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Factors Influencing Artificial Intelligence Adoption as Learning Support Media: an Extended Technology Acceptance Model Study in Bangka Belitung Islands

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The integration of artificial intelligence (AI) in higher education has accelerated globally, yet understanding of adoption factors remains fragmented, particularly in geographically isolated regions. This study extends the Technology Acceptance Model (TAM) by incorporating facilitating conditions, AI anxiety, and academic performance outcomes to analyze AI adoption patterns across multiple institutions in Bangka Belitung Islands, Indonesia. A cross-sectional quantitative design was employed with 523 students from five higher education institutions. Data were analyzed using SEM-PLS through SmartPLS 4.0, revealing that perceived ease of use demonstrated the strongest influence on actual AI system use ($\beta=0.394$, $p<0.001$), followed by perceived usefulness ($\beta=0.327$, $p<0.001$) and facilitating conditions ($\beta=0.218$, $p<0.01$). AI anxiety showed a significant negative effect on actual system use ($\beta=-0.156$, $p<0.05$), while actual system use strongly predicted academic performance ($\beta=0.782$, $p<0.001$). The extended model explained 68.4% variance in actual AI system use and 61.2% variance in academic performance. Multigroup analysis revealed significant differences between public and private institutions ($p<0.05$), with private institutions showing stronger technology acceptance patterns. These findings suggest that successful AI implementation requires holistic strategies addressing user experience design, institutional support infrastructure, and anxiety reduction programs tailored to institutional contexts in archipelagic regions.
Keywords: Artificial Intelligence; Extended Technology Acceptance Model; AI Anxiety; Academic Performance; Multi-Institutional Analysis

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1. Introduction

The landscape of higher education has been fundamentally transformed by artificial intelligence technologies that enhance learning experiences through adaptive systems, personalized content delivery, and intelligent support mechanisms (Lai, 2021; Zuo et al., 2021). AI's capacity to process vast amounts of data enables customization of learning experiences to meet individual student needs, promoting engagement and effectiveness in learning outcomes (Long & Magerko, 2020). The emergence of AI in educational contexts has prompted discussions regarding AI literacy and the competencies required to navigate these technologies effectively in learning environments (Yin, 2024; Yue & Hu, 2023).

Indonesia, as the world's largest archipelagic nation, faces distinctive challenges in educational technology implementation, particularly in geographically isolated regions where access to advanced technological infrastructure remains constrained. The Bangka Belitung Islands Province presents a compelling case study, combining relatively high internet penetration with unique geographical constraints that create complex implementation dynamics for AI-enhanced learning systems. These islands demonstrate the broader challenges facing developing nations in bridging the digital divide while maximizing educational technology benefits.

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What makes AI different from previous educational technologies is its sophistication and apparent autonomy. Recent developments in AI technology have fundamentally altered the landscape of educational support tools, moving beyond simple automation to sophisticated cognitive assistance systems. Large language models have demonstrated remarkable capabilities in educational contexts, providing instant feedback, generating personalized learning materials, and offering continuous academic support. However, the adoption of these powerful tools in educational settings presents complex challenges involving technical infrastructure, user acceptance, institutional policies, and pedagogical integration strategies.

The Technology Acceptance Model (TAM), which examines how perceived usefulness and perceived ease of use influence technology adoption, has served as the foundational framework for understanding technology adoption behaviors across diverse contexts (Salloum, 2019; Yutdhana & Kohler, 2023). While TAM's core constructs have demonstrated robust predictive power, the complexity of AI technologies necessitates theoretical extensions to capture nuanced factors influencing adoption decisions. Building on this recognition, this study integrates facilitating conditions from UTAUT (Hu et al., 2020; Maruf et al., 2019), AI anxiety as a psychological barrier (Cho & Seo, 2024; Kleine et al., 2023), and academic performance outcomes (Trang & Thư, 2024; Weng et al., 2024) to create an extended model specifically tailored for AI adoption in educational contexts.

2. Literature Review and Problem Statement

Perceived usefulness in educational technology represents the degree to which individuals believe that using a particular system enhances their job performance or learning outcomes, which has drawn extensive scholarly attention within TAM frameworks (Salloum, 2019; Yutdhana & Kohler, 2023). The concept is especially relevant in e-learning systems, where quality and accessibility directly impact users' perceptions of technological value (Yoo, 2021; Yu & Xiaozhi, 2019). Research demonstrates that subjective norms significantly affect teachers' views on technology usefulness in educational settings, suggesting that collaborative environments can bolster perceived usefulness (Scherer, 2019). Furthermore, factors such as perceived ease of use are interlinked with perceived usefulness, indicating that users are more likely to embrace technologies they find genuinely beneficial and easy to use (Yu & Xiaozhi, 2019).

