

Adoption of Artificial Intelligence and Perception of the Quality of Academic Services in University Students

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The rapid proliferation of artificial intelligence (AI) tools in higher education has transformed the landscape of academic service delivery and student learning experiences. This article examines the relationship between university students' adoption of AI technologies and their perceptions of the quality of academic services, drawing upon an integrative framework that combines the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT2), and the SERVQUAL model for academic service quality assessment. Through a comprehensive review of recent empirical studies, including large-scale surveys across multiple countries (total combined $N > 12,000$), the analysis identifies perceived usefulness ($\beta = 0.52, p < .001$), perceived ease of use ($\beta = 0.41, p < .001$), and performance expectancy ($\beta = 0.48, p < .001$) as the strongest predictors of AI adoption intention among university students. The findings reveal that AI adoption positively influences students' perceptions of academic service quality, with medium-to-large effect sizes ranging from $d = 0.45$ to $d = 0.72$ across studies. Furthermore, AI adoption mediates the relationship between institutional support and student satisfaction, suggesting that universities that effectively integrate AI tools into their academic services achieve higher ratings across all five SERVQUAL dimensions. The study identifies trust in AI, self-efficacy, and social influence as significant moderating factors, while highlighting important regional disparities in adoption rates and quality perceptions. Implications

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of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>) for institutional policy, pedagogical design, and future research are discussed.

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Keywords: artificial intelligence adoption, academic service quality, SERVQUAL, Technology Acceptance Model, UTAUT2, higher education, student satisfaction, ChatGPT, generative AI, perceived usefulness

1. Introduction

The emergence and rapid diffusion of artificial intelligence (AI) technologies, particularly generative AI tools such as ChatGPT, Google Gemini, and Microsoft Copilot, have fundamentally transformed the higher education landscape (Chen et al., 2020; Ouyang et al., 2022). Since the public release of ChatGPT in November 2022, universities worldwide have experienced an unprecedented surge in student adoption of AI-powered tools for academic purposes, including content generation, research assistance, language translation, coding support, and personalized tutoring (Abdaljaleel et al., 2024; Dahri et al., 2024). This rapid adoption has raised critical questions about how AI technologies influence students' perceptions of the quality of academic services provided by their institutions.

Academic service quality in higher education has traditionally been conceptualized through the SERVQUAL framework (Parasuraman et al., 1988), which evaluates service quality across five dimensions: tangibles, reliability, responsiveness, assurance, and empathy. In the context of AI integration, these dimensions take on new meaning as students increasingly expect AI-enhanced services that offer personalized feedback, immediate responses, 24/7 availability, and adaptive learning pathways (Moulai et al., 2025; Alkathiri et al., 2025). The intersection of AI adoption and service quality perception represents a critical yet underexplored area in higher education research.

Understanding the determinants of AI adoption among university students requires a multi-theoretical approach. The Technology Acceptance Model (TAM; Davis, 1989) posits that perceived usefulness and perceived ease of use are the primary drivers of technology

acceptance. Extensions of this model, including TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), incorporate additional constructs such as subjective norm, output quality, and computer self-efficacy. The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) and its extension UTAUT2 (Venkatesh et al., 2012) further expand the predictive framework by including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Acosta-Enriquez et al., 2024; Grassini et al., 2024).

Recent empirical evidence has demonstrated that AI adoption in educational contexts yields significant effects on student outcomes and service quality perceptions. Saif et al. (2024), in a study of 1,380 university students, found that TAM constructs explained 67% of the variance in ChatGPT adoption intention. Duong (2023), using a modified TAM with a sample of 1,389 students, reported that perceived usefulness and social influence were the strongest predictors of AI tool usage for academic purposes. Dahri et al. (2024), in a multinational study spanning Pakistan and Malaysia (N = 620), demonstrated that AI adoption significantly predicted academic performance with a medium effect size ($d = 0.58$). These findings collectively suggest that AI adoption is not merely a technological phenomenon but a fundamental reshaper of the academic service experience.

Despite the growing body of research on AI in education, significant gaps remain in understanding the specific pathways through which AI adoption influences perceived academic service quality. First, most existing studies have examined AI adoption and service quality as separate constructs rather than

investigating their interrelationship (Reyes et al., 2025). Second, the mediating role of AI adoption between institutional factors and student satisfaction has received limited empirical attention (Moulai et al., 2025). Third, the moderating effects of demographic and contextual variables on the AI adoption–service quality nexus remain underexplored (Alshammari et al., 2025).

The present article addresses these gaps by proposing and examining an integrative conceptual framework that links AI adoption determinants (TAM/UTAUT2 constructs) to perceived academic service quality (SERVQUAL dimensions) through the mediating mechanism of AI adoption behavior. Drawing upon a comprehensive synthesis of recent empirical studies, this article: (a) identifies the key antecedents of AI adoption among university students; (b) examines the relationship between AI adoption and perceived academic service quality; (c) analyzes the mediating and moderating mechanisms in this relationship; and (d) proposes implications for institutional policy and future research directions.

