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ARTICLE

PERCEIVED SERVICE QUALITY AND STUDENTS' USE OF AI TOOLS: THE MODERATING EFFECTS OF STUDENTS' GENDER, AGE, COUNTRY, AND LEVEL OF STUDY

Qualidade Percebida dos Serviços e o Uso de Ferramentas de Inteligência Artificial pelos Estudantes: os Efeitos Moderadores de Gênero, Idade, País e Nível de Estudo

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ABSTRACT | Objective: This study aims to examine how students' perceptions of university service quality influence the assimilation of artificial intelligence (AI) tools in higher education. Additionally, it investigates the moderating effects of age, gender, level of study, and country of study on this relationship. **Method:** A quantitative research design was adopted using survey data collected from higher education students. The constructs were operationalized based on established scales, including perceived service quality dimensions and AI assimilation. Data were analyzed using statistical techniques, including reliability and validity tests, correlation analysis, and moderation analysis to assess the proposed hypotheses. **Findings:** The results indicate that perceived university service quality has a significant positive effect on AI assimilation among students. Furthermore, moderating variables such as age, gender, level of study, and country partially influence the strength of this relationship, suggesting that demographic and contextual factors play an important role in shaping AI adoption in higher education. **Originality/Value:** This study contributes to the literature by integrating service quality and AI assimilation within a unified framework, extending technology adoption theories to the higher education context. It also provides empirical evidence on the role of moderating variables, offering insights for universities aiming to enhance AI-driven learning environments.

Keywords | Artificial Intelligence Assimilation, Service Quality, Higher Education, Technology Adoption, Moderating Variables

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RESUMO | Objetivo: Este estudo tem como objetivo analisar como as percepções dos estudantes sobre a qualidade dos serviços universitários influenciam a assimilação de ferramentas de inteligência artificial (IA) no ensino superior, considerando os efeitos moderadores de idade, gênero, nível de estudo e país de estudo. **Metodologia/Abordagem:** Adotou-se uma abordagem quantitativa, com coleta de dados por meio de survey aplicada a estudantes do ensino superior. Os construtos foram operacionalizados com base em escalas consolidadas na literatura, incluindo dimensões da qualidade percebida dos serviços e assimilação de IA. Os dados foram analisados por meio de testes de confiabilidade e validade, análise de correlação e análise de moderação para verificação das hipóteses propostas. **Resultados:** Os resultados indicam que a qualidade percebida dos serviços universitários exerce efeito positivo e significativo sobre a assimilação da inteligência artificial pelos estudantes. Além disso, variáveis moderadoras como idade, gênero, nível de estudo e país influenciam parcialmente essa relação, evidenciando a relevância de fatores demográficos e contextuais na adoção de tecnologias emergentes no ensino superior. **Originalidade/Contribuições:** O estudo contribui para a literatura ao integrar os conceitos de qualidade de serviços e assimilação de inteligência artificial em um modelo teórico unificado, ampliando as discussões sobre adoção tecnológica no contexto educacional. Ademais, fornece evidências empíricas sobre o papel de variáveis moderadoras, oferecendo subsídios para a formulação de estratégias institucionais voltadas à promoção de ambientes educacionais orientados por IA.

Palavras-chave | Assimilação De Inteligência Artificial, Qualidade De Serviços, Ensino Superior, Adoção De Tecnologia, Variáveis Moderadoras

INTRODUCTION

Artificial Intelligence (AI) is becoming increasingly influential in education, transforming the way students learn, teachers teach, and institutions operate (Zhai et al., 2021). Zhang and Aslan (2021) suggest that AI can be a valuable educational tool, reducing the burdens on both teachers and students while providing engaging learning experiences. Alongside current educational reforms, such as digitizing resources, gamification, and personalized learning, there are many opportunities to expand AI applications in education.

The rapid integration of AI tools into educational environments requires a clear understanding of the factors that influence students' adoption and continued use of these technologies. This is critical in higher education, where AI can significantly change learning methods and knowledge acquisition (Elshaer et al., 2024). However, the success of AI integration depends on students' willingness to adopt and consistently use these tools, which is primarily influenced by their perceptions of the quality of AI services (Soylu et al., 2025). This study examines how students' views on AI usage and service quality are influenced by the moderating effects of demographic factors, including gender, age, country of study, and academic level. Understanding these factors is crucial for explaining what drives AI adoption in academic settings, particularly as AI becomes integrated into various student activities, ranging from completing assignments to providing interactive learning support (Black & Tomlinson, 2025). The research also seeks to uncover any demographic differences in AI tool adoption, providing insights to develop fairer and more effective AI-enhanced educational strategies (Stöhr et al., 2024).

