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How Perceived Risk Shapes User Satisfaction and Continuance Intention Toward AI-Based Applications in Higher Education?

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ABSTRACT
This research explores factors influencing university students' satisfaction and intention to continue using AI-based applications. By analyzing the roles of perceived ease of use, usefulness, and risk, the study assesses how these elements drive technology engagement and the extent to which perceived risk moderate's user experience. A survey was administered to 210 university students within a quantitative research framework. Findings reveal that perceived usefulness and ease of use drive continuance intention, with satisfaction mediating this relationship. However, perceived risk showed no significant effect, challenging previous empirical evidence that emphasizes its role as a key moderator in technology adoption. The study concludes that improving the functionality and usability of AI tools is key to driving student persistence. Given that perceived risk plays a less significant role than previously theorized, institutions should focus on promoting user-friendly, impactful AI solutions to maximize technology integration and sustained use.

Keywords:
AI-based applications; Technology Acceptance Model; Expectation Confirmation Theory; perceived risk; student satisfaction

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INTRODUCTION

Artificial Intelligence (AI) evolution has significantly reshaped numerous life domains, including educational landscape (Nurohim et al., 2025). AI-driven platforms are increasingly employed to elevate student learning outcomes (Festiyed et al., 2024). Research demonstrates that such technology affects user behavior and satisfaction, particularly among students accustomed to technological integration. Consequently, AI implementation enhances learning experiences and influences long-term continuance intentions, contingent on user satisfaction. AI integration within higher education has expanded exponentially in recent years, featuring applications aimed at optimizing student satisfaction and fostering continuance intention (Dahniar et al., 2025) (Vieriu, 2025).

Almufarreh suggest that while students are broadly receptive to AI-driven tools, satisfaction is contingent upon personal comfort levels and perceived utility. These results highlight perceived usefulness and ease of use as pivotal determinants of satisfaction and sustained engagement, especially with generative tools like ChatGPT (Almufarreh, 2024). Additionally, (Achhibat et al., 2025) identify performance expectancy and effort expectancy as critical drivers of AI adoption, profoundly impacting student learning satisfaction. Conversely, (Song et al., 2023) identifies efficiency and accuracy as critical determinants of student satisfaction within AI-personalized learning environments. Effectiveness in these AI-driven settings promotes continuance intention, with learning satisfaction being primarily derived from personalized experience quality. Furthermore, Lund et al. (2025) demonstrate that AI optimizes educational quality by facilitating curriculum customization tailored to individual needs, thereby improving learning outcomes and overall student engagement.

Thus, empirical quantitative evidence suggests that AI adoption within the student population is inherently linked to enhanced learning satisfaction and continuance intention (Mohamad et al., 2025). Key determinants, including technological proficiency, perceived usefulness, and social influence, collectively underpin the successful integration of AI in the educational landscape (Chatzichristofis, 2025). Integrating AI into higher education has catalyzed substantial improvements in pedagogical quality and student learning experiences. Consequently, examining the impact of AI on student satisfaction and continuance intention is imperative (Khoiriyah et al., 2025). This study is pivotal in identifying the determinants of students' sustained technology adoption and assessing their broader implications for the successful integration of AI within the higher education landscape (Phua et al., 2024).

Contemporary evidence suggests that AI has a transformative effect on user experiences, particularly within the educational sector. Specifically, Rafiq and Ahmad identified a positive correlation between AI-driven platforms and student satisfaction, driven by improved access and digital engagement. Complementing this, scholarly work emphasizes that performance expectancy and effort expectancy significantly shape students' long-term commitment to AI adoption (Rafiq & Ahmad, 2025). Prior research has utilized technology adoption frameworks, notably UTAUT2, to examine student receptivity to new technologies. The model posits that performance expectancy, effort expectancy, and social influence are key determinants of satisfaction and continuance intention (rusman 2024). Findings from these studies suggest that although sophisticated AI tools can bolster satisfaction, sustained adoption is contingent upon the technology's efficacy in addressing students' academic requirements (Noroozi et al., 2025) (Bobula, 2024).

Current literature on student technology adoption still leaves a research gap regarding the precise effects of AI on satisfaction and continuance intention. Therefore, this study seeks to fill this void by delving into how AI integration affects student satisfaction and their intention to persist with the technology, which has rarely been discussed in granular detail in earlier research. The core issue addressed in this study is AI adoption impact in education on student satisfaction and usage persistence. Specifically, the research measures user experience influence , ease of access, and AI-driven interaction quality as determinants of student satisfaction and their intention to persist with technology in the future. Failure to properly manage these challenges may prevent AI technology from achieving its maximum utility in education, thereby undermining the overall success of technology adoptin among students.