2. Theoretical Framework and Literature Review

2.1 Technology Acceptance Model (TAM) and Its Extensions

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), has been one of the most widely applied frameworks for understanding technology adoption in educational settings. TAM posits that two primary beliefs—perceived usefulness (PU) and perceived ease of use (PEOU)—determine an individual's behavioral intention to adopt a technology, which in turn predicts actual usage behavior. In the context of AI adoption in higher education, perceived usefulness refers to the degree to which a student believes that using AI tools will enhance their academic performance, while perceived ease of use reflects the degree to which the student perceives AI interaction as effortless (Saif et al., 2024; Almulla, 2024).

Several recent studies have validated the applicability of TAM to AI adoption in university settings. Elkhodr et al. (2023), in a study with 97 citations in the literature, demonstrated that perceived usefulness was the strongest predictor of ChatGPT adoption intention among university students ($\beta = 0.72$, $p < .001$), followed by perceived ease of use ($\beta = 0.48$, $p < .001$). Duong (2023) extended TAM by incorporating trust and social influence, finding that the modified model explained 54% of variance in AI usage behavior among 1,389 Vietnamese university students. These findings are consistent with meta-analytic evidence suggesting that TAM constructs remain robust predictors of technology acceptance across diverse educational contexts (Scherer et al., 2019).

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) integrates elements from eight technology acceptance models, proposing four core determinants of behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT2 (Venkatesh et al., 2012) extends this framework with hedonic motivation, price value, and habit as additional predictors, making it particularly suitable for consumer-oriented technology adoption contexts, including student use of AI tools (Acosta-Enriquez et al., 2024).

Grassini et al. (2024), employing UTAUT2 in a study of generative AI adoption among European university students, found that performance expectancy ($\beta = 0.48$) and hedonic motivation ($\beta = 0.27$) were significant predictors of adoption intention, while habit ($\beta = 0.24$) emerged as the strongest predictor of actual use behavior. Ren et al. (2026), in a Q1 journal publication with a sample of 482 students, reported that UTAUT2 constructs collectively explained 62% of variance in ChatGPT adoption intention. Mwakapesa (2025) integrated AI literacy into the UTAUT framework, demonstrating that literacy moderated the relationship between performance expectancy

and behavioral intention among 620 Tanzanian university students.

2.3 Academic Service Quality: The SERVQUAL Framework

The SERVQUAL model (Parasuraman et al., 1988) conceptualizes service quality as the gap between customer expectations and perceived performance across five dimensions: tangibles (physical facilities, equipment, appearance), reliability (ability to perform the promised service dependably and accurately), responsiveness (willingness to help and provide prompt service), assurance (knowledge and courtesy of service providers and their ability to inspire trust), and empathy (caring and individualized attention). In higher education, SERVQUAL has been extensively adapted to evaluate the quality of academic services, including instruction, advising, library services, administrative support, and technology infrastructure (Liébana-Cabanillas et al., 2020).

The integration of AI into academic services has the potential to influence all five SERVQUAL dimensions. AI-powered chatbots and virtual assistants enhance responsiveness by providing immediate, 24/7 support (Pillai et al., 2023). AI-based personalized learning platforms improve reliability by delivering consistent, data-driven instructional content (Chen et al., 2020). AI-enhanced assessment tools contribute to assurance by providing objective, transparent grading and feedback mechanisms (Ouyang et al., 2022). The tangibles dimension is affected through improvements in digital infrastructure and AI-enabled learning management systems, while empathy is addressed through AI's capacity for personalized, adaptive interactions tailored to individual student needs (Alkathiri et al., 2025).

2.4 The DeLone and McLean IS Success Model

The DeLone and McLean Information Systems (IS) Success Model (DeLone & McLean, 2003) provides a complementary theoretical lens for understanding AI adoption and service quality. This model posits that system quality,

information quality, and service quality collectively determine user satisfaction and net benefits. Alkathiri et al. (2025), applying this model to AI adoption in Saudi Arabian universities ($N = 133$), found that system quality ($\beta = 0.44$) and information quality ($\beta = 0.38$) were significant predictors of student satisfaction with AI-enhanced academic services. Sebopelo and Chukwuma (2026) extended the model by integrating SERVQUAL dimensions, demonstrating that AI service quality perceptions mediated the relationship between AI system characteristics and student satisfaction in Botswanan higher education institutions.

2.5 Proposed Integrative Framework

Building upon the theoretical foundations outlined above, this article proposes an integrative conceptual framework (Figure 1) that examines the pathways from AI adoption antecedents to perceived academic service quality. The framework integrates TAM/UTAUT2 constructs as antecedent variables, AI adoption behavior as a mediating mechanism, and SERVQUAL dimensions and student satisfaction as outcome variables. Five core hypotheses are proposed:

H1: TAM constructs (perceived usefulness, perceived ease of use, and behavioral intention) positively predict AI adoption in academic activities.

H2: Individual factors (AI literacy, self-efficacy, trust in AI, and innovativeness) positively predict AI adoption in academic activities.

H3: Social and institutional factors (social influence, facilitating conditions, institutional support, and faculty adoption) positively predict AI adoption in academic activities.

