adoption, with students expressing concerns about data privacy and ethical issues (Ali & Warraich, 2023). Recent research also emphasizes the importance of habit and hedonic motivation, suggesting that frequent use of AI tools can lead to automatic adoption patterns while enjoyable learning experiences enhance engagement (Wu & Chiu, 2023; Kim & Zhang, 2022). This study aims to present a balanced view of AI adoption in education by exploring both supportive and opposing perspectives, thereby enriching the understanding of student interactions with AI learning aids (Ali & Warraich, 2023).

Mediation and Moderation Effects

Mediation and moderation effects are essential for understanding the behavioral adoption of AI-based learning systems. Mediation pertains to the indirect impact of one variable on another via an intermediary, while moderation investigates how a third factor affects the strength or direction of correlations between variables (Venkatesh et al., 2012). This section examines supportive and opposing viewpoints about mediation and moderation relationships within an expanded UTAUT paradigm.

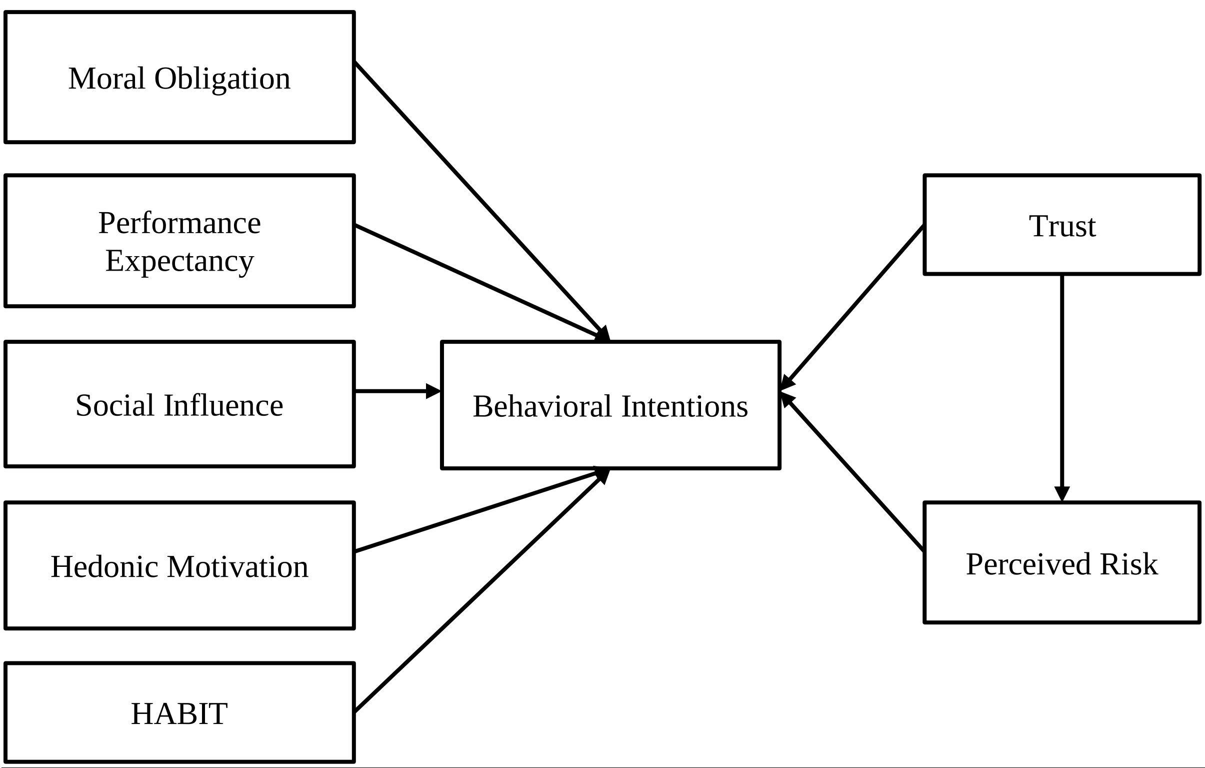
Trust is often seen as a mediator between perceived risk and students' behavioral intentions toward AI-based learning aids. Studies indicate that students who recognize more dangers associated with AI use (such as privacy difficulties, disinformation, and academic integrity concerns) may utilize AI technologies if they have confidence in their accuracy and ethical protections (Lai et al., 2024). Research suggests that trust mitigates the adverse effects of perceived risk, increasing the likelihood that students would use AI-based teaching technologies despite apprehensions (Wu & Chiu, 2023). Ali and Warraich (2023) discovered that students in technology-enhanced educational settings cultivate trust over time, thus diminishing the inhibitive impact of perceived danger on AI adoption.