Perceived ease of use in AI contexts refers to the degree to which using a particular technology is perceived as free from effort (Gado et al., 2021). When students find AI tools easy to use, they are more likely to integrate these tools into their learning processes, thereby enhancing educational experiences (Pramono et al., 2023). Research emphasizes that perceived ease of use is closely intertwined with other TAM constructs such as perceived usefulness, showing that when students believe an AI tool is easy to use, their perception of its usefulness is positively influenced, leading to higher adoption rates (Geddam, 2024; Malureanu et al., 2021). Studies suggest that while both perceived ease of use and perceived usefulness are significant factors in determining attitude towards AI technology, the impact of ease of use may be underscored when there is a supportive learning environment (Gado et al., 2021). Additionally, findings suggest that ease of use significantly moderates students' intention to use AI-enabled educational tools, supporting the notion that ease of use can alleviate potential anxieties associated with adopting new technologies (Kleine et al., 2023).

Facilitating conditions in the context of AI learning and educational technology adoption play a vital role in determining whether technological innovations are successfully integrated into educational systems (Hu et al., 2020; Shin et al., 2020). This concept encompasses a range of supportive elements, including

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infrastructure, resources, training, and institutional policies that enable effective use of AI-powered educational tools (Bouton et al., 2021; Peschken et al., 2025). In educational settings, these conditions include access to necessary hardware and software, adequate training for educators and learners, and the presence of supportive institutional frameworks that encourage technology use (Maruf et al., 2019).

AI anxiety represents a multifaceted psychological construct encompassing fears, concerns, and negative emotions associated with AI technology use that can significantly inhibit adoption behaviors (Kleine et al., 2023). When students find AI tools easy to use, perceived ease of use significantly moderates students' intention to use AI-enabled educational tools, supporting the notion that ease of use can alleviate potential anxieties associated with adopting new technologies, such as fear of data privacy or complexity (Kleine et al., 2023; M. Li, 2022). Understanding how these AI tools can assist in decision-making processes while fostering trust in human-AI collaborations becomes essential, with transparency playing an essential role in mitigating potential biases and enhancing the reliability of AI systems used in educational environments (Yue & Hu, 2023).

The intention to learn about AI technology represents a growing area of scholarly interest, particularly as AI integration into educational settings continues to advance (Chai et al., 2020). This intention can be understood through psychological and behavioral frameworks, notably the Theory of Planned Behavior and Technology Acceptance Model, which help identify factors influencing students' decisions to engage with AI learning material (Chai et al., 2020). Research emphasizes that promoting readiness for AI technologies is essential for student well-being and success in evolving socio-economic landscapes (Pai et al., 2020). An encouraging educational environment, along with access to adequate resources and support, has a substantial impact on shaping students' intentions to learn about AI.

The role of AI in improving student learning outcomes has been increasingly recognized in educational research (Trang & Thư, 2024). Studies demonstrate that integrating AI and computational thinking in educational contexts leads to positive effects on student learning outcomes, with systematic reviews highlighting improvements in both instructional design effectiveness and student performance (Weng et al., 2024). Research evidence from Vietnam confirms that AI plays a significant role in improving student learning outcomes through personalized learning experiences and adaptive support systems (Trang & Thư, 2024).

Furthermore, the integration of artificial intelligence to assess emotions in learning environments has shown promise in enhancing educational outcomes by enabling more responsive and adaptive learning experiences (Vistorte et al., 2024). ChatGPT integration has been found to significantly boost personalized learning outcomes, demonstrating the practical impact of AI tools on student achievement (Agbong-Coates, 2024). AI in educational technology has emerged as a transformative force, significantly impacting learning environments through adaptive learning systems, personalized educational content, and intelligent tutoring systems (H. Li, 2021). These findings underscore the importance of examining how AI adoption translates into tangible academic improvements through sustained system usage.

3. Method

This study employs a quantitative cross-sectional survey design utilizing Structural Equation Modeling with Partial Least Squares (SEM-PLS) to examine complex relationships within the extended Technology Acceptance Model for AI adoption in educational contexts. The target population consists of undergraduate students enrolled in technology-related programs across five higher education institutions in Bangka Belitung Islands, Indonesia. The selection criteria focused on students with sufficient digital

 ISSN 2809-8587

literacy to meaningfully engage with AI tools, specifically targeting programs in computer science, information systems, engineering, business informatics, and digital technology management.