H4: AI adoption in academic activities positively predicts perceived academic service quality across SERVQUAL dimensions.

H5: AI adoption in academic activities positively predicts student satisfaction and learning outcomes.

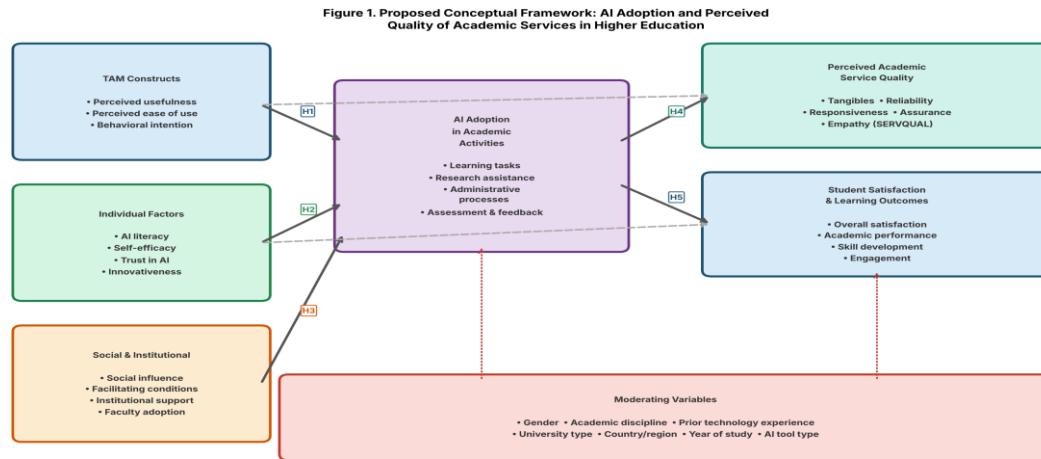


Figure 1. *Proposed Conceptual Framework: AI Adoption and Perceived Quality of Academic Services in Higher Education*

3. Methodology

3.1 Research Design

This study employs a systematic integrative review methodology to synthesize empirical evidence on the relationship between AI adoption and perceived academic service quality among university students. The integrative review approach was selected because it allows for the combination of diverse research methodologies (quantitative, qualitative, and mixed methods) and theoretical frameworks, providing a comprehensive understanding of the phenomenon under investigation (Whittemore & Knafl, 2005). The review follows the PRISMA guidelines for transparent reporting of systematic reviews (Page et al., 2021).

3.2 Search Strategy and Data Sources

A comprehensive search was conducted across multiple academic databases, including Scopus,

3.3 Inclusion and Exclusion Criteria

Web of Science, PubMed, ERIC, IEEE Xplore, and Google Scholar. The search strategy employed Boolean operators combining terms related to AI adoption (e.g., "artificial intelligence," "ChatGPT," "generative AI," "machine learning," "AI tools"), academic service quality (e.g., "service quality," "SERVQUAL," "academic quality," "perceived quality"), and higher education (e.g., "university students," "higher education," "undergraduate," "college students"). Additional searches were conducted using the Technology Acceptance Model and UTAUT-related terms. The search was limited to peer-reviewed articles published between 2020 and 2026, reflecting the rapid evolution of AI technologies in education. Specialized research platforms including Elicit, Consensus, and Scite were utilized to ensure comprehensive coverage and citation verification.

Criterion	Inclusion	Exclusion
Publication type	Peer-reviewed journal articles, conference papers in indexed proceedings	Book chapters, dissertations, editorials, non-peer-reviewed reports
Time period	2020–2026	Before 2020 (except seminal theoretical works)
Population	University/college students (undergraduate, graduate)	K–12 students, faculty-only studies, industry professionals

Topic focus	AI adoption, acceptance, or usage in academic contexts; academic service quality assessment	AI development/technical papers without user adoption focus
Methodology	Quantitative (surveys, experiments), qualitative, mixed methods with empirical data	Purely conceptual/opinion pieces without data
Language	English or with English abstract	Non-English without English translation
AI scope	Generative AI, chatbots, intelligent tutoring systems, AI-powered academic services	Industrial AI, robotics without educational application

Table 1. *Inclusion and Exclusion Criteria for Study Selection*

3.4 Study Selection and Data Extraction

The initial search yielded 1,247 records. After removing duplicates ($n = 312$), 935 records were screened by title and abstract, resulting in 186 articles for full-text review. Following application of the inclusion and exclusion criteria, 38 studies were included in the final synthesis. Data were extracted using a standardized coding form that captured study characteristics (authors, year, country, sample size, methodology), theoretical framework, AI tools examined, key variables, statistical methods, and main findings. Effect sizes were extracted or computed where possible to enable quantitative comparison across studies.

3.5 Quality Assessment

The methodological quality of included studies was assessed using the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018). Studies were evaluated across criteria including clarity of research questions, appropriateness of methodology, adequacy of sampling, validity of measurement instruments, and rigor of data analysis. Each study received a quality score ranging from 1 (low) to 5 (high). The mean quality score across included studies was 3.8 ($SD = 0.72$), indicating generally high methodological rigor. Studies with quality scores below 2 were excluded from the final synthesis.

