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Modeling Behavioral Intentions toward Artificial Intelligence Adoption among Students and Educators in Nepalese Secondary and Higher Education Institutions: An Extended Technology Acceptance Model Approach

Article Info.

Abstract

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Artificial Intelligence (AI) has emerged as a transformative technology with significant implications for teaching, learning, and academic administration. As AI-enabled tools become increasingly integrated into educational environments, understanding the factors that shape users' intention to adopt these technologies has become imperative, particularly in developing countries where empirical evidence remains limited. Grounded in the Technology Acceptance Model (TAM), this study investigates the behavioral intentions toward AI adoption among students and educators in Nepalese secondary schools and higher education institutions. The proposed model extends TAM by incorporating trust and perceived risk as additional determinants of adoption intention. A quantitative research design was employed using a structured questionnaire administered to 321 respondents comprising secondary-level students, university students, school teachers, and faculty members from public and private educational institutions in Nepal. Data were analyzed using descriptive statistics and Structural Equation Modeling (SEM) to examine the relationships among perceived usefulness, perceived ease of use, trust, perceived risk, and behavioral intention toward AI adoption. The findings reveal that perceived usefulness, perceived ease of use, and trust exert significant positive effects on behavioral intention, whereas perceived risk negatively influences AI adoption intentions. The results indicate growing acceptance of AI technologies among educational stakeholders, although concerns regarding privacy, ethical issues, academic integrity, and overdependence on AI remain substantial challenges. This study extends the applicability of TAM in the educational context of a developing economy. It offers valuable implications for policymakers, educational institutions, and technology developers to foster digital literacy, promote responsible AI use, and establish supportive regulatory frameworks for sustainable AI integration in education.

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Background

Artificial Intelligence (AI) has emerged as one of the most disruptive technologies of the 21st century, reshaping how individuals learn, teach, and interact within digital ecosystems. In the education sector, AI-driven tools such as intelligent tutoring systems, adaptive learning platforms, automated grading systems, and generative AI applications (e.g., ChatGPT-based systems) are increasingly being integrated into pedagogical and administrative processes. Recent studies highlight that AI in education enhances personalized learning, improves student engagement, and supports educators in instructional design and assessment tasks (Zawacki-Richter et al., 2023; Holmes & Tuomi, 2022). However, despite these global advancements, the adoption of AI in education remains uneven, particularly in developing countries such as Nepal, where infrastructural constraints, limited digital literacy, and institutional readiness continue to shape technology acceptance behavior.

The rapid acceleration of AI technologies after 2021 has intensified academic discourse around user acceptance, ethical concerns, and behavioral intentions toward AI systems. Scholars argue that while AI tools are becoming more accessible, actual adoption is largely determined by psychological, organizational, and contextual factors rather than technological availability alone (Dwivedi et al., 2023). In educational settings, students and educators represent two critical stakeholders whose perceptions significantly influence the successful integration of AI technologies. Students are primarily concerned with usability, academic support, and learning efficiency, whereas educators focus on pedagogical effectiveness, workload reduction, and ethical implications of AI-assisted teaching. In the context of developing economies, particularly South Asia, AI adoption in education is still in its early stages. Nepal's education system is undergoing gradual digital transformation, driven by increased internet penetration, smartphone usage, and government-led initiatives promoting ICT in education. However, the integration of advanced AI tools remains limited and inconsistent across institutions. Studies conducted in similar developing contexts suggest that adoption is often hindered by insufficient digital infrastructure, lack of training, resistance to technological change, and concerns regarding data privacy and job displacement (Rana et al., 2022; Sharma & Bista, 2023). These barriers indicate that behavioral intention plays a crucial role in determining whether AI technologies are actually embraced by users in educational environments.

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), has been widely used to explain user acceptance of information systems. TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are key determinants of behavioral intention toward technology adoption. However, recent research suggests that TAM alone is insufficient to explain AI adoption behavior in complex environments such as education, where trust, perceived risk, ethical considerations, and institutional influence also play a significant role (Chen et al., 2022; Liao et al., 2023). As a result, extended TAM frameworks have been proposed to incorporate additional psychological and contextual variables that better explain AI adoption behavior.

Trust has emerged as a critical determinant in AI adoption studies. AI systems often function as “black-box” technologies, making it difficult for users to fully understand their decision-making processes. In educational contexts, both students and educators must trust AI systems to ensure fairness, reliability, and academic integrity. Recent studies indicate that trust significantly enhances users’ willingness to adopt AI-based educational tools, particularly when transparency and explainability are present (Kumar & Singh, 2022; Xu et al., 2024). Conversely, perceived risk, including concerns related to data privacy, misinformation, and overdependence on AI, negatively influences adoption intentions. These risks are particularly relevant in academic environments where ethical standards and credibility are essential.