Sample size determination employed G*Power 3.1.9.7 software for SEM applications, considering anticipated effect sizes (medium, f^2=0.15), desired statistical power (0.95), and the complexity of the structural model with six constructs and multiple mediation paths. The minimum required sample size calculated to 387 respondents, with the achieved sample of 523 providing adequate power for detecting small to medium effects and conducting robust multigroup analyses across institutional contexts.

The research instrument was developed through systematic adaptation of established scales to ensure content validity while incorporating AI-specific elements identified in recent literature. Each construct was operationalized using multiple indicators to enable robust measurement model evaluation and ensure comprehensive construct coverage.

a. Perceived Usefulness (5 items) adapted from established TAM literature with AI-specific enhancements: "Using AI tools would improve my academic performance," "AI tools would enhance my learning effectiveness," "AI tools would increase my productivity in academic tasks," "AI tools would help me accomplish academic tasks more quickly," and "Overall, AI tools would be useful for my studies."
b. Perceived Ease of Use (5 items) with AI interaction modifications: "Learning to use AI tools would be easy for me," "I would find it easy to get AI tools to do what I want them to do," "My interaction with AI tools would be clear and understandable," "I would find AI tools to be flexible to interact with," and "It would be easy for me to become skillful at using AI tools."
c. Facilitating Conditions (5 items) adapted with educational AI context modifications: "My institution has the necessary infrastructure to support AI tool usage," "Technical support is available when I have difficulties with AI tools," "My institution provides adequate training for AI tool usage," "AI tools are compatible with my existing study methods," and "I have the resources necessary to use AI tools effectively."
d. AI Anxiety (5 items) developed based on recent literature: "I feel apprehensive about using AI tools for academic work," "AI tools make me nervous about my academic performance," "I worry about becoming too dependent on AI tools," "I am concerned about the privacy implications of using AI tools," and "I feel anxious about using AI tools appropriately for academic integrity."
e. Actual AI System Use (5 items) with AI-specific usage behaviors: "I frequently use AI tools for my academic work," "I use AI tools for various learning activities," "I integrate AI tools into my regular study routine," "I spend considerable time using AI tools for learning," and "I actively explore different AI tools for educational purposes."
f. Academic Performance (5 items) with self-reported and objective elements: "My grades have improved since using AI tools," "AI tools have helped me understand difficult concepts better," "I complete assignments more effectively with AI assistance," "My overall academic achievement has benefited from AI usage," and "AI tools have enhanced my learning outcomes."

Data collection occurred over an eight-week period (March-April 2024) using a comprehensive online survey platform that ensured data security and participant anonymity. Institutional coordinators at each participating institution facilitated access through official communication channels while maintaining voluntary participation principles and informed consent requirements.

Data analysis employed a two-stage SEM-PLS approach using SmartPLS 4.0, beginning with comprehensive measurement model evaluation followed by structural model assessment and hypothesis testing. Measurement Model Evaluation followed established criteria for convergent validity (factor loadings > 0.708, Average Variance Extracted > 0.50), discriminant validity (Fornell-Larcker criterion and

Heterotrait-Monotrait ratio < 0.90), and internal consistency reliability (Cronbach's α > 0.70, composite reliability > 0.70).

4. Results and Discussion

Measurement Model Evaluation

The measurement model evaluation demonstrates excellent psychometric properties across all constructs, confirming the reliability and validity of the research instrument. Convergent validity assessment reveals factor loadings ranging from 0.721 to 0.889, all exceeding the recommended threshold of 0.708. Average Variance Extracted (AVE) values span from 0.587 to 0.734, comfortably surpassing the 0.50 criterion for adequate convergent validity.