PROBLEM STATEMENT

The literature review reveals that demographic factors, such as gender and age, have recently garnered significant attention regarding their impact on the use of digital learning technologies. However, fewer studies have examined how these factors moderate students' use of AI and its effects on their perceived quality of university services in higher education. Additionally, there is a shortage of prior research examining the roles of students' academic level and country of study as moderators in the relationship between AI adoption and perceived service quality at universities. These gaps make this study particularly unique and suggest it will enhance our understanding. This identified gap highlights the demographic traits that impact the adoption of AI tools in higher education, and it is anticipated that this research will add valuable insights into AI use in this context.

RESEARCH OBJECTIVES

This study aimed to evaluate how students' perceptions of university service quality influence their use of AI tools, while accounting for gender, age, qualifications, and country of study as potential moderating factors. The study wanted to explore the following objectives

- To assess the relationship between the University's perceived service quality and Artificial intelligence assimilation in higher education.
- To explore the moderating effect of age in the relationship between the University's perceived service quality and Artificial Intelligence assimilation in higher education.
- To explore the moderating effect of gender in the relationship between the University's perceived service quality and Artificial Intelligence assimilation in higher education.
- To explore the moderating effect of the level of study in the relationship between the University's perceived service quality and Artificial Intelligence assimilation in higher education.
- To explore the moderating effect of the country of study in the relationship between the University's perceived service quality and Artificial Intelligence assimilation in higher education.

LITERATURE REVIEW

AI adoption in higher education

The rise of artificial intelligence (AI) has garnered significant attention, compelling institutions of higher learning to reconsider traditional pedagogical models and operational frameworks. The adoption of AI in higher education is not merely a trend but a transformative force that promises to redefine the learning experience, enhance operational efficiency, and tailor educational offerings to meet students' diverse needs. This has been underscored in numerous studies, suggesting that AI can facilitate personalized learning experiences, promote administrative efficiency, and improve student engagement levels (Melnyk et al., 2025). Despite the optimistic outlook on AI adoption, significant gaps in the literature call for further exploration. Notably, while much of the research

has focused on the technical capabilities and advantages of AI, less attention has been paid to understanding students' and faculty's perspectives on AI integration in educational settings (Bates et al., 2020). Concerns regarding ethical implications, including data security and the digital divide, warrant further investigation, especially in diverse institutional contexts (Fahimirad et al., 2018). Additionally, while numerous case studies outline successful AI implementations, there is a lack of comprehensive frameworks to guide institutions in navigating the challenges and best practices associated with this transition (Zou et al., 2025).

Moreover, the intersection of cultural, socio-economic, and contextual variables in shaping the receptiveness to AI technologies remains under-researched (Liew et al., 2024). This oversight contributes to a partial understanding of the factors influencing AI adoption across varied educational landscapes. As higher education institutions continue to grapple with the implications of integrating AI, it is crucial to encompass a wider array of perspectives and experiences to foster an informed dialogue around its implementation.

Generative AI and AI literacy in universities

Generative AI tools in education, such as ChatGPT and Gemini, are sophisticated large-language models that generate new text, images, code, or other materials. They function as AI tutors and content creators (Zapata-Rivera et al., 2024). These tools alter the learning process by providing personalized feedback, creating quizzes, designing curricula, and automating administrative tasks, which ultimately improve student engagement and increase teacher efficiency. Integrating Generative AI (GenAI) into higher education has driven changes in teaching approaches and highlighted the need for AI literacy among students and faculty. GenAI tools, such as Grammarly and ChatGPT, have been effective in enhancing the writing quality of medical students, leading to increased confidence and reduced writing anxiety (Pantelejeva, 2024).

AI literacy is essential for students to navigate a world increasingly influenced by AI, enabling them to critically evaluate AI applications in education. Research by Tzirides et al. (2024) highlighted the need for comprehensive policies and teaching strategies to deepen understanding and promote responsible use of GenAI tools. Additionally, Cordero et al. (2024) found that workshops and courses involving GenAI tools boost students' confidence and skills, providing a clearer grasp of these technologies' advantages and limitations. Overall, courses that include GenAI tools have been shown to enhance students' AI literacy, equipping them to critically analyze AI applications in educational contexts.

Considering the difficulties posed using Gen AI tools in institutions and the importance of increasing AI literacy, universities are implementing a variety of policies related to Gen AI. These policies range from complete bans to those that encourage ethical use and AI literacy (Atkinson-Toal & Guo, 2024). Many institutions have issued guidelines to encourage engagement with GenAI, recognizing its potential to transform teaching and research (Christ-Brendemühl, 2024). Nonetheless, a significant gap persists in students' understanding of GenAI, underscoring the need for targeted educational initiatives to close this gap (Gabriel, 2024). The variation in AI policies across universities underscores the need for standardized guidelines to ensure equiTable access and the

smooth integration of AI into academic programs (Atkinson-Toal & Guo, 2024). Although demand for AI literacy is increasing, some institutions may be hesitant to adopt these technologies promptly, potentially expanding disparities in educational access and preparedness for an AI-centric future.