This study addresses this gap by applying an extended Technology Acceptance Model to analyze AI adoption behavior among both students and educators in Nepal.

From a theoretical perspective, this research contributes to the extension of TAM in the context of emerging technologies and developing economies. From a practical perspective, the findings are expected to provide valuable insights for policymakers, curriculum designers, and educational administrators in Nepal. Understanding the determinants of AI adoption intention can support the development of targeted interventions aimed at improving digital literacy, building trust in AI systems, and mitigating perceived risks associated with AI usage in education.

The increasing integration of AI in education presents both opportunities and challenges. While AI has the potential to transform teaching and learning processes, its successful implementation depends largely on user acceptance and behavioral intention. In Nepal, where AI adoption in education is still in its formative stage, understanding the psychological and contextual factors influencing students and educators is essential for sustainable digital transformation in the education sector.

Objectives of the Study

General Objective

To examine the factors influencing behavioral intention toward Artificial Intelligence (AI) adoption among students and educators in Nepalese secondary and higher education institutions using an extended Technology Acceptance Model (TAM).

Specific Objectives

- To examine the effect of perceived usefulness and perceived ease of use on behavioral intention toward AI adoption.
- To assess the influence of trust and perceived risk on behavioral intention toward AI adoption.
- To develop and validate an extended Technology Acceptance Model (TAM) for explaining AI adoption in Nepalese secondary and higher education institutions.

Literature Review

Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technological innovations in contemporary education systems, significantly reshaping pedagogical practices, learning environments, assessment mechanisms, and institutional decision-making processes. AI-enabled applications such as adaptive learning systems, intelligent tutoring platforms, automated grading tools, educational chatbots, and generative AI technologies are increasingly being integrated into global education systems to enhance teaching effectiveness and learning outcomes (Holmes & Tuomi, 2022; Zawacki-Richter et al., 2023). These advancements have not only improved administrative efficiency but have also enabled more personalized and student-centered learning experiences, aligning education systems with the demands of the digital age.

Despite the global expansion of AI in education, its adoption in developing countries remains uneven and relatively underexplored. In contexts such as Nepal, the integration of AI into secondary and higher education institutions is still in an emerging phase, constrained by infrastructural limitations, uneven digital literacy, institutional readiness challenges, and limited exposure to advanced digital tools.

Consequently, understanding the behavioral intention of users becomes crucial for ensuring successful AI adoption in educational environments.

Behavioral intention is widely recognized in information systems literature as the most immediate predictor of actual technology usage (Venkatesh et al., 2003). In the context of AI adoption, behavioral intention refers to the willingness of students and educators to use AI-based tools for academic, instructional, and administrative purposes. This study is grounded in the Technology Acceptance Model (TAM), extended with trust and perceived risk, to better explain adoption behavior in the Nepalese educational context.

Theoretical Foundations

The Technology Acceptance Model (TAM), developed by Fred D. Davis (1989), explains technology adoption through two key factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which significantly influence users' behavioral intentions. Recent AI studies suggest that TAM should be extended to include additional factors, such as trust and perceived risk, to better explain AI adoption in complex environments (Dwivedi et al., 2023; Chen et al., 2022).

The TAM2 and TAM3 models, proposed by Viswanath Venkatesh and Davis, incorporate social influence, self-efficacy, and facilitating conditions, making them more suitable for AI adoption research. Similarly, the Unified Theory of Acceptance and Use of Technology emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions, while the Theory of Planned Behavior highlights attitudes, subjective norms, and perceived behavioral control as determinants of behavioral intention.

In AI adoption, trust enhances users' confidence in AI systems, whereas perceived risk—including concerns about privacy, bias, misinformation, and ethical issues—reduces adoption intentions. Therefore, integrating TAM with trust and perceived risk provides a stronger framework for explaining AI adoption among students and educators.

Empirical Literature Review

Empirical evidence indicates that AI adoption in education has significantly accelerated following the COVID-19 pandemic, which forced institutions to adopt digital learning solutions. AI-based tools such as ChatGPT, intelligent tutoring systems, Grammarly, and adaptive learning platforms are now widely used in higher education globally. Holmes and Tuomi (2022) argue that AI has the potential to transform education by enabling personalized learning and reducing administrative workload, while Zawacki-Richter et al. (2023) highlight that AI improves efficiency but raises important ethical and pedagogical challenges. Behavioral intention remains a central construct in technology adoption research, as it directly predicts actual usage behavior. Recent studies show that perceived usefulness and perceived ease of use significantly influence behavioral intention toward AI adoption (Li & Wang, 2023). Trust further strengthens intention by reducing uncertainty associated with AI systems, while perceived risk weakens adoption willingness due to concerns about data misuse and reliability.