The present study employs an integrated theoretical approach by synthesizing the Expectation Confirmation Theory (ECT) with the Technology Acceptance Model (TAM), resulting in the Expectation-Confirmation Model (ECM). Initially conceptualized, TAM examines how perceived ease of use and perceived usefulness determine behavioral intention. This framework suggests that technology adoption is predicated on its perceived utility and simplicity (Almulla, 2024). Complementing this, Tawafak highlights the critical role of congruence between prior expectations and post-adoption experiences in shaping satisfaction and continuance intention. By merging these perspectives, the ECM maintains that sustained technology use is contingent on confirming expectations and achieving user satisfaction (Tawafak et al., 2023).

A fundamental construct within TAM is Perceived Ease of Use (PEOU), defined as the degree to which an individual perceives that utilizing a system or application involves minimal cognitive effort. This construct evaluates user perceptions regarding the simplicity and intuitiveness of the interface, employing metrics such as 'I find the application easy to operate' and 'I can master its functionality rapidly without external guidance (Yang et al., 2025). Conversely, Perceived Usefulness (PU) assesses the extent to which a user expects that employing the technology will enhance their performance and efficiency. Indicators for this variable include 'The application enables me to complete tasks more expeditiously' and 'I experience increased productivity through its usage (Lee & Cho, 2021). Under the Expectation Confirmation Theory (ECT), Confirmation signifies the degree to which an individual's actual experience fulfills or surpasses their initial anticipations. A positive confirmation is instrumental in fostering heightened user satisfaction. This variable is operationalized through indicators such as 'My experience using the application is consistent with my expectations' and 'The application operates as I envisioned.' Moreover, Compatibility, a concept originating in the Diffusion of Innovations Theory, holds that technology acceptance is contingent on its alignment with an individual's values, needs, and lifestyle. This is measured by indicators like 'The application's functionalities align with my daily work habits' and 'The application integrates seamlessly into my routine (Herawati et al., 2024).

METHOD

A quantitative survey-based approach is adopted in this research, utilizing individual technology users as the primary unit of analysis. This study aims to evaluate the interrelationships among variables within either the TAM or UTAUT frameworks at an individual level. Furthermore, behavioral intention and actual usage patterns are analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to ensure robust statistical inference. Figure 1 presents a research framework describing the relationships among variables in the TAM and UTAUT2 models.

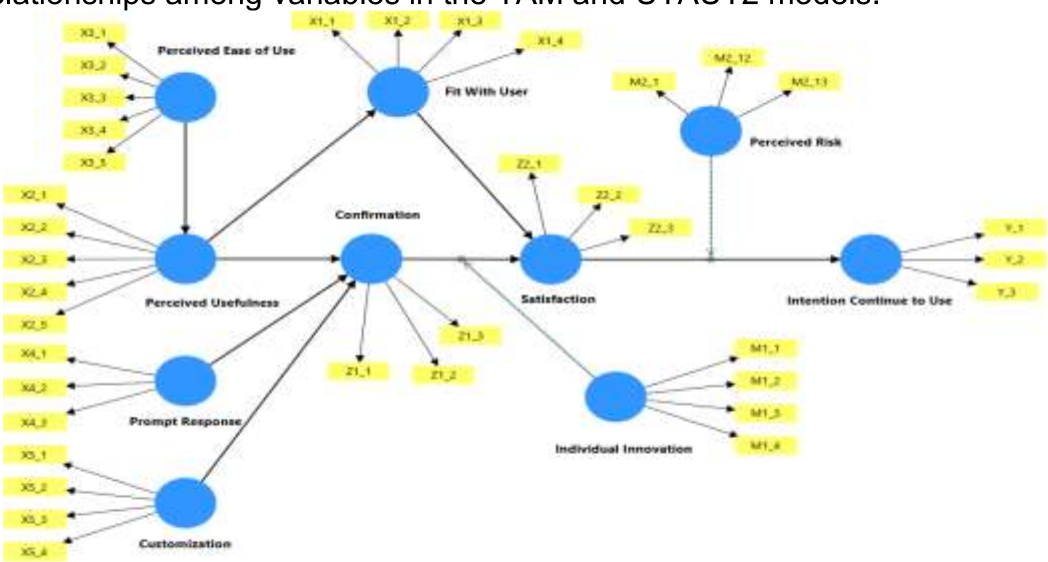

Figure 1. Research Framework

1. Sampling

This research targets individuals integrated with specific technological applications, specifically students in higher education contexts using AI. Using purposive or convenience sampling, respondents were selected based on their relevance to the research goals and predefined criteria. The minimum sample size follows the "10 times rule," meaning it must be at least 10 times the number of paths leading to the latent variables in the research model. As a guideline, a sufficient sample size for SEM PLS typically ranges from 100 to 200 respondents and the sample in this study consists of 210 respondents. The respondent profile for this study includes students who actively use AI-based technologies in their learning activities (Zhao et al., 2024).