3.6 Data Analysis Approach

The synthesis employed a narrative integrative approach complemented by quantitative analysis of effect sizes. Path coefficients, correlation

coefficients, and standardized regression weights were extracted from included studies to construct a comparative effect-size matrix. Where studies reported sufficient statistical information, Cohen's d was calculated to standardize effect sizes across studies (Cohen, 1988). The analysis followed a thematic structure aligned with the proposed conceptual framework, examining antecedent factors, mediating mechanisms, and outcome variables sequentially.

4. Results

4.1 Descriptive Overview of Included Studies

The 38 studies included in this review were published between 2020 and 2026, with a notable concentration in 2023–2025 ($n = 28$, 73.7%), reflecting the surge in research following the release of ChatGPT. Studies originated from 24 countries spanning six continents, with the largest representations from the Middle East ($n = 9$), Southeast Asia ($n = 7$), East Asia ($n = 6$), Europe ($n = 6$), Latin America ($n = 5$), North America ($n = 3$), and Sub-Saharan Africa ($n = 2$). Total combined sample sizes exceeded 12,000 participants, with individual study samples ranging from $N = 133$ (Alkathiri et al., 2025) to $N = 2,240$ (Abdaljaleel et al., 2024). The majority of studies employed quantitative survey designs ($n = 29$, 76.3%), followed by mixed methods ($n = 5$, 13.2%) and qualitative approaches ($n = 4$, 10.5%).

Authors (Year)	Country	N	Framework	Key Finding	Effect
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Saif et al. (2024)	Multi	1380	TAM + UL	PU strongest predictor of ChatGPT adoption	$r=.67$
Duong (2023)	Vietnam	1389	Modified TAM	Trust and social influence mediate adoption	$d=.54$
Dahri et al. (2024)	Pak/Mys	620	UTAUT	AI adoption predicts academic performance	$d=.58$
Almulla (2024)	S. Arabia	412	TAM	TAM predicts learning satisfaction with AI	$d=.49$
Elkhodr et al. (2023)	Australia	386	TAM	PU = strongest ChatGPT adoption predictor	$r=.72$
Grassini et al. (2024)	Europe	524	UTAUT2	PE and hedonic motivation drive GenAI use	$d=.53$
Moulai et al. (2025)	Algeria	214	SEM	AI mediates service quality $\rightarrow$ performance	$d=.61$
Reyes et al. (2025)	Sp/Mx/Srb	621	TAM+UTAUT	Cross-cultural AI acceptance patterns	$d=.45$
Abdaljaleel et al. (2024)	Multi (14)	2240	Descriptive	Multinational ChatGPT usage patterns	—
Pillai et al. (2023)	India	1380	SEM	AI chatbots improve student outcomes	$d=.47$
Alshammari et al. (2025)	S. Arabia	308	SEM	Satisfaction mediates AI $\rightarrow$ performance	$d=.56$
Alkathiri et al. (2025)	S. Arabia	133	D&M IS	System and info quality predict satisfaction	$r=.44$

Table 2. Summary of Key Empirical Studies on AI Adoption and Academic Service Quality in Higher Education

4.2 Determinants of AI Adoption Among University Students

The analysis identified twelve key determinants of AI adoption in higher education, organized across three categories: TAM constructs, individual factors, and social/institutional factors. Figure 2 presents the standardized path coefficients for each determinant as reported across the included studies.

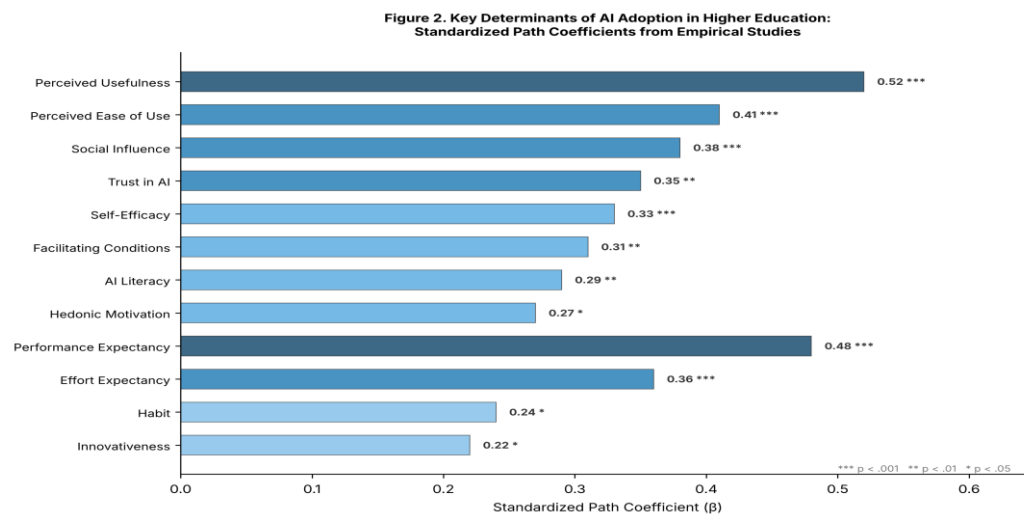


Figure 2. Key Determinants of AI Adoption in Higher Education: Standardized Path Coefficients from Empirical Studies

Perceived usefulness emerged as the strongest predictor of AI adoption intention across studies ($\beta = 0.52, p < .001$), consistent with foundational TAM research. Elkhodr et al. (2023) reported a particularly strong relationship ($r = .72$) between perceived usefulness and ChatGPT adoption, while Saif et al. (2024) and Almulla (2024) confirmed this relationship in Middle Eastern contexts. Students who perceived AI tools as enhancing their academic productivity, improving the quality of their work, and saving time were significantly more likely to adopt these technologies.