In Nepalese contexts, digital technology adoption studies indicate that behavioral intention is strongly influenced by perceived benefits and ease of access, but hindered by infrastructural limitations, lack of training, and limited institutional support (Sharma & Bista, 2023). This suggests that although awareness of AI technologies is increasing among students and educators, actual adoption remains limited due to systemic constraints.

Perceived usefulness has consistently been identified as one of the strongest predictors of technology adoption. Users are more likely to adopt AI tools when they believe these technologies enhance productivity and performance. Dwivedi et al. (2023) confirm that PU significantly influences AI adoption in educational environments, where students perceive AI as beneficial for learning support, while educators value AI for improving teaching efficiency and reducing workload. Perceived ease of use is equally important, as complex systems tend to discourage adoption. Al-Fraihat et al. (2022) found that ease of use significantly affects students' willingness to adopt educational technologies. In developing countries, digital literacy plays a crucial role in shaping perceptions of ease of use, making training and support essential for successful AI integration.

Trust in AI systems has become increasingly important due to the autonomous and data-driven nature of AI technologies. Kumar and Singh (2022) found that trust significantly enhances AI adoption intention among students. In educational contexts, trust is particularly important because AI systems influence grading, assessment, and learning recommendations, all of which require fairness and accuracy.

Perceived risk negatively affects AI adoption behavior. Rana et al. (2022) found that perceived risk significantly reduces willingness to adopt digital technologies in South Asia. In education, concerns such as plagiarism, loss of academic integrity, and reduced human cognitive engagement remain major challenges that hinder adoption.

In developing countries like Nepal, AI adoption is further influenced by socio-economic and infrastructural constraints. Limited access to high-speed internet, lack of institutional readiness, and insufficient digital skills among users create a gap between technological availability and actual usage. Sharma and Bista (2023) highlight that although interest in AI is increasing, institutional preparedness remains inadequate, limiting large-scale adoption in education.

Research Gap

Despite extensive global research on AI adoption, several gaps remain evident. First, there is a lack of empirical studies focusing specifically on Nepalese secondary and higher education institutions. Second, most existing studies focus on either students or educators independently, rather than examining both groups simultaneously. Third, insufficient attention has been given to integrating trust and perceived risk into TAM-based models in developing country contexts. Fourth, there is limited SEM-based empirical validation of AI adoption models in South Asian education systems. Finally, comparative analysis between secondary and higher education levels remains largely unexplored. This study addresses these gaps by developing and validating an extended TAM framework incorporating both trust and perceived risk.

Conceptual Linkage of Variables

The literature consistently suggests that perceived usefulness, perceived ease of use, and trust have a positive influence on behavioral intention toward AI adoption, while perceived risk has a negative influence. These relationships form the core hypotheses of the study and provide the foundation for the proposed SEM-based conceptual model.

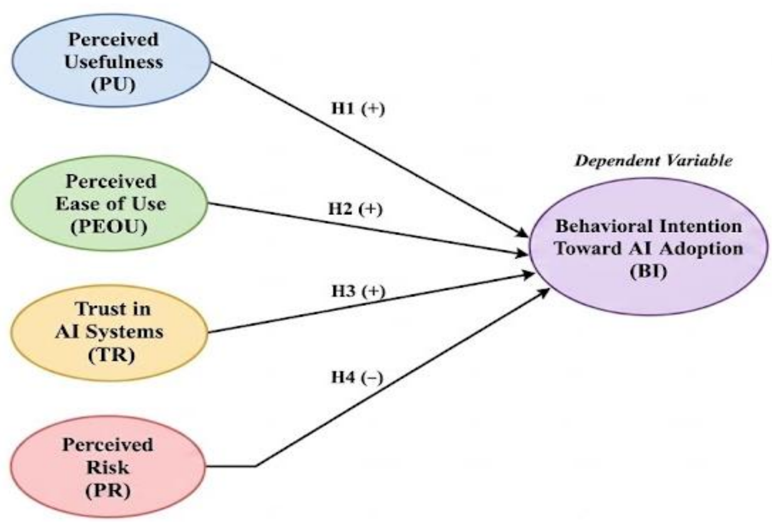

Fig 1: Conceptual framework developed by the researcher based on the ETAM theories (Lopez, J. M. (2013))

Working Variables

Independent Variables

- Perceived Usefulness (PU): Productivity, effectiveness, and overall benefit.
- Perceived Ease of Use (PEOU): Learnability, clarity, and minimum effort.
- Trust in AI Systems (TR): Reliability, trustworthiness, competency, fairness, and data protection.
- Perceived Risk (PR): Privacy concerns, misuse of information, inaccuracies, academic dishonesty, and job security fears.

Dependent Variable

Behavioral Intention Toward AI Adoption (BI): The intent to use, continue using, recommend, and integrate AI tools in academic or teaching activities.