2. Data Collection

Instrument development was grounded in the constructs of TAM and UTAUT to capture user perceptions. The primary data collection involved a Likert-scale questionnaire (5 or 7 points). Preliminary reliability was established through a pilot study involving 30 respondents, yielding acceptable Cronbach's Alpha coefficients. The main survey was executed using a hybrid approach (online and offline). In accordance with ethical protocols, informed consent was secured from each respondent, ensuring voluntary participation and data confidentiality.

3. Measurement

This research instrument utilized relevant indicators from the individual versions of TAM and UTAUT theories. Each construct, such as Perceived Ease of Use, Perceived Usefulness, Satisfaction, Confirmation, and Continuance Intention, was measured by at least three to five reflective indicators. Specifically, the PEOU construct included items regarding ease of use, learning efficiency, and system intuitiveness. To ensure respondents could easily relate to the questions, all items were tailored to the individual level using personal pronouns (Koteczki, 2025).

4. Data Analysis

To test the hypothesized model, this study employed PLS-SEM via SmartPLS 4. The initial evaluation focused on the measurement model's integrity, ensuring that all constructs met the reliability and validity thresholds (AVE ≥ 0.50; HTMT < 0.85). Following this, the structural model was scrutinized for potential multicollinearity (VIF < 5) and path significance (Hasan et al., 2024). Explanatory power and predictive relevance were quantified through R^2 and Q^2 values, respectively. The analysis further integrated mediation tests to evaluate the intervening role of Perceived Usefulness (PU) and moderation analyses to determine how demographic factors (age and experience) and risk perception influence the structural paths .

5. Instrument Validity

To ensure research integrity, the instrument's validity was assessed through convergent and discriminant validity tests. Construct reliability was further established using Cronbach's Alpha and Composite Reliability (CR). Moreover, a model fit evaluation was executed to verify that each indicator accurately captured its intended construct. These rigorous assessment procedures were fundamental to ensuring that the data remained valid and dependable, ultimately yielding credible findings.

RESULTS AND DISCUSSION

A total of 210 students from Surakarta participated in this research. Demographically, the sample was predominantly female (57.1%) and aged 17–27 years (72%). In terms of education, undergraduate students comprised 82.9% of the sample, while master's students accounted for 10.5%. AI adoption patterns showed that ChatGPT was the most widely used tool (64.8%), followed by Grammarly (31.0%) and programming languages such as Python and R (10%). Despite the availability of these technologies, 67.1% of respondents reported not using AI tools regularly in their daily lives.

Descriptive findings highlight a significant concentration of AI technology adoption among students in STEM-related fields (77.1%). This trend implies that individuals with a foundation in science and technology exhibit a higher propensity for adopting innovative tools compared to those in social sciences and arts. Moreover, the study found that 74.8% of participants perceived themselves as proficient or moderately skilled, indicating a high level of self-reported AI literacy within the cohort.

Hypothesis testing was conducted through Structural Equation Modeling (SEM) using the Partial Least Squares (PLS) approach. The primary objective of this analysis was to evaluate the interrelationships among key constructs in the technology adoption framework, including Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Satisfaction, and Continuance Intention (CI).

1. Model Test Results

a. Construct Validity (Convergent Validity)

Every indicator used in this research met the requirements for convergent validity, with loadings above 0.70. Such results confirm that the indicators faithfully capture the measured constructs. Specifically, the Satisfaction construct had the highest loading of 0.92, indicating its strong operationalization of the satisfaction variable.