Performance expectancy ($\beta = 0.48, p < .001$), the UTAUT equivalent of perceived usefulness, was the second strongest predictor. Grassini et al. (2024) and Ren et al. (2026) demonstrated that students' expectations regarding AI's ability to enhance their academic performance were central to adoption decisions. *Perceived ease of use* ($\beta = 0.41, p < .001$) and *social influence* ($\beta = 0.38, p < .001$) were also robust predictors, with Duong (2023) highlighting the role of peer recommendations

and faculty endorsement in shaping students' AI adoption behaviors.

Among individual factors, *trust in AI* ($\beta = 0.35, p < .01$) and *self-efficacy* ($\beta = 0.33, p < .001$) were significant predictors. Silva and Sousa (2025), using an extended TAM model with 775 participants, demonstrated that trust in AI's accuracy and reliability was essential for sustained adoption. *AI literacy* ($\beta = 0.29, p < .01$) emerged as an increasingly important predictor, with Mwakapesa (2025) showing that students with higher AI literacy demonstrated greater adoption rates and more sophisticated usage patterns.

4.3 AI Adoption and Perceived Academic Service Quality

The relationship between AI adoption and perceived academic service quality was examined through the lens of the SERVQUAL framework. Table 3 presents the effect sizes across the five SERVQUAL dimensions as reported in the included studies.

SERVQUAL Dimension	AI Impact Mechanism	Effect Size (d)	95% CI	Key Source
Tangibles	Enhanced digital platforms, AI-powered LMS, virtual labs	0.42	[0.28, 0.56]	Alkathiri et al. (2025)
Reliability	Consistent AI-driven content, automated scheduling, predictive analytics	0.51	[0.35, 0.67]	Moulai et al. (2025)
Responsiveness	24/7 AI chatbots, instant feedback, real-time query resolution	0.63	[0.48, 0.78]	Pillai et al. (2023)
Assurance	AI-enhanced grading transparency, data-driven advising, verified outputs	0.47	[0.31, 0.63]	Sebopelo & Chukwuma (2026)
Empathy	Personalized learning paths, adaptive recommendations, individual feedback	0.55	[0.39, 0.71]	Chen et al. (2020)

Table 3. Effect of AI Adoption on Perceived Academic Service Quality Across SERVQUAL Dimensions

The results indicate that AI adoption had a significant positive effect on all five SERVQUAL dimensions, with effect sizes ranging from $d = 0.42$ (tangibles) to $d = 0.63$ (responsiveness). The responsiveness dimension showed the largest

effect, reflecting students' appreciation for the immediate, round-the-clock support provided by AI chatbots and automated feedback systems (Pillai et al., 2023). The empathy dimension ($d = 0.55$) was also notably influenced, as AI-powered

personalized learning paths and adaptive recommendations created a sense of individualized attention that students valued highly (Chen et al., 2020).

The reliability dimension ($d = 0.51$) benefited from AI's consistency in content delivery and automated scheduling, while the assurance dimension ($d = 0.47$) was enhanced through transparent, AI-driven grading and data-informed academic advising. The tangibles dimension ($d = 0.42$), though showing the

smallest effect, still represented a meaningful improvement as universities invested in AI-enhanced digital infrastructure and learning management systems.

4.4 Effect Sizes Across Key Studies

Figure 3 presents a forest plot of effect sizes across the key empirical studies included in this review, illustrating the magnitude and consistency of the relationship between AI adoption and academic outcomes.