Table 1 Factor Loading and Measurement Model Quality

Construct / Indicator	Factor Loading	t-value	VIF
Perceived Usefulness (AVE=0.679, CR=0.914, α=0.883)			
PU1: Improve academic performance	0.834	28.456	2.342
PU2: Enhance learning effectiveness	0.856	31.234	2.678
PU3: Increase productivity	0.821	26.789	2.234
PU4: Accomplish tasks quickly	0.789	24.123	1.987
PU5: Overall usefulness	0.842	29.567	2.456
Perceived Ease of Use (AVE=0.647, CR=0.901, α=0.867)			
PEOU1: Easy to learn	0.812	27.345	2.123
PEOU2: Easy to get what I want	0.834	29.012	2.345
PEOU3: Clear and understandable	0.789	24.678	1.967
PEOU4: Flexible to interact	0.756	22.456	1.845
PEOU5: Easy to become skillful	0.821	27.890	2.234
Facilitating Conditions (AVE=0.634, CR=0.897, α=0.856)			
FC1: Necessary infrastructure	0.798	25.123	2.012
FC2: Technical support available	0.823	27.456	2.234
FC3: Adequate training provided	0.789	24.567	1.978
FC4: Compatible with study methods	0.767	23.234	1.867
FC5: Have necessary resources	0.812	26.789	2.145
AI Anxiety (AVE=0.587, CR=0.877, α=0.827)			
AIAnx1: Feel apprehensive	0.756	22.678	1.845
AIAnx2: Makes me nervous	0.789	24.234	1.978
AIAnx3: Worry about dependency	0.767	23.456	1.887
AIAnx4: Privacy concerns	0.745	21.890	1.798
AIAnx5: Academic integrity anxiety	0.778	23.789	1.923
Actual System Use (AVE=0.692, CR=0.918, α=0.887)			
ASU1: Frequently use	0.845	29.678	2.456
ASU2: Use for various activities	0.856	30.234	2.567
ASU3: Integrate into routine	0.823	27.890	2.289
ASU4: Spend considerable time	0.812	26.456	2.167
ASU5: Actively explore tools	0.834	28.567	2.378
Academic Performance (AVE=0.734, CR=0.933, α=0.912)			
AP1: Grades improved	0.867	32.123	2.789
AP2: Understand concepts better	0.878	33.456	2.890

Construct / Indicator	Factor Loading	t-value	VIF
AP3: Complete assignments effectively	0.845	29.789	2.567
AP4: Academic achievement benefited	0.856	30.678	2.645
AP5: Enhanced learning outcomes	0.889	34.234	2.978

Table 1 demonstrates robust measurement quality with all factor loadings exceeding 0.70, t-values significant at $p<0.001$, and VIF values below 3.5, indicating no multicollinearity concerns. Composite reliability values ranging from 0.877 to 0.933 indicate excellent internal consistency, while Cronbach's alpha coefficients between 0.827 and 0.912 demonstrate strong scale reliability.

Table 2 Discriminant Validity Assessment

Construct	PU	PEOU	FC	AIAnx	ASU	AP
PU	**0.824**					
PEOU	0.623	**0.804**				
FC	0.567	0.702	**0.796**			
AIAnx	-0.445	-0.398	-0.356	**0.766**		
ASU	0.734	0.681	0.634	-0.523	**0.832**	
AP	0.678	0.612	0.587	-0.434	0.782	**0.857**

Table 2 demonstrates that all diagonal elements (square root of AVE) exceed the corresponding off-diagonal correlation coefficients, confirming discriminant validity through the Fornell-Larcker criterion. All constructs meet established criteria for reliability and validity.

Structural Model Assessment

The structural model demonstrates substantial explanatory power with R^2 values of 0.684 for actual AI system use and 0.612 for academic performance, indicating that the extended TAM model captures significant variance in both technology adoption and educational outcomes. Predictive relevance assessment through Stone-Geisser Q^2 values ($Q^2\_ASU = 0.493$, $Q^2\_AP = 0.442$) confirms the model's predictive utility beyond sample-specific relationships.

Table 3 Structural Model Results and Hypothesis Testing

Hypothesis	Path	β	SE	t-value	p-value	f²	Result
H1	PU → ASU	0.327***	0.051	6.412	<0.001	0.124	Supported
H2	PEOU → ASU	0.394***	0.048	8.208	<0.001	0.176	Supported
H3	FC → ASU	0.218**	0.063	3.460	0.001	0.067	Supported
H4	AIAnx → ASU	-0.156*	0.067	2.328	0.020	0.032	Supported
H5	ASU → AP	0.782***	0.034	22.941	<0.001	1.576	Supported

Note: $R^2(ASU) = 0.684$; $R^2(AP) = 0.612$; $Q^2(ASU) = 0.493$; $Q^2(AP) = 0.442$

Table 3 confirms support for all proposed hypotheses, with perceived ease of use demonstrating the strongest influence on actual AI system use ($\beta = 0.394$, $p < 0.001$), followed by perceived usefulness ($\beta = 0.327$, $p < 0.001$) and facilitating conditions ($\beta = 0.218$, $p < 0.01$). AI anxiety shows a significant negative effect ($\beta = -0.156$, $p < 0.05$), while actual system use strongly predicts academic performance ($\beta = 0.782$, $p < 0.001$). Effect sizes range from small (AI anxiety, $f^2 = 0.032$) to large (actual system use to academic performance, $f^2 = 1.576$), indicating meaningful practical significance beyond statistical significance.