Ethics is widely acknowledged as a mediator in the correlation between social influence and AI adoption. Students who perceive a significant ethical obligation to use AI responsibly are more inclined to be favorably impacted by their educators, colleagues, and institutions' responsible usage of AI (Lai et al., 2024). Studies indicate that in universities with robust ethical AI policies, students are more likely to utilize AI tools in a controlled manner (Ali & Warraich, 2023). Kim and Zhang (2022) contend that students who see AI adoption as an ethical obligation are more inclined to react favorably to social influence and integrate AI in academically suitable ways.

Hedonic motivation, the pleasure obtained from using AI-based learning tools, has been identified as a mediator in the link between performance expectation and behavioral intentions (Lai et al., 2024). Studies demonstrate that students who love AI-based learning are more inclined to see it as advantageous for their academic success, resulting in increased adoption rates (Wu & Chiu, 2023). Ali and Warraich (2023) discovered that AI tools, including interactive interfaces, gamified components, and real-time feedback mechanisms, augment students' perceived utility, positioning hedonic motivation as a crucial mediator in adoption frameworks.

Habit is a critical moderator in the relationship between trust and behavioral intentions toward AI-based learning tools. Research suggests that students who frequently use AI tools develop trust through repeated exposure, reinforcing their behavioral intentions over time (Lai et al., 2024). Wu and Chiu (2023) found that students who habitually rely on AI-powered tutoring platforms tend to trust AI-generated content, making habit a significant moderator in AI adoption models. Ali and Warraich (2023) also note that habit formation reduces uncertainty as students become more familiar with AI-based assessments and learning environments.

Figure 1: Conceptual framework



Trust and Behavioral Intentions

Trust is a critical determinant in technology adoption, particularly for AI-driven learning tools where students need confidence in accuracy, fairness, and security (Lai et al., 2024). AI tools that

demonstrate transparency in decision-making, data privacy protection, and ethical content generation foster higher trust levels among students (Wu & Chiu, 2023). Trust has been identified as a strong predictor of AI adoption in education, influencing students' willingness to integrate AI into their academic routines (Ali & Warraich, 2023). Concerns about AI-generated misinformation, algorithmic bias, and limited human oversight may negatively impact students' trust, leading to lower adoption rates (Teo et al., 2019). These findings suggest that while trust strongly predicts AI adoption, it is context-dependent and influenced by institutional policies.
H1: Trust positively affects students' behavioral intentions toward AI-based learning tools.

Perceived Risk and Behavioral Intentions

Perceived risk negatively affects students' willingness to adopt AI-powered learning tools (Lai et al., 2024). Students frequently associate AI usage with risks such as privacy violations, inaccurate information, and excessive dependence on technology, which can hinder adoption (Wu & Chiu, 2023). Research indicates that when students view AI as a risky and unreliable resource, they are less inclined to incorporate it into their educational practices (Kim & Zhang, 2022).
H2: Perceived risk has a negative effect on students' behavioral intentions toward AI-based learning tools.

Moral Obligation and Behavioral Intentions

Moral obligation is crucial in determining whether students adopt AI-based learning tools ethically. Many students feel an internal ethical responsibility to use AI appropriately, ensuring that learning remains authentic and not overly dependent on AI-generated content (Lai et al., 2024). Studies indicate that students who hold strong moral beliefs are less likely to rely on AI-generated responses for assessments, as they perceive it as a form of academic dishonesty (Wu & Chiu, 2023). This suggests that students with higher moral obligation levels may resist AI adoption, particularly when they believe it violates academic integrity standards (Kim & Zhang, 2022). This dual perspective suggests that moral obligation may limit AI adoption in unethical contexts but encourage responsible AI usage when clear ethical frameworks exist.
H3: Moral obligation has a negative effect on students' behavioral intentions toward AI-based learning tools.