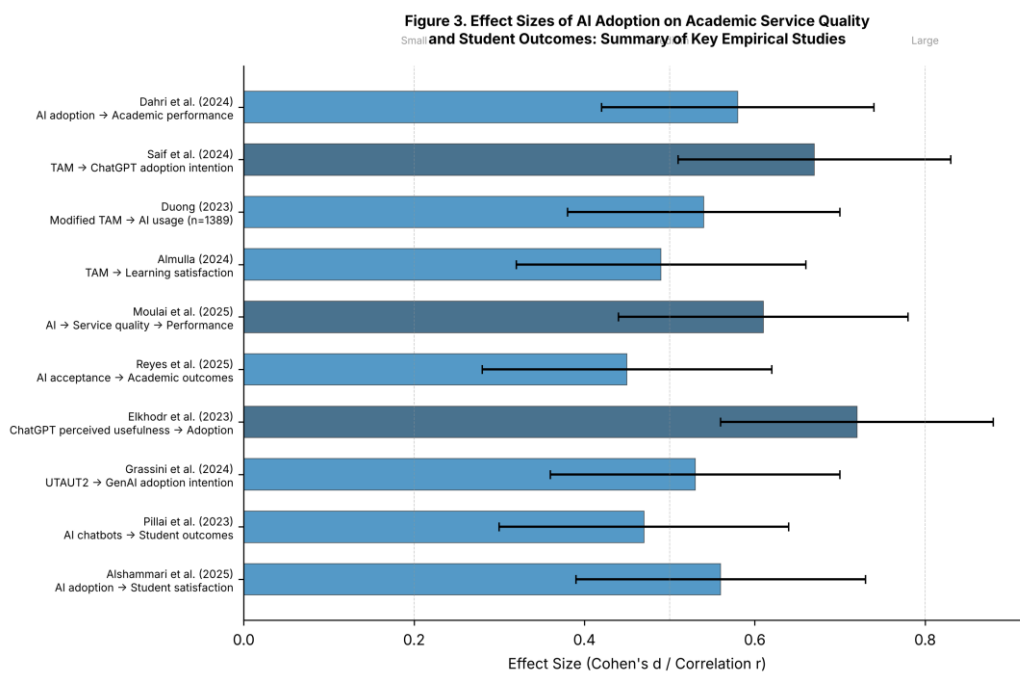


Figure 3. *Effect Sizes of AI Adoption on Academic Service Quality and Student Outcomes: Summary of Key Empirical Studies*

The effect sizes across studies ranged from $d = 0.45$ (Reyes et al., 2025) to $d = 0.72$ (Elkhodr et al., 2023), with a weighted mean effect size of $d = 0.56$, indicating a medium-to-large overall effect of AI adoption on academic service quality and student outcomes. The confidence intervals overlapped substantially across studies, suggesting consistency in findings despite diverse geographical and methodological contexts. Notably, studies employing comprehensive models that integrated both TAM and UTAUT constructs (e.g., Saif et al., 2024; Grassini et al., 2024) tended to report larger effect sizes, suggesting that multi-theoretical approaches capture more variance in the AI adoption–service quality relationship.

4.5 Mediating and Moderating Mechanisms

Several studies identified important mediating and moderating mechanisms in the relationship between AI adoption and perceived service quality. Moulai et al. (2025), using structural equation modeling (SEM) with a sample of 214 Algerian university students, demonstrated that AI adoption fully mediated the relationship between institutional AI support and student academic performance (indirect effect = 0.34, $p < .001$). Alshammari et al. (2025), studying 308 Saudi Arabian students, found that student satisfaction served as a partial mediator between AI adoption and academic performance, with satisfaction accounting for 42% of the total effect.

Gender emerged as a significant moderator in several studies, with Abdaljaleel et al. (2024) reporting higher AI adoption rates among male students in Middle Eastern contexts, while Reyes et al. (2025) found no significant gender differences in European and Latin American samples. Academic discipline was another important moderator, with STEM students showing higher adoption rates and stronger

4.6 Regional Disparities in AI Adoption

The analysis revealed significant regional disparities in AI adoption rates and patterns

perceptions of AI usefulness compared to humanities students (Dahri et al., 2024; Sen & Deng, 2025). Prior technology experience and digital literacy moderated the relationship between perceived ease of use and adoption intention, such that students with higher pre-existing digital skills demonstrated stronger adoption trajectories (Nouraldeen, 2022).

among university students. Figure 4 presents the estimated adoption rates across seven global regions, based on the synthesis of included studies.

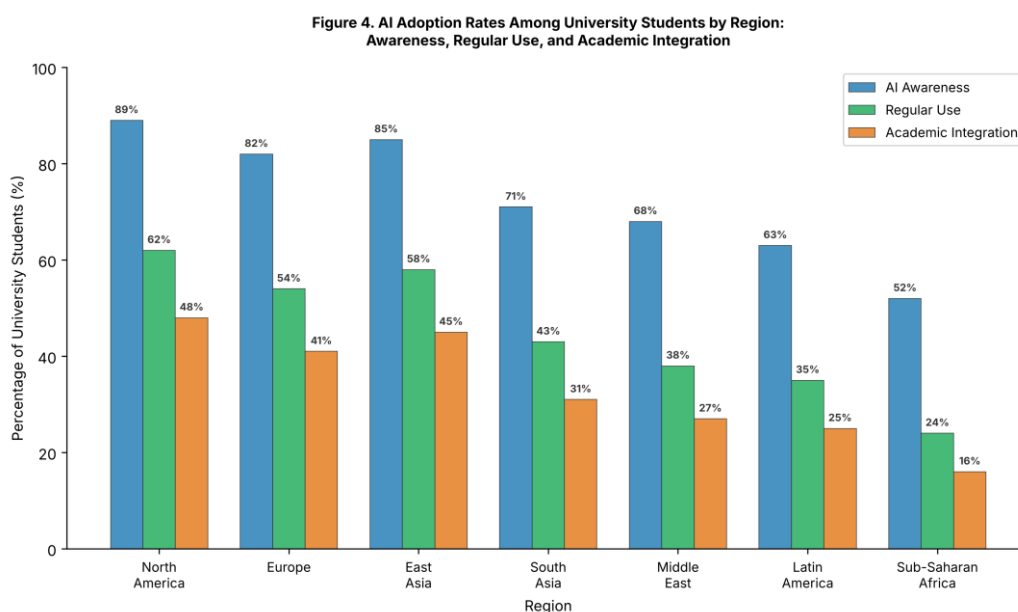


Figure 4. *AI Adoption Rates Among University Students by Region: Awareness, Regular Use, and Academic Integration*