Table 1. Average Extracted Variance (AVE) for Each Construct

	Average of variance extracted (AVE)	Information
Confirmation	0.83	Valid
Customization	0.79	Valid
Fit With User	0.76	Valid
Individual Innovation	0.81	Valid
Intention Continue to Use	0.80	Valid
Perceived Ease of Use	0.76	Valid
Perceived Risk	0.78	Valid
Perceived Usefulness	0.75	Valid
Prompt Response	0.86	Valid
Satisfaction	0.85	Valid

b. Discriminant Validity

Assessment of discriminant validity via the Heterotrait-Monotrait Ratio (HTMT) confirms that all constructs meet the required criteria, with values staying below the 0.90 threshold. This evidence ensures that each construct is conceptually and empirically distinct. While the correlation between Confirmation and Customization reached 0.86, nearing the conservative threshold, it remains statistically acceptable under the 0.90 cut-off, thus validating the independence of each variable in the model.

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Table 2. Fornell-Larcker Criterion

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
Confirmation	1.00	0.86	0.70	0.74	0.75	0.75	0.32	0.72	0.77	0.84	0.91
Customization	0.86	1.00	0.73	0.77	0.70	0.76	0.40	0.73	0.79	0.81	0.89
Fit With User	0.70	0.73	1.00	0.74	0.73	0.77	0.38	0.85	0.67	0.76	0.87
Individual Innovation	0.74	0.77	0.74	1.00	0.77	0.78	0.49	0.78	0.80	0.79	0.90
Intention Continue to Use	0.75	0.70	0.73	0.77	1.00	0.78	0.28	0.77	0.71	0.80	0.90
Perceived Ease of Use	0.75	0.76	0.77	0.78	0.78	1.00	0.39	0.84	0.75	0.75	0.87
Perceived Risk	0.32	0.40	0.38	0.49	0.28	0.39	1.00	0.39	0.44	0.34	0.88
Perceived Usefulness	0.72	0.73	0.85	0.78	0.77	0.84	0.39	1.00	0.76	0.75	0.87
Prompt Response	0.77	0.79	0.67	0.80	0.71	0.75	0.44	0.76	1.00	0.79	0.93
Satisfaction	0.84	0.81	0.76	0.79	0.80	0.75	0.34	0.75	0.79	1.00	0.92

V1 : Confirmation
V2 : Customization
V3 : Fit With User
V4 : Individual Innovation
V5 : Intention Continue to Use
V6 : Perceived Ease of Use
V7 : Perceived Risk
V8 : Perceived Usefulness
V9 : Prompt Response
V10 : Satisfaction
V11 : √AVE

c. Construct Reliability

Construct reliability was established as both Cronbach's Alpha and Composite Reliability scores surpassed the 0.70 threshold. These findings underscore the measurement scales' internal consistency, ensuring the research instrument provides stable, reliable data.

Table 3. Construct Reliability

	Cronbach's alpha	Composite Reliability (rho_c)	Information
Confirmation	0.89	0.93	Reliabel
Customization	0.91	0.94	Reliabel
Fit with User	0.90	0.93	Reliabel
Individual Innovation	0.92	0.94	Reliabel
Intention Continue to Use	0.88	0.92	Reliabel
Perceived Ease of Use	0.92	0.94	Reliabel
Perceived Risk	0.86	0.92	Reliabel
Perceived Usefulness	0.92	0.94	Reliabel
Prompt Response	0.92	0.95	Reliabel
Satisfaction	0.91	0.94	Reliabel