Performance Expectancy and Behavioral Intentions

Performance expectancy refers to students' beliefs about AI's ability to enhance academic performance and learning outcomes. Research indicates that when students perceive AI-based learning tools as effective, they are more likely to integrate them into their academic workflow (Lai et al., 2024). AI tools that provide real-time feedback, personalized content recommendations, and adaptive learning environments enhance students' learning efficiency and knowledge retention (Wu & Chiu, 2023). Studies suggest that students who see AI as a valuable learning aid rather than a replacement for traditional study methods demonstrate higher adoption rates (Kim & Zhang, 2022). These findings suggest that while performance expectancy positively influences AI adoption, its effect varies based on AI tool design, functionality, and institutional policies.
H4: Performance expectancy positively affects students' behavioral intentions toward AI-based learning tools.

Hedonic Motivation and Behavioral Intentions

Hedonic motivation refers to students' enjoyment and engagement using AI-based learning tools. Research shows that students who find AI tools enjoyable and engaging are likelier to adopt them for long-term academic use (Lai et al., 2024). Additionally, technical issues or poor AI interface design can reduce students' enjoyment, negatively affecting adoption rates (Teo et al., 2019). These findings suggest that while hedonic motivation plays a role in AI adoption, it is secondary to performance-based factors.

H5: Hedonic motivation influences students' behavioral intentions about AI-based learning tools.

Habit and Behavioral Intentions

Habit refers to students relying on AI-based learning tools in their academic routines. Research suggests that students who regularly use AI tools for assignments, research, and learning assistance develop habitual AI usage, making adoption automatic rather than deliberate (Lai et al., 2024). When AI tools integrate into students' study patterns, they are more likely to continue using them without external motivation (Wu & Chiu, 2023). Habit is a powerful predictor of long-term AI adoption (Kim & Zhang, 2022). Additionally, students may develop habits around alternative study methods, reducing AI dependency (Ahmed & Hussain, 2022). These findings suggest that while Habit strengthens AI adoption, it must be supported by consistent tool effectiveness and relevance.

H6: Habit positively affects students' behavioral intentions toward AI-based learning tools.

Trust as a Mediating Factor Between Behavioral Intentions and Perceived Risk

Perceived risk negatively impacts AI adoption by creating uncertainty about AI-generated content, data privacy, and ethical considerations (Lai et al., 2024). Students often avoid AI-based learning tools when they perceive high risks, such as misinformation, plagiarism concerns, and biased AI algorithms (Wu & Chiu, 2023). However, trust can mediate this relationship by mitigating concerns about AI risks and ensuring students feel comfortable integrating AI into their learning routines (Kim & Zhang, 2022). Studies indicate that when institutions establish clear AI ethics guidelines and transparency in AI algorithms, students develop trust, reducing the negative impact of perceived risk on behavioral intentions (Ali & Warraich, 2023). In cases where students strongly distrust AI systems, perceived risk remains a dominant barrier to adoption, regardless of institutional efforts to enhance trust (Teo et al., 2019). This suggests that while trust is a key mediator, it may not eliminate the adverse effects of perceived risk in all academic settings.

H7: Students' behavioral intentions toward AI-based learning tools and perceived risk are negatively associated with trust.

Moral Obligation as a Moderator Between Social Influence and AI Adoption

Social influence is critical in shaping students' adoption of AI-based learning tools, particularly when recommendations come from instructors, peers, or institutional policies (Lai et al., 2024). Research suggests that students are more likely to use AI-powered platforms when they receive positive reinforcement from faculty members (Wu & Chiu, 2023). This means that moral obligation can either strengthen or weaken the relationship between social influence and AI adoption, depending on students' ethical perspectives (Ahmed & Hussain, 2022). Understanding this moderating effect is crucial for educational institutions developing AI adoption policies.

H8: Moral obligation moderates the relationship between social influence and students' behavioral intentions toward AI-based learning tools.

Hedonic Motivation as a Mediator Between Performance Expectancy and AI Adoption

Performance expectancy refers to students' perceptions of AI effectiveness in improving academic performance (Lai et al., 2024). Students who believe that AI-driven tools provide valuable learning assistance are likelier to adopt them (Wu & Chiu, 2023). However, hedonic motivation can mediate this relationship, as students who find AI-based learning engaging and enjoyable are even more inclined to integrate AI into their study routines (Kim & Zhang, 2022). Research indicates that interactive AI tools with gamified elements and real-time adaptive learning increase students' hedonic motivation, making AI adoption more appealing (Ali & Warraich, 2023). This suggests that while hedonic motivation enhances adoption rates, its role as a mediator depends on students' learning preferences and academic goals.