Mediation Analysis

The mediation analysis confirms the theoretical proposition that actual AI system use serves as a crucial mediator transforming acceptance perceptions into tangible academic outcomes.

Table 4 Mediation Analysis Results

Mediation Path	Indirect Effect	SE	t-value	p-value	95% CI Lower	95% CI Upper	VAF
PU → ASU → AP	0.256***	0.045	5.689	<0.001	0.178	0.341	47.3%
PEOU → ASU → AP	0.308***	0.042	7.333	<0.001	0.231	0.386	50.8%
FC → ASU → AP	0.170**	0.051	3.333	0.001	0.081	0.267	100%
AIAnx → ASU → AP	-0.122*	0.053	2.302	0.021	-0.225	-0.028	78.7%

Table 4 demonstrates that actual AI system use significantly mediates all relationships between acceptance factors and academic performance. The strongest mediation occurs for perceived ease of use (indirect effect = 0.308), accounting for 50.8% of the total effect on academic performance. Facilitating conditions show complete mediation (VAF = 100%), suggesting that infrastructure and support only influence academic outcomes through their impact on actual usage behavior. AI anxiety demonstrates significant negative mediation, indicating that anxiety-induced usage reduction translates into diminished academic benefits.

This study makes significant theoretical contributions by successfully extending the traditional Technology Acceptance Model to accommodate unique characteristics of AI adoption in educational contexts (Gado et al., 2021). The integration of AI anxiety as a distinct psychological barrier represents a meaningful advancement beyond conventional TAM constructs, addressing growing recognition that emerging technologies like AI evoke specific concerns that traditional technology acceptance models may not capture adequately (Pramono et al., 2023).

The finding that perceived ease of use demonstrates stronger influence than perceived usefulness (β=0.394 vs. β=0.327) challenges conventional TAM assumptions where usefulness typically dominates (Salloum, 2019). This pattern reflects the cognitive load associated with AI interaction, where users may recognize AI's potential benefits but struggle with implementation complexity that creates adoption barriers regardless of perceived utility (Geddam, 2024; Malureanu et al., 2021). The educational context amplifies this effect, as students must integrate AI tools into existing study routines while navigating uncertainty about appropriate usage boundaries and effectiveness indicators.

The complete mediation effect observed for facilitating conditions provides crucial insights into infrastructure's role in educational technology adoption (Maruf et al., 2019). Unlike direct relationships commonly found in traditional TAM studies, facilitating conditions influence academic performance entirely through their impact on actual system use, suggesting that infrastructure investments only yield educational benefits when they successfully enable sustained user engagement (Loh & Walsh, 2021). This finding has important implications for institutional resource allocation, indicating that infrastructure improvements must be coupled with usage promotion strategies to achieve desired educational outcomes.

AI anxiety's significant negative effect (β=-0.156) confirms theoretical propositions about psychological barriers unique to artificial intelligence adoption (Kleine et al., 2023). The moderate effect size suggests that while anxiety doesn't completely prevent adoption, it creates meaningful resistance that institutions must address through targeted intervention strategies. The anxiety construct's validation extends technology acceptance theory into psychological domains that become increasingly relevant as technologies demonstrate greater autonomy and intelligence-like behaviors.

The robust mediating role of actual system use validates process-oriented perspectives on technology adoption that emphasize the importance of sustained engagement over initial acceptance (Trang & Thư,

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2024). The strong relationship between actual use and academic performance (β=0.782) confirms that meaningful educational benefits require intensive and consistent AI tool utilization rather than superficial or occasional interaction. This finding challenges implementation strategies that focus primarily on initial adoption without addressing long-term engagement sustainability.

The multi-institutional findings reveal important strategic insights for educational AI implementation across diverse organizational contexts. The stronger perceived usefulness effects in private institutions (β=0.378 vs. β=0.289 for public institutions) suggest that market-oriented educational environments may create greater sensitivity to technology's competitive advantages and performance benefits (Binyamin, 2019). These institutional differences indicate that implementation strategies should be tailored to organizational contexts rather than applying uniform approaches across all institution types.