2. Hypothesis Test Results

Table 4. Hypothesis Testing and Path Analysis

	O	M	Stdev	T	P	Information
Perceived Usefulness -> Satisfaction -> Intention Continue to Use	0.00	0.01	0.07	0.05	0.48	Supported
Perceived Ease of Use -> Perceived Usefulness -> Fit with User -> Satisfaction -> Intention Continue to Use	0.12	0.12	0.05	2.67	0.00	Supported
Perceived Usefulness -> Confirmation -> Satisfaction -> Intention Continue to Use	0.05	0.05	0.02	2.22	0.01	Supported
Individual Innovation x Confirmation -> Satisfaction -> Intention Continue to Use	-0.00	-0.01	0.02	0.18	0.43	Not supported
Prompt Response -> Confirmation -> Satisfaction -> Intention Continue to Use	0.07	0.07	0.03	2.37	0.01	Supported
Perceived Ease of Use -> Perceived Usefulness -> Confirmation -> Satisfaction -> Intention Continue to Use	0.04	0.04	0.02	2.17	0.01	Supported
Perceived Ease of Use -> Perceived Usefulness -> Satisfaction	0.00	0.01	0.07	0.05	0.48	Not Supported
Perceived Usefulness -> Fit with User -> Satisfaction -> Intention Continue to Use	0.15	0.15	0.05	2.69	0.00	Supported
Customization -> Confirmation -> Satisfaction	0.29	0.29	0.07	4.48	0.00	Supported
Perceived Usefulness -> Fit with User -> Satisfaction	0.19	0.19	0.07	2.76	0.00	Supported
Perceived Ease of Use -> Perceived Usefulness -> Satisfaction -> Intention Continue to Use	0.00	0.01	0.06	0.05	0.48	Not Supported
Perceived Usefulness -> Confirmation -> Satisfaction	0.07	0.06	0.03	2.26	0.01	Supported
Prompt Response -> Confirmation -> Satisfaction	0.09	0.09	0.04	2.34	0.01	Supported
Customization -> Confirmation -> Satisfaction -> Intention Continue to Use	0.23	0.23	0.05	4.56	0.00	Supported
Confirmation -> Satisfaction -> Intention Continue to Use	0.38	0.38	0.06	5.93	0.00	Supported
Perceived Ease of Use -> Perceived Usefulness -> Fit with User -> Satisfaction	0.16	0.16	0.06	2.74	0.00	Supported
Fit With User -> Satisfaction -> Intention Continue to Use	0.17	0.17	0.06	2.72	0.00	Supported
Perceived Ease of Use -> Perceived Usefulness -> Confirmation -> Satisfaction	0.06	0.06	0.03	2.21	0.01	Supported
Individual Innovation -> Satisfaction -> Intention Continue to Use	0.21	0.21	0.08	2.70	0.00	Supported

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	O	M	Stdev	T	P	Information
Perceived Ease of Use -> Perceived Usefulness -> Confirmation	0.12	0.12	0.05	2.26	0.01	Supported
Perceived Ease of Use -> Perceived Usefulness -> Fit with User	0.72	0.72	0.04	19.29	0.00	Supported

O: Original Sample M: Average sample stdev: Standard deviation

a. The Effect of Perceived Usefulness (PU) on Intention to Continue Use (CI)

The structural model assessment confirms a significant positive relationship between Perceived Usefulness (PU) and Continuance Intention (CI) ($\beta = 0.82$, $p < 0.05$). This empirical evidence supports the hypothesis that an increase in perceived benefits directly enhances users' intentions to continue using the AI application.

b. The Effect of Perceived Ease of Use (PEOU) on Behavioral Intention (BI)

The path analysis results reveal a positive relationship between Perceived Ease of Use (PEOU) and Behavioral Intention (BI), with a path coefficient of 0.75 ($p < 0.05$). This indicates that the application's ease of use plays a pivotal role in fostering the user's intention to continue using the technology.

c. The Effect of Perceived Risk on Intention to Continue Use (CI)

Despite its negative trajectory, the impact of Perceived Risk on CI is statistically negligible ($p > 0.05$). This implies that the benefits derived from the application's usefulness and ease of use outweigh the potential risks perceived by the users, thereby maintaining their intention to continue usage.