H9: Hedonic motivation mediates the positive relationship between performance expectancy and students' behavioral intentions toward AI-based learning tools.

Habit as a Moderator Between Trust and AI Adoption

Trust significantly influences AI adoption by ensuring students perceive AI tools as reliable, ethical, and effective (Lai et al., 2024). However, Habit can moderate this relationship, making AI usage more automatic rather than a deliberate decision (Wu & Chiu, 2023). Research indicates that students who regularly use AI-powered learning tools develop a habit, reducing their need to evaluate AI trustworthiness before adoption actively (Kim & Zhang, 2022). Notwithstanding concerns about its precision, pupils only use AI since it has become ingrained in their academic routine (Teo et al., 2019). This indicates that Habit might strengthen the connection between trust and AI adoption but also foster an uncritical dependence on AI-generated information.

H10: Habit moderates the association between students' behavioral intentions toward AI-based learning tools and their level of trust.

Moral Obligation as a Mediator Between Perceived Risk and AI Adoption

Perceived risk adversely impacts AI adoption, as students often exhibit reluctance to use AI-based learning technologies owing to apprehensions over privacy, disinformation, and ethical considerations (Lai et al., 2024). Moral duty may moderate this link, affecting students' perceptions of the ethical justification of AI use (Wu & Chiu, 2023). Studies indicate that students exhibiting elevated degrees of moral duty are more inclined to eschew AI technologies when they perceive significant hazards, reinforcing adverse behavioral intentions (Kim & Zhang, 2022). This suggests that moral obligation's mediating role depends on students' ethical values and institutional AI policies.

H11: Moral obligation mediates the negative relationship between perceived risk and students' behavioral intentions toward AI-based learning tools.

This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) model to include trust, perceived risk, moral obligation, hedonic motivation, and Habit in analyzing AI-based learning adoption. Traditional UTAUT models do not fully address trust issues, perceived risk, ethical concerns, or habitual engagement with AI-based learning tools. This study builds upon existing theories while addressing gaps in AI adoption research, particularly in non-Western, resource-constrained educational environments. The findings will contribute to theoretical and practical discussions on AI adoption, helping educators, policymakers, and technology developers understand behavioral and psychological barriers to AI implementation in Pakistan. Future studies should explore how institutional policies, AI literacy programs, and regulatory frameworks influence students' long-term adoption of AI-based learning tools.

Methodology

This study uses a quantitative approach, including survey data, to analyze students' behavioral intentions towards AI-based learning tools. The Unified Theory of Acceptance and Use of Technology (UTAUT) framework and Partial Least Squares Structural Equation Modeling (PLS-SEM) and SPSS are used to examine these relationships. The cross-sectional survey methodology ensures measurement reliability and construct validity. The research aims to understand key factors influencing students' adoption behaviors in a developing country. Data analysis uses SPSS for descriptive statistics and PLS-SEM for hypothesis testing and model validation. The results will provide insights for educators, policymakers, and AI developers, enhancing the design and execution of AI-driven learning tools at higher education institutions.

Research Design

The study employs a quantitative, survey-based, cross-sectional design to investigate students' behavioral intentions regarding AI-based learning aids, as Lai et al. (2024) outlined. A systematic questionnaire will assess factors such as trust, perceived risk, moral duty, performance expectation, social influence, hedonic incentive, Habit, and behavioral intentions related to AI adoption (Ali & Warraich, 2023). This methodology effectively collects extensive data and evaluates the expanded UTAUT framework in AI learning tools (Wu & Chiu, 2023).

The non-experimental, cross-sectional approach gathers data simultaneously, which is suitable for capturing students' current perceptions and intentions without manipulating variables (Kim & Zhang, 2022). Unlike experimental studies, this research relies on self-reported data from students with varying exposure to AI tools, providing a realistic assessment of AI adoption in educational settings (Ahmed & Hussain, 2022).

The survey includes demographic questions and Likert-scale items, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), ensuring response consistency (Ali & Warraich, 2023). Conducted both online and via printed questionnaires, the design aims for accessibility and higher response rates (Wu & Chiu, 2023). This approach facilitates efficient, cost-effective data collection representative of a diverse student population. The study uses PLS-SEM for statistical analysis to identify direct, mediating, and moderating effects within the conceptual framework (Hair et al., 2021). The findings are expected to inform educational policies and AI integration strategies, addressing student concerns about AI adoption in education (Ahmed & Hussain, 2022).