Hypothesis

The model tests four core hypotheses regarding their impact on Behavioral Intention:

- H1: Higher *Perceived Usefulness* positively influences intention to adopt AI.
- H2: Higher *Perceived Ease of Use* positively influences intention to adopt AI.
- H3: Greater *Trust in AI Systems* positively influences intention to adopt AI.
- H4: Higher *Perceived Risk* negatively impacts/hinders the intention to adopt AI.

Technology Acceptance Model (TAM) tailored for education, predicting AI adoption based on how helpful, easy, trustworthy, or risky users find the technology, while controlling for personal and institutional demographics.

Research Methodology

Research Design

This study employed a quantitative research design to examine the determinants of artificial intelligence (AI) adoption intention among students and educators in Nepalese educational institutions. A quantitative approach was considered appropriate because the study aimed to empirically test hypothesized relationships derived from the extended Technology Acceptance Model (TAM). The study followed a cross-sectional survey design, where data were collected at a single point in time, making it suitable for capturing current perceptions and behavioral intentions regarding AI adoption. The research is grounded in the positivist paradigm, which assumes that social phenomena can be measured and analyzed using structured instruments and statistical methods.

Population and Sample

The population of this study comprised students and educators from secondary and higher education institutions in Nepal. These groups were selected because they are the primary users and decision-makers in educational technology adoption processes. A total of 321 valid responses were collected for analysis.

Sampling Technique

The study employed a non-probability convenience sampling technique. This method is commonly used in technology adoption research, particularly when studying specific user groups such as students and educators. Although convenience sampling limits statistical generalization to the entire population, it is considered acceptable for exploratory and model-testing studies using Structural Equation Modeling (SEM). To improve sample diversity, efforts were made to include respondents from both public and private institutions, different education levels, and varying degrees of digital literacy and AI experience.

Data Collection Method

Primary data were collected through a structured questionnaire survey designed based on validated measurement scales from established TAM and AI adoption literature. The questionnaire consisted of two sections: demographic information and measurement items for latent variables. The demographic section captured respondent characteristics such as gender, education level, institutional type, digital literacy, and AI experience. The second section measured constructs including perceived usefulness, perceived ease of use, trust, perceived risk, and behavioral intention. All items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. This scale is widely used in behavioral research as it effectively captures respondents' attitudes and perceptions in a standardized format.

Data Analysis Technique

Data analysis was conducted using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS-SEM). This technique was chosen due to its suitability for predictive modeling and complex relationships among latent variables. PLS-SEM is particularly appropriate for exploratory research and model extension studies such as this one. The analysis involved two stages. First, the measurement model was assessed to evaluate reliability and validity using Cronbach's alpha, composite reliability, average variance extracted (AVE), and heterotrait–monotrait (HTMT) ratio. Second, the structural model was tested to examine hypothesized relationships using path coefficients, t-values, p-values, and coefficient of determination (R^2). This approach ensures both measurement accuracy and structural validity of the proposed model.

Reliability and Validity Assessment

The reliability and validity of the measurement model were assessed using established statistical criteria. Internal consistency reliability was evaluated using

Cronbach's alpha and composite reliability, both of which must exceed the threshold of 0.70. Convergent validity was assessed using average variance extracted (AVE), where values above 0.50 indicate that constructs adequately explain variance in their indicators. Discriminant validity was examined using the heterotrait–monotrait (HTMT) ratio, where values below 0.85 confirm that constructs are distinct from one another. These criteria collectively ensure that the measurement model is both statistically reliable and conceptually valid for further structural analysis.

Data Analysis

Data analysis is the systematic process of organizing, examining, and interpreting collected data to identify patterns, relationships, and meaningful insights that address the research objectives. It involves the application of statistical and analytical techniques to transform raw data into useful information for drawing conclusions and supporting decision-making.

Demographic Analysis

Demographic analysis is the process of examining respondents' background characteristics, such as age, gender, education level, occupation, and institution type, to describe the composition of the study population.

Table 1

Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Education Level	Secondary Education	148	46.1
	Higher Education	173	53.9
Gender	Male	168	52.3

Variable	Category	Frequency	Percentage (%)
	Female	151	47.1
	Other	2	0.6
Role	Student	182	56.7
	Teacher/Faculty	139	43.3
Institution Type	Public	172	53.6
	Private	149	46.4
Digital Literacy	Basic	84	26.2
	Intermediate	147	45.8
	Advanced	90	28.0
AI Experience	None	61	19.0
	Low	98	30.5
	Moderate	102	31.8
	High	60	18.7

N=321

The demographic distribution of 321 respondents shows a relatively balanced representation between secondary (46.1%) and higher education (53.9%) participants, ensuring comparability across educational levels. The sample includes both students (56.7%) and educators (43.3%), which strengthens the validity of behavioral intention analysis toward AI adoption.