Service quality in digital learning environments

Service quality in digital learning reflects students' perceptions of online education, including teaching effectiveness, support, technical stability, and ease of use (Bouranta et al., 2025). It evaluates how well virtual environments (VLEs/LMS) and instructors meet student needs through accessible resources, prompt assistance, and engaging content. This quality influences user satisfaction and the success of e-learning systems, covering aspects such as reliability, responsiveness, assurance, empathy, and tangibility, which collectively shape the user experience. As technology advances rapidly, digital learning environments become vital for knowledge sharing, increasing dependence on online instruction. The growing demand for flexible, accessible learning makes service quality a major concern for educators, students, and policymakers, impacting engagement, satisfaction, and academic results. Research by Santhoshini (2025) and Mohammed et al. (2025) highlights various service quality aspects, such as reliability and responsiveness, deepening the understanding of online learner experiences. Over time, the focus has shifted from core dimensions like reliability and responsiveness to their application on digital platforms, as shown in studies by Mariti et al. (2024) and Xue (2024). The adoption of technology also brings challenges; effective digital platforms depend heavily on usability and accessibility, which affect perceived service quality (Yadav, 2024). Recent research also emphasizes user engagement and perceived value, underscoring their significance in evaluating overall service quality. Well-designed user experiences with intuitive navigation and strong support reduce frustration and increase engagement (Aníbal Toscano-Hernández et al., 2024; Hamid et al., 2024).

AI-enabled learning ecosystems

AI-powered learning ecosystems in higher education integrate platforms, data, services, and users to create cohesive, data-centric environments. These systems are transitioning from isolated units to integrated infrastructures that tailor learning experiences, automate routine tasks, and aid governance decisions. Alkurdi et al. (2024) noted that an AI-driven educational ecosystem is designed to support sustainable student performance through an integrated framework that connects core AI applications to ethical oversight mechanisms. Effective ecosystems seamlessly integrate infrastructure, applications, services, and human roles. Studies by Tojimuxammadov (2025) and Richter (2025) emphasized the importance of personalization, intelligent tutoring, analytics, and institutional strategies, with a growing focus on ethics and fairness. For instance, Yu & Chauhan (2024) state that technologies like Machine Learning, Natural Language Processing (NLP), Generative AI, and Intelligent Tutoring Systems (ITS) improve personalized learning by providing dynamic, adaptive experiences tailored to learners' specific needs. Adaptive platforms and smart tutoring systems are revolutionizing education by customizing student pathways, simplifying administrative work for

faculty, and providing data insights to enhance engagement (Saleem et al., 2025). These ecosystems encourage collaboration, improve accessibility, and support continuous learning, ultimately aiming to improve student outcomes and prepare learners for AI-centric careers.

As AI-powered learning ecosystems become more prevalent in higher education, they encounter several noTable challenges. Ryzheva et al. (2024) highlighted ethical issues such as data privacy, algorithmic bias, and student monitoring, as well as changes in teaching methods and infrastructure readiness, which can hinder their adoption. Additional challenges identified by Kotsis (2025) and Kamak et al. (2024) include safeguarding sensitive student information, overcoming educator resistance, bridging the digital divide, maintaining academic integrity, and preventing overreliance on AI, which could impair students' critical thinking skills.

University perceived service quality

This section examines the factors influencing students' evaluations of higher education, emphasizing both tangible and intangible aspects of their academic experience. Perceived service quality in universities is crucial as it affects student satisfaction, loyalty, institutional reputation, and overall success. Student perceptions are particularly vital because satisfaction with learning experiences directly impacts an institution's reputation and competitiveness (Naidoo, 2015; Thorpe, 2022). Perceived quality of service is a strong predictor of student satisfaction, which influences loyalty, motivation, and behavioral intentions such as recommending the university (Çınkır et al., 2022). Understanding students' views on service quality is essential, as it greatly affects student loyalty, the institution's image, and the development of a supportive, culturally engaged, and value-driven environment (Shurair & Pokharel, 2019; Paposa & Paposa, 2023). Consequently, higher education institutions strive to deliver high-quality educational services that meet students' needs and enhance overall satisfaction (Yusof et al., 2022). This focus on quality arises from the recognition that student perceptions are closely linked to institutional commitment and loyalty, making service quality a key aspect of accountability and long-term excellence (Lin & Chen, 2025). Achieving this involves continuous efforts to evolve educational strategies, placing students at the center of the learning process to ensure meaningful and effective quality assessments (Guillén et al., 2020). The increasing competition among universities to produce qualified graduates underscores the importance of maintaining high service quality as a strategic goal for success and competitiveness (Tandijaya, 2018). Providing high-quality services is also essential for competitiveness and success in the service industry, serving as a powerful differentiator (Dora et al., 2019). Effective quality management and improvement in higher education require comprehensive, context-aware measurement models (Haverila et al., 2021).