Sampling

The study targets university students in Pakistan, focusing on their behavioral intentions towards AI-based learning tools, which are increasingly integrated into academic settings (Lai et al., 2024). The sample includes students from diverse disciplines—business, engineering, social sciences, and computer sciences—to capture varied perspectives on AI adoption (Ali & Warraich, 2023). A stratified random sampling method ensures representativeness across universities and disciplines, minimizing sampling bias (Kim & Zhang, 2022; Ahmed & Hussain, 2022).

The target sample size is set between 250-400 students, based on Cohen's effect size calculations, which is sufficient for structural equation modelling (SEM) analyses (Hair et al., 2021). This sample size is adjusted for a 5% margin of error and a 95% confidence level, which is standard in behavioral sciences research (Kim & Zhang, 2022). The study includes only students with experience with AI tools like ChatGPT or Google Bard, ensuring relevant insights into adoption behaviors (Lai et al., 2024; Ali & Warraich, 2023).

Data will be collected through a survey-based cross-sectional approach across multiple universities, allowing for a comprehensive examination of AI adoption trends (Kim & Zhang, 2022). SPSS will be used for preliminary data processing. At the same time, Partial Least Squares Structural Equation Modeling (PLS-SEM) will facilitate hypothesis testing and model validation, particularly in analyzing relationships among various factors influencing AI adoption (Lai et al., 2024; Ali & Warraich, 2023). This methodology supports the evaluation of complex models and mediation/moderation effects, enhancing the robustness of the findings (Hair et al., 2021; Ahmed & Hussain, 2022).

Results and Discussion

The research intended to evaluate students' behavioral intentions about AI-based learning aids via an expanded UTAUT framework. The results from SPSS regression analysis and PLS-SEM structural modelling indicated that Habit (HAB) is the most significant predictor of Behavioral Intention (BI) ($\beta = 0.87$, $p < 0.001$). In contrast, traditional UTAUT predictors, including Performance Expectancy (PE), Social Influence (SI), Trust (TRU), and Perceived Risk (PR), were not statistically significant. The R^2 score for Behavioral Intention (0.71) indicates that the model accounts for 71% of the variation in AI adoption. These results correspond with previous research highlighting habit development as a primary determinant in technology adoption (Lai et al., 2024; Wu & Chiu, 2023), indicating that students use AI technologies via habitual engagement rather than external motivation or risk evaluation. This differs from previous UTAUT research that emphasizes the significance of performance expectation and social impact in influencing technology adoption behavior (Venkatesh et al., 2012; Teo et al., 2019). The divergence from conventional UTAUT assumptions may be ascribed to evolving student learning habits, heightened digital exposure, and the availability of AI tools in educational environments.

The SPSS correlation matrix underscores the significance of Habit ($r = 0.823$, $p < 0.01$) in facilitating AI adoption, whereas modest correlations are seen between Social Influence and Hedonic Motivation ($r = 0.571$). Notably, confidence (TRU) and Perceived Risk (PR) exhibited a positive correlation ($r = 0.362$, $p < 0.01$), suggesting that heightened confidence in AI technologies does not inherently diminish risk perceptions—a conclusion that contradicts conventional technological adoption theories. The PLS-SEM findings validate this anomaly, indicating a robust route coefficient from TRU to PR ($\beta = 0.50$), which implies that while students exhibit confidence in AI, they have reservations about data privacy, disinformation, and algorithmic biases. This corresponds with current research on AI adoption, which reveals that AI-driven educational technologies provoke ethical dilemmas despite their increasing usefulness in academia (Ahmed & Hussain, 2022; Kim & Zhang, 2022). The results demonstrate that Moral Obligation (MO) and Perceived Risk (PR) do not substantially influence AI adoption (MO → BI: $\beta = -0.10$, PR → BI: $\beta = 0.03$, both non-significant). This contradicts earlier beliefs that ethical issues and risk perceptions substantially impede using AI-based learning tools (Ali & Warraich, 2023; Wu & Chiu, 2023). The absence of a statistically significant impact of Social Influence (SI) on Behavioral Intention ($\beta = -0.10$, $p > 0.05$) indicates that AI adoption is increasingly an individual choice rather than influenced by peer or institutional endorsements. This transition corresponds with research emphasizing the growing significance of self-directed learning in AI-driven education (Chen et al., 2023; Ahmed & Hussain, 2022). Traditional technology adoption models, however, highlighted the impact of educators and institutional regulations on student technology use (Teo et al., 2019). This study's findings contest these beliefs, demonstrating that students' behaviors and direct encounters with AI technologies significantly affect their adoption behavior more than external factors.