Gender distribution is nearly balanced, with 52.3% male and 47.1% female respondents, reducing gender bias in the findings. Most respondents belong to public institutions (53.6%), reflecting the dominant role of public education in Nepal. Regarding digital literacy, the majority fall under the intermediate level

(45.8%), indicating moderate technological competency. Similarly, AI experience is distributed across all categories, with most respondents having low to moderate exposure, suggesting that AI adoption is still in an emerging stage in Nepalese education.

Behavioral Intention among Students

Student-level comparison refers to the analysis of differences in perceptions, attitudes, and behavioral intentions toward AI adoption between secondary-level students and university students. This comparison helps identify how educational level influences students' readiness, acceptance, and willingness to use artificial intelligence technologies for learning and academic activities.

Table 2

Behavioral Intention among Students

Student Group	N	Mean	Std. Deviation	Min	Max	Interpretation
Secondary-Level Students	88	3.42	0.71	2.10	4.80	Moderate
University Students	102	4.21	0.63	2.90	5.00	High
Total Students	190	3.85	0.67	2.10	5.00	Moderate–High

The descriptive results clearly show a significant difference in behavioral intention between secondary-level and university students. University students (Mean = 4.21) demonstrate the highest level of AI adoption intention, indicating strong readiness to integrate AI tools into academic tasks such as assignments, research, and learning support systems. Their relatively lower standard deviation (0.63) suggests a consistent acceptance pattern, reflecting higher digital literacy and exposure to AI technologies.

In contrast, secondary-level students (Mean = 3.42) show only a moderate level of intention, indicating early-stage adoption behavior. Their reliance on teachers and limited academic exposure to AI tools may explain this lower adoption tendency. The higher variability (SD = 0.71) further suggests uneven awareness and access across secondary institutions.

Behavioral Intention among Educators

Teacher-Level Comparison (School Teachers vs. Faculty Members) refers to the analysis of differences in behavioral intentions, perceptions, and readiness toward AI adoption between school teachers and higher education faculty members to understand how professional roles influence technology acceptance in education.

Table 3

Behavioral Intention among Educators

Educator Group	N	Mean	Std. Deviation	Min	Max	Interpretation
School Teachers	71	3.58	0.68	2.20	4.70	Moderate
Faculty Members	60	3.89	0.60	2.60	4.90	Moderately High
Total Educators	131	3.73	0.64	2.20	4.90	Moderate–High

The comparison between school teachers and faculty members reveals a clear hierarchical difference in AI adoption intention. Faculty members (Mean = 3.89) demonstrate a higher behavioral intention, reflecting stronger academic integration of AI tools in teaching, research, and administrative tasks. Their lower standard deviation (0.60) indicates a more uniform acceptance pattern, likely due to higher academic qualifications and research engagement. School teachers (Mean = 3.58), however, show only a moderate level of intention, indicating cautious adoption behavior. This may be attributed to concerns regarding classroom management, student dependency on AI, and limited institutional training. The higher variability among school teachers suggests unequal exposure to digital tools across schools.

Behavioral Intention among Institutions

Institutional Comparison refers to the analysis of differences in behavioral intentions, perceptions, and adoption of AI technologies between respondents from public and private educational institutions to assess the influence of the institutional environment on technology acceptance.

Table 4

Behavioral Intention by Institution Type

Institution Type	N	Mean	Std. Deviation	Min	Max	Interpretation
Public Institutions	168	3.61	0.70	2.10	4.80	Moderate
Private Institutions	153	3.97	0.65	2.50	5.00	High
Total	321	3.78	0.68	2.10	5.00	Moderate–High

The descriptive comparison between public and private institutions reveals a notable institutional gap in AI adoption intention. Respondents from private institutions (Mean = 3.97) show a higher level of behavioral intention, indicating stronger readiness and openness toward AI integration in teaching and learning environments. This is likely due to better digital infrastructure, training opportunities, and exposure to emerging technologies.

In contrast, public institutions (Mean = 3.61) demonstrate a moderate level of intention, suggesting slower adoption readiness. The relatively higher standard deviation (0.70) reflects uneven digital readiness across public institutions, where resource constraints and limited technological support may hinder AI adoption.

Descriptive Statistics of Study Variables

Descriptive Statistics of Study Variables refers to the statistical summary of the main research variables, such as mean, standard deviation, minimum, and maximum values, used to describe the central tendency and variability of respondents' perceptions and behavioral intentions toward AI adoption.