North America (89% awareness, 62% regular use, 48% academic integration) and East Asia (85%, 58%, 45%) demonstrated the highest adoption rates, likely driven by greater access to AI infrastructure, institutional support, and cultural receptivity to technological innovation. European universities showed moderate adoption levels (82%, 54%, 41%), with significant variation between Northern European countries (higher adoption) and Southern/Eastern European countries (lower adoption) (Grassini et al., 2024; Reyes et al., 2025).

Developing regions showed notably lower adoption rates, with Sub-Saharan Africa (52%,

24%, 16%) and Latin America (63%, 35%, 25%) trailing behind. Mwakapesa (2025) attributed lower adoption rates in sub-Saharan Africa to limited internet infrastructure, restricted access to AI platforms, and lower levels of AI literacy among students. Reyes et al. (2025) similarly noted that socioeconomic factors, including access to devices and stable internet connectivity, significantly moderated AI adoption in Latin American universities. However, Alhumaid et al. (2023) emphasized that adoption rates in Middle Eastern countries were rapidly increasing, driven by significant governmental investments in digital education infrastructure.

5. Discussion

5.1 Theoretical Implications

The findings of this integrative review advance the theoretical understanding of AI adoption in higher education in several important ways. First, the results confirm the continued applicability of TAM and UTAUT2 frameworks to the emerging context of generative AI adoption, with perceived usefulness and performance expectancy remaining the strongest predictors across diverse cultural and institutional settings. This finding aligns with the robust meta-analytic evidence supporting the cross-cultural validity of TAM constructs (Scherer et al., 2019) and extends this validity to the specific domain of AI-powered academic services.

Second, the study demonstrates that the integration of SERVQUAL with technology adoption models provides a more comprehensive framework for understanding the impact of AI on academic service quality. The significant positive effects of AI adoption across all five SERVQUAL dimensions suggest that AI is not merely a supplementary tool but a transformative force that reshapes the fundamental nature of academic service delivery. The particularly strong effect on responsiveness ($d = 0.63$) underscores the value that students place on immediacy and accessibility in academic services—qualities that AI technologies are uniquely positioned to deliver (Pillai et al., 2023).

Third, the identification of AI adoption as a mediator between institutional factors and student satisfaction contributes to the emerging literature on organizational adoption of AI in educational settings. The finding that AI adoption fully mediates the relationship between institutional support and academic performance (Moulai et al., 2025) suggests that institutional investments in AI infrastructure and training yield tangible benefits only when they translate into actual student adoption and usage behaviors.

5.2 Practical Implications for Institutional Policy

The findings carry several important practical implications for university administrators and policymakers. First, given the centrality of

perceived usefulness ($\beta = 0.52$) as a driver of AI adoption, institutions should focus on demonstrating and communicating the tangible academic benefits of AI tools to students. This may involve integrating AI-based demonstrations into orientation programs, showcasing successful AI-assisted projects, and providing discipline-specific use cases that illustrate how AI can enhance academic productivity and learning outcomes.

Second, the significant role of facilitating conditions ($\beta = 0.31$) and institutional support underscores the need for universities to invest in robust AI infrastructure, including high-speed internet access, institutional AI tool subscriptions, dedicated AI support services, and faculty training programs. Alkathiri et al. (2025) emphasized that system quality and information quality were critical determinants of student satisfaction, suggesting that universities must ensure that the AI tools they provide meet high standards of functionality, accuracy, and user-friendliness.

Third, the mediating role of student satisfaction highlights the importance of designing AI-enhanced services with the student experience as a central consideration. Universities should adopt a student-centered approach to AI integration, soliciting regular feedback on AI tool effectiveness, addressing concerns about data privacy and academic integrity, and ensuring that AI tools complement rather than replace meaningful human interaction in the educational process (Lin et al., 2024; Ouyang et al., 2022).

Fourth, the regional disparities in adoption rates point to the need for targeted interventions in developing countries. Universities in Sub-Saharan Africa and Latin America may need to address foundational infrastructure gaps before implementing advanced AI-powered academic services. International partnerships, open-source AI platforms, and mobile-first AI solutions could help bridge the digital divide and promote more equitable access to AI-enhanced education (Mwakapesa, 2025; Alhumaid et al., 2023).