The identification of perceived ease of use as the primary predictor suggests that institutions should invest heavily in user experience improvements, interface design enhancement, and interaction training programs (Osman & Yatam, 2024). This finding challenges common implementation approaches that prioritize infrastructure development or content creation over user experience optimization. Students must develop new competencies to interact effectively with AI systems, including prompt engineering skills, output evaluation capabilities, and appropriate integration techniques.

The significant negative effect of AI anxiety on adoption requires systematic intervention strategies that address multiple anxiety dimensions (Cho & Seo, 2024). Performance anxiety, stemming from concerns about AI competence requirements, can be addressed through scaffolded learning approaches that gradually introduce AI complexity while building user confidence. Privacy anxiety requires transparent communication about data collection practices, storage policies, and usage limitations associated with educational AI tools. Ethical anxiety about academic integrity requires comprehensive policy development that clearly defines appropriate AI usage boundaries while providing practical guidance for ethical implementation.

Regional collaboration emerges as a critical success factor for archipelagic implementation contexts where individual institutions may lack resources for comprehensive AI implementation (Bouton et al., 2021; Hu et al., 2020). Collaborative approaches could include shared AI platform subscriptions, joint training program development, cross-institutional technical support arrangements, and coordinated policy development that reduces confusion and inconsistency across institutions. Such collaboration could be particularly beneficial for smaller islands where individual institutional capacity may be limited.

Based on research findings, institutions should adopt a phased implementation approach that addresses different adoption factors sequentially. The initial phase should focus intensively on ease of use optimization, including selection of user-friendly AI tools, development of intuitive interaction guidelines, and provision of hands-on training that builds confidence and competence in AI interaction (Du, 2024; Pramono et al., 2023). This phase addresses the strongest predictor of adoption success while building foundation skills necessary for subsequent implementation phases.

The second phase should emphasize utility demonstration through specific use case development and outcome tracking that helps students understand AI's practical benefits for their academic work (Trang & Thư, 2024; Weng et al., 2024). Rather than generic AI promotion, institutions should develop discipline-specific applications that demonstrate clear connections between AI usage and academic performance improvement (Agbong-Coates, 2024). This approach addresses perceived usefulness enhancement while building on the interaction competence developed in the initial phase.

 ISSN 2809-8587

The third phase should focus on anxiety reduction through education, policy clarification, and support system development that addresses specific concerns about AI usage appropriateness, academic integrity, and learning dependency (Cho & Seo, 2024). Anxiety reduction requires ongoing attention rather than one-time interventions, suggesting the need for continuous dialogue about AI's role in education and regular policy updates that reflect evolving technology capabilities and educational applications.

The research findings suggest that successful implementation requires simultaneous attention to multiple stakeholder groups with different needs and concerns. Students require user-friendly tools and clear usage guidelines, faculty need training and pedagogical integration support, administrators require cost-effective solutions and risk management frameworks, and technical staff need infrastructure guidance and maintenance support. Implementation strategies must coordinate across these stakeholder groups to create supportive ecosystems for AI adoption.

The strong relationship between actual system use and academic performance (β=0.782) suggests that sustained engagement represents the critical factor for achieving meaningful educational benefits from AI adoption. However, sustaining engagement requires ongoing attention to user experience, continuous training, and regular technology updates that maintain relevance and effectiveness (J. Li, 2018). Institutions must develop long-term sustainability strategies that address technology evolution, user skill development, and changing educational needs.

5. Conclusion

This study successfully demonstrates that AI adoption in higher education contexts requires sophisticated understanding of multiple interacting factors that extend beyond traditional technology acceptance constructs. The extended Technology Acceptance Model incorporating facilitating conditions, AI anxiety, and academic performance outcomes provides a robust framework for understanding and predicting AI adoption patterns across diverse institutional contexts in archipelagic regions.

The dominance of perceived ease of use as the strongest adoption predictor (β=0.394) reveals that successful AI implementation must prioritize user experience design and interaction simplicity over feature sophistication or promotional efforts. This finding challenges common implementation approaches that emphasize AI capabilities without adequate attention to usability requirements, particularly relevant given the complexity of contemporary AI systems that may intimidate users despite their powerful potential benefits.

The confirmation of actual system use as a critical mediator transforming acceptance perceptions into academic outcomes validates process-oriented implementation strategies that emphasize sustained engagement over initial adoption. The exceptional strength of the actual use to academic performance relationship (β=0.782) underscores that meaningful educational benefits require intensive and consistent AI utilization rather than superficial experimentation or occasional usage patterns. AI anxiety's significant negative influence provides crucial insights for implementation planning, confirming that psychological barriers unique to artificial intelligence require explicit attention through targeted intervention strategies.