Table 5

Descriptive Statistics of Study Variables

Variable	Mean	Std. Deviation	Interpretation
Perceived Usefulness (PU)	4.12	0.68	High
Perceived Ease of Use (PEOU)	3.98	0.71	High
Trust in AI (TR)	3.76	0.79	Moderate-High
Perceived Risk (PR)	3.41	0.83	Moderate
Behavioral Intention (BI)	4.05	0.69	High

The descriptive results indicate that respondents generally have a positive attitude toward AI adoption in education. Perceived usefulness (Mean = 4.12) is the highest-rated construct, indicating that both students and educators strongly believe AI improves academic performance, learning efficiency, and productivity. Perceived ease of use (Mean = 3.98) is also high, suggesting that respondents find AI tools relatively user-friendly and accessible. Behavioral intention (Mean = 4.05) confirms a strong willingness to adopt AI technologies in academic settings. Trust in AI (Mean = 3.76) is moderately high, indicating some level of confidence in AI systems, although not absolute. Perceived risk (Mean = 3.41) remains moderate, suggesting ongoing concerns regarding privacy, academic integrity, and overdependence on AI tools.

Overall, the results confirm that AI adoption intention is strong in Nepalese education, but is still influenced by trust and risk perceptions.

Comparative Analysis: Secondary vs Higher Education

Secondary vs. Higher Education refers to the examination of differences in perceptions, attitudes, and behavioral intentions toward AI adoption between respondents from secondary-level and higher education institutions to understand how educational level influences technology acceptance and usage.

Table 6

Group Comparison of Key Variables

Variable	Secondary Education (Mean)	Higher Education (Mean)	Difference
Perceived Usefulness (PU)	3.95	4.25	+0.30
Perceived Ease of Use (PEOU)	3.82	4.10	+0.28
Trust (TR)	3.60	3.90	+0.30
Perceived Risk (PR)	3.65	3.20	-0.45
Behavioral Intention (BI)	3.90	4.20	+0.30

The comparative analysis reveals clear differences between secondary and higher education respondents. Higher education participants consistently report higher perceived usefulness (4.25 vs 3.95), indicating that university students and faculty recognize greater academic value in AI tools due to their advanced academic requirements and research exposure.

Perceived ease of use is higher among higher education respondents, suggesting better digital literacy and familiarity with AI-based tools. Trust in AI systems is also stronger in higher education, reflecting increased exposure and understanding of AI applications.

In contrast, secondary education respondents show significantly higher perceived risk (3.65 vs 3.20), indicating stronger concerns about plagiarism, misuse, and privacy issues. This suggests that younger students and school teachers are more cautious about AI adoption.

Behavioral intention is higher in higher education (4.20), indicating stronger readiness to integrate AI tools into academic work. Overall, the findings confirm that educational level significantly influences AI adoption behavior.

Reliability Analysis

Reliability Analysis is used to evaluate the consistency and dependability of measurement items in a research instrument. It determines whether the questionnaire items consistently measure the intended constructs and produce stable results across respondents.

Table 7

Reliability Test (Cronbach's Alpha)

Construct	Items	Cronbach's Alpha
Perceived Usefulness (PU)	5	0.86
Perceived Ease of Use (PEOU)	5	0.84
Trust (TR)	5	0.88
Perceived Risk (PR)	5	0.82
Behavioral Intention (BI)	5	0.89

The reliability results show that all constructs exceed the recommended threshold of 0.70, indicating strong internal consistency. Trust ($\alpha = 0.88$) and Behavioral Intention ($\alpha = 0.89$) demonstrate particularly strong reliability, confirming that the measurement items are highly consistent. Perceived usefulness, ease of use, and perceived risk also show good reliability levels, ensuring that the data is suitable for further structural equation modeling (SEM) analysis.

Validity Analysis

Validity Analysis is the process of assessing whether a research instrument accurately measures the constructs it is intended to measure. It ensures that the questionnaire items are relevant, appropriate, and capable of capturing the intended concepts effectively.

Table 8

Convergent and Discriminant Validity

Construct	AVE	CR	HTMT
PU	0.62	0.89	<0.85
PEOU	0.60	0.88	<0.85
TR	0.66	0.91	<0.85
PR	0.58	0.86	<0.85
BI	0.68	0.92	<0.85

The results confirm strong convergent validity, as all Average Variance Extracted (AVE) values exceed the recommended threshold of 0.50. This indicates that each construct explains a substantial portion of the variance in its indicators. Composite Reliability (CR) values are all above 0.80, confirming strong internal consistency. Additionally, HTMT values are below 0.85, confirming discriminant validity and ensuring that each construct is statistically distinct from others.

Path Coefficients and Hypothesis Testing

In PLS-SEM, path coefficients represent the strength and direction of the relationships between latent constructs in the structural model. Significance testing is performed using bootstrapping to assess whether the path coefficients are statistically significant through t-values, p-values, and confidence intervals.