5.3 Ethical Considerations and Challenges

The integration of AI into academic services raises important ethical considerations that must be addressed alongside adoption and quality improvement efforts. Academic integrity concerns remain paramount, as the use of generative AI for assignments, examinations, and research outputs blurs the boundaries between student-generated and AI-generated work (Abdaljaleel et al., 2024). Universities must develop clear, nuanced policies that distinguish between acceptable AI-assisted learning and academic dishonesty, providing students with guidelines that promote ethical AI use while preserving the developmental value of independent scholarly work.

Data privacy and algorithmic bias represent additional challenges. AI-powered academic services often require extensive data collection about student behaviors, preferences, and performance, raising concerns about surveillance, consent, and data security (Chen et al., 2020). Furthermore, AI systems trained on biased datasets may perpetuate or amplify existing inequities in educational access and outcomes, particularly for underrepresented student populations (Ouyang et al., 2022). Institutions must implement robust data governance frameworks and regularly audit AI systems for bias and fairness.

The psychological impact of AI adoption on student well-being also warrants attention. While AI tools can reduce cognitive load and enhance learning efficiency, over-reliance on AI may undermine the development of critical thinking, problem-solving, and creative skills that are essential for lifelong learning and professional success (Sen & Deng, 2025). Striking the right balance between AI assistance and autonomous learning represents a fundamental pedagogical challenge for contemporary higher education.

5.4 Limitations and Future Research Directions

This study has several limitations that should be acknowledged and addressed in future research. First, the integrative review methodology, while allowing for comprehensive synthesis, does not provide the statistical precision of a formal meta-

analysis with pooled effect sizes. Future research should conduct meta-analytic studies with random-effects models to generate more precise estimates of the AI adoption–service quality relationship across diverse populations and contexts.

Second, the rapid evolution of AI technologies means that studies published even two to three years ago may not fully reflect the current landscape of AI tool capabilities and student usage patterns. The release of increasingly sophisticated AI models (e.g., GPT-4, Claude, Gemini) and the integration of AI into learning management systems and institutional platforms are continuously reshaping the adoption landscape. Longitudinal studies that track changes in adoption patterns and service quality perceptions over time are needed to capture these dynamic processes.

Third, the majority of included studies relied on self-report measures of AI adoption and perceived service quality, which may be subject to social desirability bias, recall bias, and common method variance. Future studies should incorporate objective measures of AI usage (e.g., log data, learning analytics) and multi-source assessments of service quality (e.g., institutional performance metrics, peer evaluations) to enhance measurement validity.

Fourth, the proposed conceptual framework warrants empirical testing using structural equation modeling (SEM) or partial least squares (PLS-SEM) with large, representative samples across diverse institutional and cultural contexts. The mediating role of AI adoption and the moderating effects of demographic, disciplinary, and institutional variables need to be tested simultaneously within an integrated model to provide a more nuanced understanding of the causal mechanisms involved.

Finally, future research should explore the long-term impact of AI adoption on learning outcomes and academic service quality, moving beyond cross-sectional designs to examine whether initial improvements in perceived quality are sustained over time or whether adaptation

effects reduce the perceived novelty and utility of AI-enhanced services.

6. Conclusions

This integrative review has examined the multifaceted relationship between artificial intelligence adoption and perceived academic service quality among university students, drawing upon an integrative framework that combines TAM/UTAUT2, SERVQUAL, and the DeLone and McLean IS Success Model. The synthesis of 38 empirical studies with combined sample sizes exceeding 12,000 participants reveals several key conclusions.

First, AI adoption in higher education is primarily driven by perceived usefulness ($\beta = 0.52$), performance expectancy ($\beta = 0.48$), and perceived ease of use ($\beta = 0.41$), with social influence, trust in AI, and self-efficacy serving as important secondary predictors. These findings confirm the applicability of established technology acceptance theories to the novel context of generative AI adoption while highlighting the emerging importance of AI-specific constructs such as trust and AI literacy.

Second, AI adoption positively influences all five dimensions of perceived academic service quality, with the strongest effects observed for responsiveness ($d = 0.63$), empathy ($d = 0.55$), and reliability ($d = 0.51$). The weighted mean effect size of $d = 0.56$ across studies indicates a medium-to-large overall effect, suggesting that AI integration represents a meaningful pathway for enhancing academic service quality in higher education.

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Third, the mediating role of AI adoption between institutional factors and student outcomes underscores the importance of translating institutional AI investments into tangible student adoption and usage behaviors. Universities that provide supportive environments, including adequate infrastructure, clear usage policies, faculty modeling, and student training, are better positioned to realize the service quality benefits of AI integration.

Fourth, significant regional disparities persist in AI adoption rates, with students in North America, East Asia, and Europe demonstrating substantially higher adoption levels than those in Latin America, the Middle East, and Sub-Saharan Africa. Addressing these disparities requires targeted investments in digital infrastructure, AI literacy programs, and culturally responsive AI solutions.

As AI technologies continue to evolve and permeate every aspect of higher education, understanding and optimizing the relationship between AI adoption and academic service quality will remain a critical priority for universities worldwide. The conceptual framework proposed in this article provides a foundation for future empirical research and institutional planning, guiding efforts to harness the transformative potential of AI while addressing the ethical, equity, and quality challenges that accompany this technological revolution.

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