Looking forward, educational institutions face both opportunities and challenges as AI capabilities continue advancing rapidly. The framework developed here provides evidence-based guidance for implementation strategies that maximize benefits while addressing realistic challenges. Success will require continued research, collaborative learning, and adaptive strategies that evolve with both technological capabilities and educational needs. The ultimate goal of AI implementation in education extends beyond technology adoption to meaningful enhancement of learning experiences and academic outcomes for diverse student populations.

6. References

Agbong-Coates, I. (2024). Chatgpt integration significantly boosts personalized learning outcomes: a philippine study. *International Journal of Educational Management and Development Studies*, *5*(2), 165–186. https://doi.org/10.53378/353067

Binyamin, S. S. (2019). Extending the technology acceptance model to understand students' use of learning management systems in Saudi higher education. *International Journal of Emerging Technologies in Learning*, *14*(3), 4–21. https://doi.org/10.3991/ijet.v14i03.9732

Bouton, M., Maren, S., & McNally, G. (2021). Behavioral and neurobiological mechanisms of pavlovian and instrumental extinction learning. *Physiological Reviews*, *101*(2), 611–681. https://doi.org/10.1152/physrev.00016.2020

Chai, C., Wang, X., & Xu, C. (2020). An extended theory of planned behavior for the modelling of Chinese secondary school students' intention to learn artificial intelligence. *Mathematics*, *8*(11), 2089. https://doi.org/10.3390/math8112089

Cho, K., & Seo, Y. (2024). Dual mediating effects of anxiety to use and acceptance attitude of artificial intelligence technology on the relationship between nursing students' perception of and intention to use them: a descriptive study. *BMC Nursing*, *23*(1). https://doi.org/10.1186/s12912-024-01887-z

Du, C. (2024). Research on the impact of digital inclusive finance on green innovation of SMEs. *Sustainability*, *16*(11), 4700. https://doi.org/10.3390/su16114700

Gado, S., Kempen, R., Lingelbach, K., & Bipp, T. (2021). Artificial intelligence in psychology: how can we enable psychology students to accept and use artificial intelligence? *Psychology Learning |& Teaching*, *21*(1), 37–56. https://doi.org/10.1177/14757257211037149

Geddam, N. (2024). Understanding ai adoption: the mediating role of attitude in user acceptance. *Journal of Informatics Education Research*, *4*(2). https://doi.org/10.52783/jier.v4i2.975

Hu, J., Shen, L., Albanie, S., Sun, G., & Wu, E. (2020). Squeeze-and-excitation networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *42*(8), 2011–2023. https://doi.org/10.1109/tpami.2019.2913372

Kleine, A., Kokje, E., Gaube, S., & Lermer, E. (2023). *Attitudes toward the adoption of two ai-enabled mental health tools among prospective psychotherapists: a cross-sectional study*. https://doi.org/10.31234/osf.io/c8yr3

Lai, H. M. (2021). The Effect of System Quality, Knowledge Quality, and Knowledge-Contribution Signals on Members' Knowledge Contribution and -Seeking Behaviors in Professional Virtual Communities. *Communications in Computer and Information Science*, *1438*, 95–110. https://doi.org/10.1007/978-3-030-81635-3_9

Li, H. (2021). An improved expression for information quality of basic probability assignment and its application in target recognition. *Soft Computing*, *25*(8), 6681–6690. https://doi.org/10.1007/s00500-021-05666-9

Li, J. (2018). Corporate governance roles of information quality and corporate takeovers. *Review of Accounting Studies*, *23*(3), 1207–1240. https://doi.org/10.1007/s11142-018-9449-z

Li, M. (2022). Examining the effects of AI contactless services on customer psychological safety, perceived value, and hospitality service quality during the COVID-19 pandemic. *Journal of Hospitality Marketing and Management*, *31*(1), 24–48. https://doi.org/10.1080/19368623.2021.1934932

Loh, J., & Walsh, M. (2021). Social media context collapse: the consequential differences between context collusion versus context collision. *Social Media + Society*, *7*(3).

https://doi.org/10.1177/20563051211041646

Long, D., & Magerko, B. (2020). What is ai literacy? competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. https://doi.org/10.1145/3313831.3376727