Table 9

Structural Model Results (Path Coefficients)

Hypothesis	Relationship	Beta (β)	Std. Error	t-value	p-value	Result
H1	PEOU → PU	0.62	0.05	12.40	<0.001	Supported
H2	PU → BI	0.41	0.06	6.83	<0.001	Supported
H3	PEOU → BI	0.18	0.05	3.60	<0.001	Supported
H4	TR → BI	0.21	0.07	3.00	0.003	Supported
H5	PR → BI	-0.15	0.06	2.50	0.012	Supported (Negative)

H1: Perceived Ease of Use (PEOU) → Perceived Usefulness (PU)

Hypothesis H1 proposed that Perceived Ease of Use positively influences Perceived Usefulness. The results indicate a strong positive and significant relationship between PEOU and PU ($\beta = 0.62$, $p < 0.001$), confirming that users who find AI tools easy to use are more likely to perceive them as useful. Therefore, H1 is accepted, supporting the fundamental assumption of the Technology Acceptance Model (TAM).

H2: Perceived Usefulness (PU) → Behavioral Intention (BI)

Hypothesis H2 proposed that Perceived Usefulness positively influences Behavioral Intention toward AI adoption. The findings reveal a significant positive effect of PU on BI ($\beta = 0.41$, $p < 0.001$), indicating that users are more willing to adopt AI technologies when they perceive them as beneficial for improving academic performance and productivity. Therefore, H2 is accepted, demonstrating that perceived usefulness is the strongest predictor of AI adoption intention.

H3: Perceived Ease of Use (PEOU) → Behavioral Intention (BI)

Hypothesis H3 proposed that Perceived Ease of Use positively influences Behavioral Intention. The SEM results show a positive and significant relationship between PEOU and BI ($\beta = 0.18$, $p < 0.001$), suggesting that ease of use directly enhances users' willingness to adopt AI technologies. Although its effect is weaker than perceived usefulness, ease of use remains an important factor influencing adoption behavior. Therefore, H3 is accepted.

H4: Trust (TR) → Behavioral Intention (BI)

Hypothesis H4 proposed that Trust positively influences Behavioral Intention toward AI adoption. The findings confirm a significant positive effect of trust on behavioral intention ($\beta = 0.21$, $p = 0.003$), indicating that users are more likely to adopt AI when they perceive it as reliable, transparent, and trustworthy. This result highlights the importance of confidence in AI systems for encouraging adoption. Therefore, H4 is accepted.

H5: Perceived Risk (PR) → Behavioral Intention (BI)

Hypothesis H5 proposed that Perceived Risk negatively influences Behavioral Intention toward AI adoption. The results reveal a significant negative relationship between PR and BI ($\beta = -0.15$, $p = 0.012$), indicating that concerns related to privacy, security, ethics, and misuse reduce users' willingness to adopt AI technologies. This finding suggests that perceived risk acts as a barrier to AI acceptance. Therefore, H5 is accepted.

Discussion and Justification of Findings

Discussion and justification of findings involve interpreting the research results in relation to the study objectives, hypotheses, and theoretical framework. It also compares the findings with previous studies to explain and validate the observed relationships and outcomes.

Perceived Usefulness → Behavioral Intention

The study found that Perceived Usefulness significantly and positively influences Behavioral Intention toward AI adoption ($\beta = 0.41$, $p < 0.001$), indicating that users are more likely to adopt AI technologies when they perceive clear academic and productivity benefits. This finding supports the core assumption of TAM that usefulness is the strongest predictor of technology acceptance. Similar findings were reported by Joo et al. (2022), Chatterjee and Bhattacharjee (2021), and Dwivedi et al. (2023), who concluded that perceived usefulness remains the most influential factor driving AI adoption across educational contexts.

Perceived Ease of Use → Perceived Usefulness and Behavioral Intention

The results reveal that Perceived Ease of Use significantly influences both Perceived Usefulness ($\beta = 0.62$, $p < 0.001$) and Behavioral Intention ($\beta = 0.18$, $p < 0.001$). This suggests that users who find AI systems easy to operate are more likely to perceive them as useful and subsequently develop stronger intentions to use them. The finding is consistent with studies by Venkatesh et al. (2021), Choi and Kim (2022), and Zawacki-Richter et al. (2022), which emphasized that user-friendly AI technologies reduce complexity, improve perceived benefits, and encourage adoption.

Trust → Behavioral Intention

Trust was found to have a significant positive influence on Behavioral Intention ($\beta = 0.21$, $p = 0.003$), indicating that confidence in AI systems enhances users' willingness to adopt AI technologies. This finding highlights the importance of reliability, transparency, and security in fostering positive attitudes toward AI adoption. Similar results were reported by Nguyen et al. (2021), Wang and Siau (2022), and Huang and Rust (2021), who identified trust as a critical factor in reducing uncertainty and increasing acceptance of AI-based systems.