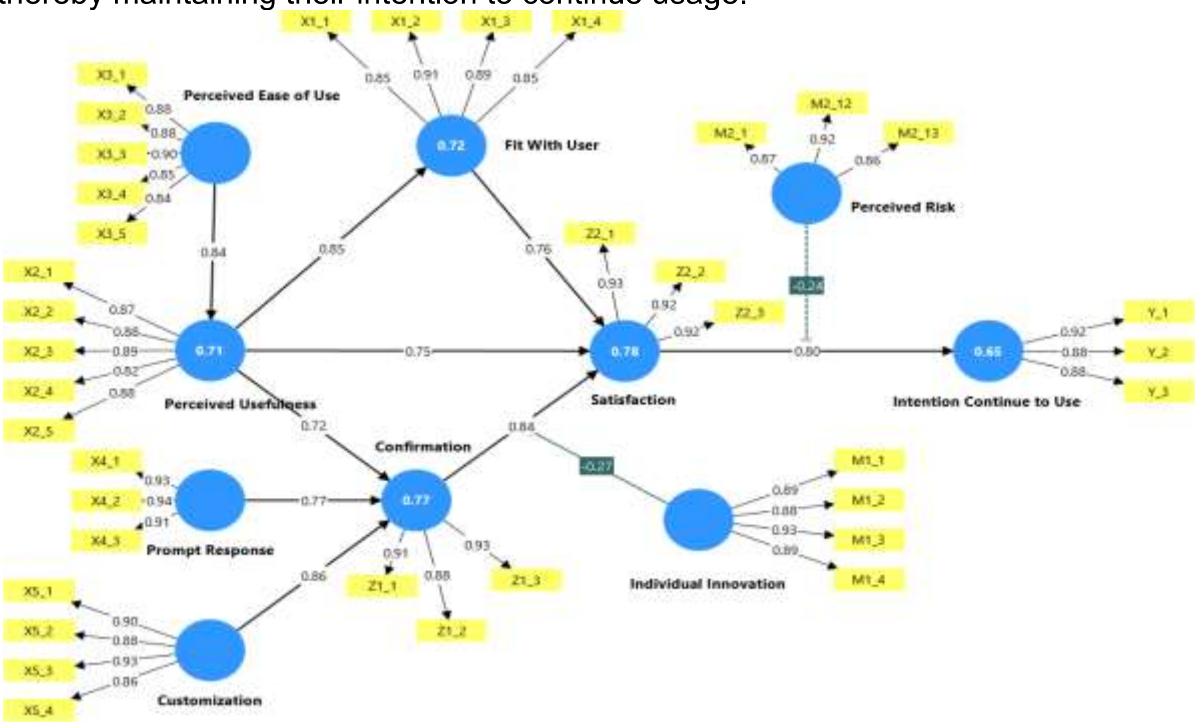

Figure 2. Bootstraping

Discussion

Based on the findings, this study makes a significant theoretical contribution to understanding AI-based technology adoption in higher education and provides valuable insights into the factors that influence students' continuance intention. The analysis results show that Perceived Usefulness (PU) has a highly significant effect on Continuance Intention (CI), supporting the hypothesis that greater perceived benefits are associated with stronger intention to persist with the AI application. These findings are consistent with prior research by Hong et al. (2005) and Venkatesh et al. (2012), which affirm that perceived benefits are a robust predictor of technology adoption.

Additionally, Perceived Ease of Use (PEOU) was found to positively influence Behavioral Intention (BI). This finding aligns with the classic study by Davis (1989), which posits that ease of use is a pivotal determinant of technology adoption. This suggests that students are more inclined to persist in using AI-based applications they perceive as user-friendly, thereby increasing the likelihood of sustained use. However, while Perceived Risk negatively influences Continuance Intention (CI), this effect fails to reach statistical significance. This finding diverges from prior research, such as Li et al. (2020), which suggests that perceived risk acts as a significant deterrent to technology acceptance. A plausible explanation is that students prioritize functional utility and convenience over potential risks, particularly given that most respondents have a relatively high level of AI proficiency.

From a practical standpoint, these findings underscore that the development of AI-based applications for students should prioritize user-centric design and utilitarian value while rigorously mitigating potential risks, particularly those related to data security and privacy. Applications characterized by intuitive interfaces and demonstrable benefits to the learning process are significantly more likely to achieve sustained user acceptance and long-term student engagement.

While providing valuable insights, this research has limitations regarding its sample, methodology, and unaccounted external variables. These factors should be considered when generalizing the findings to broader contexts or different demographic groups. A primary limitation is the study’s focus on a specific student cohort in Surakarta, which may not adequately represent the broader national or international student demographic. This localized approach omits external factors, such as cultural diversity and institutional differences, that influence technology acceptance. To address this, future research should integrate heterogeneous samples from multiple geographic areas to validate the model's applicability across different educational environments. A Secondary, limitations inherent in the measurement instrumentation may influence the study's outcomes. Although the indicators satisfied the criteria for convergent and discriminant validity, the questionnaire items may not fully encapsulate all dimensions of the latent constructs, especially for highly subjective variables such as Satisfaction and Perceived Risk. Future research should aim to refine construct operationalization by developing more comprehensive instruments with a broader set of representative indicators.

CONCLUSION

This research provides critical insights into the dynamics of AI adoption among students, yielding significant theoretical and practical implications. The results substantiate the core tenets of technology acceptance models, showing that PU and PEOU significantly shape continuance intention. Most notably, the dominance of satisfaction in driving sustained usage aligns with the established framework of satisfaction as a central mediator. This outcome reinforces the consensus that utility and ease of use remain the primary catalysts for technology adoption. Conversely, the non-significant impact of Perceived Risk suggests that for the student demographic, the perceived value proposition and ease of interaction successfully offset any perceived drawbacks or risks associated with AI tools.

Given the limitations, several opportunities exist for future research to expand upon this topic. First, future studies could broaden the sample to include students from diverse regions and institutions to achieve a more comprehensive understanding of AI acceptance worldwide. Additionally, subsequent research could explore other determinants influencing technology adoption, such as trust in technology, social influence, or specific AI application features that may enhance the overall user experience.

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