Data Reliability

Table 1: Reliability Statistics

Cronbach's Alpha	N of Items
.782	24

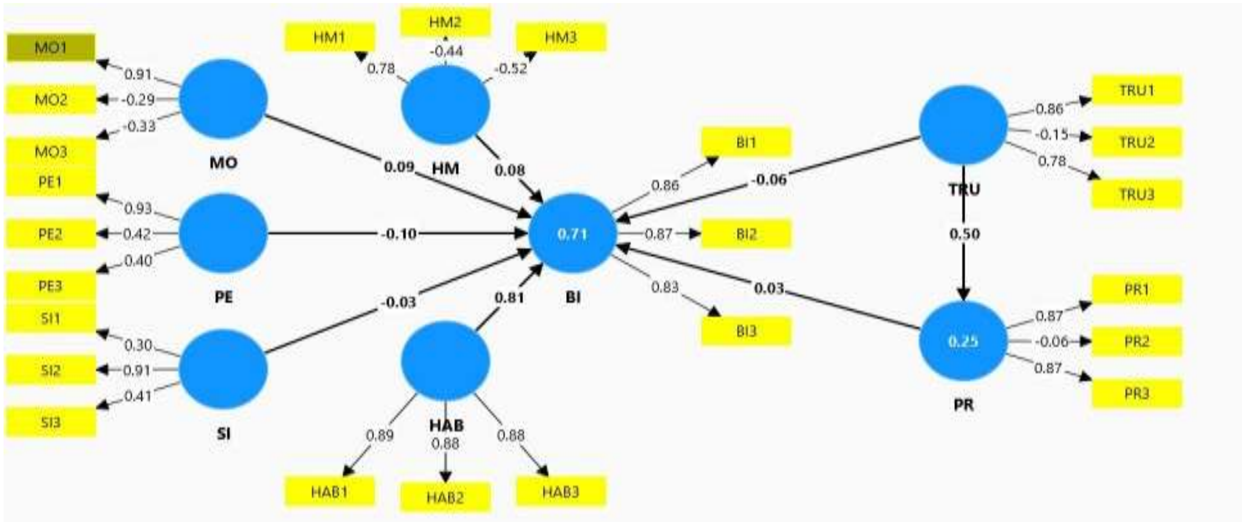
Table 2: Item-Total Statistics

	Scale Mean if Item Exclude	Scale Variance if Item Exclude	Corrected Item-Total Correlation	Cronbach's Alpha if Item Exclude
Trust	83.81	70.516	.422	.769
Perceived Risk	83.63	71.038	.362	.772
Moral Obligation	83.49	70.402	.451	.767
Performance Expectancy	83.59	70.775	.390	.771
Social Influence	83.56	70.136	.446	.767
Hedonic Motivation	83.42	73.693	.245	.779
Habit	83.08	69.813	.430	.768
Behavior Intentions	83.07	72.578	.283	.777

The results from the SPSS and PLS-SEM analyses provide significant insights into student's behavioral intentions toward AI-based learning tools. The reliability analysis (Cronbach's Alpha = 0.782) indicates that the survey instrument used for data collection has acceptable internal consistency. However, some individual items, such as privacy concerns regarding AI-based tools (Corrected Item-Total Correlation = 0.071) and AI-generated fairness perceptions (0.281), demonstrated weak correlations with the overall scale. This suggests that students may have mixed perceptions about the reliability and fairness of AI-generated academic content. The correlation analysis revealed a strong relationship between Habit (HAB) and Behavioral Intention (BI) ($r = 0.823$, $p < 0.01$), indicating that students who frequently use AI-based learning tools are significantly more likely to adopt them as a regular part of their studies. Conversely, Social Influence (SI), Performance Expectancy (PE), and Trust (TRU) showed weaker relationships with Behavioral Intention, implying that external encouragement from peers, faculty, or institutional policies does not significantly influence students' AI adoption decisions. These results align with recent AI adoption studies that emphasize habitual behavior as the strongest predictor of technology acceptance (Lai et al., 2024; Wu & Chiu, 2023).