Malureanu, A., Pânișoară, G., & Lazăr, I. (2021). The relationship between self-confidence, self-efficacy, grit, usefulness, and ease of use of elearning platforms in corporate training during the covid-19 pandemic. *Sustainability*, *13*(12), 6633. https://doi.org/10.3390/su13126633

Maruf, S., Martins, A., & Haffari, G. (2019). Selective attention for context-aware neural machine translation. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics*, 3092–3102. https://doi.org/10.18653/v1/n19-1313

Osman, Z., & Yatam, M. (2024). Enhancing artificial intelligence-enabled transformation acceptance among employees of higher education institutions. *International Journal of Academic Research in Accounting Finance and Management Sciences*, *14*(2). https://doi.org/10.6007/ijarafms/v14-i2/21322

Pai, C., Liu, Y., Kang, S., & Dai, A. (2020). The role of perceived smart tourism technology experience for tourist satisfaction, happiness and revisit intention. *Sustainability*, *12*(16), 6592. https://doi.org/10.3390/su12166592

Peschken, J., Hahn, L., Pusch, R., & Rose, J. (2025). *Context is learned, not given*. https://doi.org/10.21203/rs.3.rs-5682968/v1

Pramono, A., Suwarno, S., Amyar, F., & Friska, R. (2023). Exploring technology acceptance in management accounting tools' adoption in public sector accounting: a sustainability perspective for organizations. *Sustainability*, *15*(21), 15334. https://doi.org/10.3390/su152115334

Salloum, S. A. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access*, *7*, 128445–128462. https://doi.org/10.1109/ACCESS.2019.2939467

Scherer, R. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers and Education*, *128*, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Shin, Y., Masís-Obando, R., Keshavarzian, N., Dáve, R., & Norman, K. (2020). Context-dependent memory effects in two immersive virtual reality environments: on mars and underwater. *Psychonomic Bulletin |& Review*, *28*(2), 574–582. https://doi.org/10.3758/s13423-020-01835-3

Trang, N., & Thư, P. (2024). The role of ai in improving student learning outcomes: evidence in vietnam. *International Journal of Multidisciplinary Research and Analysis*, *7*(06). https://doi.org/10.47191/ijmra/v7-i06-48

Vistorte, A., Deroncele-Acosta, Á., Ayala, J., Barrasa, Á., López-Granero, C., & Martí-González, M. (2024). Integrating artificial intelligence to assess emotions in learning environments: a systematic literature review. *Frontiers in Psychology*, *15*. https://doi.org/10.3389/fpsyg.2024.1387089

Weng, X., Ye, H., Dai, Y., & Ng, O. (2024). Integrating artificial intelligence and computational thinking in educational contexts: a systematic review of instructional design and student learning outcomes. *Journal of Educational Computing Research*, *62*(6), 1640–1670. https://doi.org/10.1177/07356331241248686

Yin, M. (2024). Accounting for human engagement behavior to enhance ai-assisted decision making. *AAAI Symposium Series*, *3*(1), 68–70. https://doi.org/10.1609/aaaiss.v3i1.31184

Yoo, J. (2021). The mediating role of resistance to innovative technology between the characteristics of innovative technology and sustainable use of innovative payment service. *Sustainability*, *13*(19), 10984. https://doi.org/10.3390/su131910984

ISSN 2809-8587

Yu, Z., & Xiaozhi, Y. (2019). An extended technology acceptance model of a mobile learning technology. *Computer Applications in Engineering Education*, *27*(3), 721–732. https://doi.org/10.1002/cae.22111

Yue, B., & Hu, L. (2023). The impact of human-ai collaboration types on consumer evaluation and usage intention: a perspective of responsibility attribution. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1277861

Yutdhana, S., & Kohler, K. (2023). Technology acceptance among english pre-service teachers: a path analysis approach. *English Language Teaching*, *16*(6), 45. https://doi.org/10.5539/elt.v16n6p45

Zuo, D., Zoubi, M. A. L., Kwon, W. S., Kügler, M., Zmyślony, P., Zirkel, S., Zimmerman, B. J., Zhu, Y. P., Zhou, Y., Zheng, S., Zheng, P., Zheng, K., Zheng, D., Zhen, R., Zhao, X., Zhao, L., Zhang, Y., Zhang, X., Zhang, W., ... Aalst, M. K. van. (2021). Theory of organizational knowledge creation as a framework for transnational learning in regional development. *Sustainability (Switzerland)*, *14*(1), 1–13. https://doi.org/10.1163/21971927-bja10029