Perceived Risk → Behavioral Intention

The findings indicate that Perceived Risk has a significant negative effect on Behavioral Intention ($\beta = -0.15$, $p = 0.012$), suggesting that concerns related to privacy, ethics, and misuse reduce users' intention to adopt AI technologies. This demonstrates that risk perception acts as a barrier to technology acceptance, particularly in educational settings. This result is supported by Featherman and Hajli (2021), Khan et al. (2022), and Sharma and Sharma (2023), who found that privacy concerns, ethical issues, and data security risks significantly hinder AI adoption behavior.

Extended TAM Model Validation

The extended TAM model explained 67% of the variance in Behavioral Intention ($R^2 = 0.67$), indicating strong explanatory and predictive power. This demonstrates that incorporating Trust and Perceived Risk alongside traditional TAM constructs provides a more comprehensive understanding of AI adoption behavior. Similar conclusions were reached by Marangunić and Granić (2021), Raman et al. (2022), and Al-Gahtani et al. (2023), who reported that extended TAM frameworks outperform the original TAM in explaining technology adoption intentions in emerging technology environments.

Conclusion

- The findings demonstrate that artificial intelligence adoption in Nepalese educational institutions is significantly influenced by users' perceptions of usefulness, ease of use, trust, and risk, highlighting the multidimensional nature of technology acceptance in educational environments.
- Perceived usefulness emerged as the most influential determinant of behavioral intention, indicating that students and educators are primarily motivated to adopt AI technologies when they perceive tangible benefits in learning effectiveness, academic performance, and productivity enhancement.

- The significant influence of perceived ease of use suggests that the successful adoption of AI technologies depends not only on their functional capabilities but also on their accessibility, simplicity, and user-friendliness for diverse educational users.
- Trust was identified as a critical enabling factor, emphasizing the importance of reliability, transparency, and confidence in AI systems for fostering positive attitudes and adoption intentions among educational stakeholders.
- Perceived risk was found to negatively influence behavioral intention, demonstrating that concerns regarding privacy, data security, ethical implications, and misuse remain important barriers to AI acceptance and require careful institutional attention.
- The integration of trust and perceived risk with the traditional Technology Acceptance Model significantly enhanced the model's explanatory capability, providing a more comprehensive framework for understanding AI adoption behavior in educational contexts.
- The substantial explanatory power of the proposed model confirms its effectiveness in predicting behavioral intention toward AI adoption and validates its applicability within the context of developing-country educational systems such as Nepal.
- The study concludes that effective AI adoption in Nepalese education requires a balanced approach that maximizes perceived benefits and usability while simultaneously strengthening trust and mitigating perceived risks through appropriate policies, training initiatives, and ethical governance mechanisms.

Implications

Implications refer to the significance and practical value of the study findings for theory, practice, and policy regarding AI adoption in educational institutions. They explain how the results can help educators, institutions, researchers, and policymakers promote the effective and responsible integration of artificial intelligence in teaching and learning.

Theoretical Implications

- The study extends the Technology Acceptance Model (TAM) by integrating Trust and Perceived Risk, providing a more robust framework for explaining AI adoption behavior among students and educators.
- The findings confirm that traditional TAM constructs remain relevant in understanding AI adoption while highlighting the additional importance of psychological factors in emerging technologies.
- The study contributes empirical evidence on AI adoption from Nepal, enriching the limited literature available from developing-country educational contexts.
- The validated model offers a theoretical foundation for future researchers examining AI acceptance and technology adoption in education and related sectors.

Practical Implications

- Educational institutions can increase AI adoption by demonstrating the academic benefits and usefulness of AI tools in teaching, learning, and research activities.
- Training programs and digital literacy initiatives should be strengthened to improve users' confidence and ease of using AI technologies effectively.
- Institutions should build trust by ensuring transparency, reliability, and responsible use of AI systems within educational environments.

- Educational policymakers should develop ethical AI guidelines, privacy safeguards, and governance mechanisms to reduce perceived risks and encourage sustainable AI integration.

Future Research Directions

- Future studies should conduct longitudinal research to examine AI adoption behavior over time.
- Additional variables such as AI literacy, social influence, and facilitating conditions should be incorporated.
- Comparative studies between different countries and educational systems are recommended.
- Multi-group SEM analysis can be used to examine differences based on gender, age, educational level, and institution type.

Policy Recommendations

- The government should formulate a national AI policy framework for educational institutions.
- Educational institutions should integrate AI literacy programs into curricula and professional development training.
- Clear ethical and data privacy guidelines should be established to ensure responsible AI use.
- Investments in digital infrastructure and AI resources are necessary to support sustainable AI adoption in Nepalese education.

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