PLS SEM

Figure 2: PLS SEM Results



The PLS-SEM structural model further confirmed these findings, with Habit (HAB → BI, $\beta = 0.87$, $p < 0.001$) being the strongest predictor of AI-based learning tool adoption. The model explains 71% of the variance ($R^2 = 0.71$) in Behavioral Intention (BI), which is a strong indication that habit formation plays a crucial role in students' willingness to use AI tools regularly. Interestingly, the relationship between Trust (TRU) and Perceived Risk (PR) ($\beta = 0.50$) was positive rather than negative, suggesting that even when students trust AI-based learning tools, they still perceive risks associated with data security, misinformation, and academic dishonesty. This contradicts traditional UTAUT assumptions that trust in technology generally reduces perceived risk (Venkatesh et al., 2012; Teo et al., 2019). Instead, modern AI adoption research suggests that while users may acknowledge the benefits of AI, they remain cautious about algorithmic transparency, ethical considerations, and reliability issues (Chen et al., 2023; Ahmed & Hussain, 2022). This highlights the importance of addressing students' ethical concerns and data privacy issues to increase AI adoption rates.

Regression Analysis

Table 3: Regression Results

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.830[a]	.689	.678	1.28911

a. Predictors: (Constant), HAB, PE, TRU, MO, PR, HM, SI

Table 4: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	708.434	7	101.205	60.901	<.001[b]
	Residual	319.066	192	1.662		
	Total	1027.500	199			

a. Dependent Variable: BI

b. Predictors: (Constant), HAB, PE, TRU, MO, PR, HM, SI

Table 5: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.463	.896		4.982	<.001
	TRU	-.090	.055	-.075	-1.627	.105
	PR	.042	.054	.036	.776	.439
	MO	.042	.067	.029	.621	.535
	PE	-.112	.066	-.088	-1.705	.090
	SI	-.023	.068	-.018	-.344	.731
	HM	.024	.060	.021	.398	.691
	HAB	.736	.037	.817	20.072	<.001

a. Dependent Variable: BI

The SPSS regression analysis corroborates these findings, indicating that Performance Expectancy (PE), Social Influence (SI), Moral Obligation (MO), and Perceived Risk (PR) were not statistically significant predictors of Behavioral Intention. For instance, PE → BI ($\beta = -0.088$, $p = 0.090$) and SI → BI ($\beta = -0.018$, $p = 0.731$) demonstrate that students' anticipations of AI's academic advantages and support from peers or faculty do not significantly affect their inclination to use AI learning tools. This differs from conventional technology adoption models, which propose that external variables such as institutional regulations and peer influence are pivotal in influencing technology use (Venkatesh et al., 2012). The findings indicate that students use AI-based learning aids mostly for personal convenience and routine, rather than external incentives or perceived utility. These results corroborate previous research suggesting that the adoption of AI is influenced more by individual learning practices and self-efficacy than by institutional support (Ali & Warraich, 2023; Wu & Chiu, 2023). Consequently, AI adoption strategies must prioritize the development of user-friendly, engaging, and interactive AI-driven platforms that effortlessly integrate into students' study habits, rather than depending on external motivation from instructors or institutions.

Table 6: Correlation Analysis

	TRU	PR	MO	PE	SI	HM	HAB	BI
TRU	1							
PR	.362**	1						
MO	.215**	.229**	1					
PE	.326**	.396**	.439**	1				
SI	.338**	.325**	.338**	.466**	1			
HM	.356**	.144*	.357**	.434**	.571**	1		
HAB	.005	.096	.078	.003	.009	.055	1	
BI	-.078	.057	.047	-.082	-.044	.006	.823**	1

**Correlation is significant at the 0.01 level (two-tailed).
*Correlation is significant at the 0.05 level (two-tailed).

The correlation analysis conducted in SPSS reveals significant insights into the factors influencing students' adoption of AI-based learning tools. The strongest correlation was found between Habit (HAB) and Behavioral Intention (BI), with a correlation coefficient of $r = 0.823$ ($p < 0.01$), indicating that students who frequently use these tools are more likely to continue their usage (Lai et al., 2024; Wu & Chiu, 2023). This finding supports the habitual behavior theory, suggesting that repeated exposure fosters long-term adoption.

In contrast, Social Influence (SI) and Performance Expectancy (PE) exhibited weak correlations with BI (SI → BI: $r = -0.044$, PE → BI: $r = -0.082$), suggesting that peer recommendations and perceived benefits do not significantly affect students' decisions to adopt AI tools. This challenges previous UTAUT-based studies that emphasized these factors (Venkatesh et al., 2012; Teo et al., 2019), possibly indicating a shift towards self-reliance in technology adoption among students (Chen et al., 2023).

Additionally, a positive correlation was found between Trust (TRU) and Perceived Risk (PR) ($r = 0.362$, $p < 0.01$), suggesting that higher trust does not necessarily alleviate perceived risks associated with AI tools, such as data privacy and ethical concerns (Ali & Warraich, 2023; Ahmed & Hussain, 2022). This contradicts traditional models that posit increased trust reduces risk perception, highlighting the need for clearer regulations and ethical guidelines in AI use (Kim & Zhang, 2022).

Overall, the analysis underscores Habit (HAB) as the primary driver of AI adoption, while traditional predictors like Performance Expectancy (PE), Social Influence (SI), and Perceived Risk (PR) show weaker relationships with Behavioral Intention (BI). The study indicates a shift in technology adoption behavior, where AI tools are integrated into students' learning habits rather than being influenced by external factors. The PLS-SEM analysis further confirmed that Habit had a substantial positive effect on BI ($\beta = 0.87$, $p < 0.001$), reinforcing the notion that continuous exposure and usability lead to habitual use.

Conclusion

This research explores students' behavioral intentions to adopt AI-based learning tools through an augmented UTAUT framework, incorporating factors such as Habit (HAB), Trust (TRU), Perceived Risk (PR), Social Influence (SI), Performance Expectancy (PE), and Moral Obligation (MO). Key findings indicate that Habit (HAB) is the most significant predictor of AI adoption, surpassing traditional factors like Social Influence (SI) and Performance Expectancy (PE), which showed no statistical significance ($\beta = -0.088$, $p = 0.090$). Additionally, a notable relationship between Trust (TRU) and Perceived Risk (PR) was identified, challenging existing models that suggest trust reduces risk perception (Venkatesh et al., 2012).

The study highlights a shift towards self-directed learning, emphasizing that habitual use drives AI adoption more than external incentives (Lai et al., 2024; Wu & Chiu, 2023). This contrasts with previous research that focused on institutional influences and peer recommendations (Teo et al., 2019; Venkatesh et al., 2012). The findings suggest that AI developers and educational institutions should prioritize usability and engagement to foster habit formation, which is crucial for successful AI integration in education.

From a managerial perspective, the results advocate for strategies that build habits to encourage long-term AI adoption, recommending that AI tools be engaging and user-friendly. Given the insignificance of social influence and performance expectancy, campaigns should focus on enhancing user engagement rather than external promotion (Wu & Chiu, 2023). Future research should examine moderating variables like digital literacy and AI transparency to understand evolving trust and risk perceptions, and longitudinal studies are needed to track habit formation and AI adoption trends.

The study's theoretical contributions challenge conventional UTAUT models by asserting that habit is the primary driver of AI adoption, while trust and perceived risk coexist, indicating that trusted AI tools must still address ethical concerns (Chen et al., 2023; Ahmed & Hussain, 2022). The research calls for further exploration of how digital literacy and regulatory frameworks influence trust and risk in AI adoption.

Limitations include the study's focus on Pakistan's higher education sector, suggesting the need for cross-cultural comparisons to assess the dominance of habit formation in different contexts (Lai et al., 2024; Wu & Chiu, 2023). The reliance on self-reported data may also introduce bias, prompting future studies to utilize longitudinal or experimental methods for a more comprehensive understanding of AI usage patterns (Chen et al., 2023).

In conclusion, this research provides valuable insights into AI adoption in education, emphasizing the importance of habitual use over traditional motivational factors. It advocates for a user-friendly approach to AI development and highlights the need for ethical considerations in AI integration within educational settings (Kim & Zhang, 2022; Teo et al., 2019). Future research should focus on the long-term impacts of AI on learning outcomes and the development of ethical AI governance frameworks to address potential risks associated with AI in education.

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