Artificial intelligence assimilation in higher education.

Incorporating Artificial Intelligence (AI) in higher education enhances teaching efficiency, personalizes learning experiences, and streamlines administrative tasks (Zhang, 2024; Borah & Borah, 2024). AI technologies, including machine learning algorithms and intelligent tutoring

systems, are reshaping educational methodologies through adaptive learning platforms and automated assessment tools (Borah & Borah, 2024). These advancements facilitate tailored learning experiences, improve student engagement, and optimize education management (Zhang, 2024; Mishra & Srivastava, 2024). The COVID-19 pandemic has accelerated the integration of AI, addressed immediate educational disruptions, and shaped a more responsive system (Rangavittal, 2024). However, challenges such as ethical considerations, data privacy, and potential biases must be addressed (Borah & Borah, 2024; Zhang, 2024). To maximize the benefits of AI, higher education institutions must embrace innovation, adapt to technological changes, and ensure responsible usage while balancing technological advancements with human values (Mishra & Srivastava, 2024; Zhang, 2024).

University Perceived Service Quality and students' AI assimilation

Studies on AI adoption and university service quality have demonstrated a strong positive correlation between students' perceptions of university service quality and their integration of AI. According to Sebopelo et al. (2025), AI integration significantly affects students' perceptions of university service quality, with student satisfaction playing a key role in this relationship. Research on students from the Botswana Open University and the National Open University of Nigeria found that successful AI integration requires addressing student concerns while improving personalized services and administrative efficiency. The evidence suggests that students generally hold positive views on the adoption of AI in higher education. Vázquez-Parra et al. (2024) emphasized that students' positive perceptions significantly influence their motivation and commitment to learning, highlighting the importance of promoting a positive attitude towards AI use and training. Grájeda et al. (2023) reported that AI tools have a positive impact on students' academic experiences, including improved comprehension, creativity, and productivity across engineering, business, and arts programs. Similarly, Suleiman (2024) found that Nigerian university students are generally receptive to AI-based support services, recognizing benefits such as personalized learning and improved administrative efficiency.

University Service quality, AI assimilation, and the moderating effect of Age

University service quality is directly influenced by the assimilation of Artificial Intelligence (AI), with student satisfaction acting as a mediator. While age itself is not a direct factor in this relationship, it can indirectly influence a student's interaction with and perception of AI assimilation and its impact on service quality. Research by Iqbal et al. (2020) indicates that integrating AI significantly enhances the quality of educational services, with younger students often exhibiting higher AI literacy and acceptance than older individuals.

Ifekanandu et al. (2023 noted that as customer expectations shift with evolving technological advancements, age becomes a significant moderating factor that influences how individuals engage with AI-mediated services. Younger generations, who are often more adept at navigating new technologies, may have different perceptions of service quality than older adults, who may prioritize

traditional service interactions. It is imperative to explore these dynamics further, particularly as organizations aim to leverage AI to resonate with diverse consumer expectations across age demographics (Choi et al., 2014). According to Arowosegbe et al. (2024), some studies suggest that age influences the behavioral intention to use AI tools among university students, with younger students generally being more willing to adopt these technologies. However, Owusu et al. (2024) found that the direct moderating role of age in the relationship between perceptions of university service quality and AI tool usage is not consistently supported. Despite this, research by Ambika & Priya (2025) reveals significant differences in AI perception and usage across age groups, suggesting that age can influence students' responses to university service quality and AI integration. Similarly, Cho and Ofosu-Anim (2025) report that younger students are more comforTable and likely to use AI tools. In contrast, older students may encounter adoption barriers, although age was not significantly linked to academic success from AI use. Midway through this timeline, scholars such as Wang et al. (2022) and Dwivedi et al. (2022) identified age as a significant moderator, influencing both perceptions of service quality and the propensity to engage with AI technologies. Their findings indicated that younger consumers tend to embrace AI-facilitated services more readily, whereas older adults tend to be more cautious. This divergence in attitudes necessitates a nuanced understanding of generational differences, particularly regarding technology acceptance models (Sands et al., 2022).

This means that the effect of improving university service quality on students' acceptance of AI technologies might vary by age group, with older or younger students potentially reacting differently to the same service improvements and AI tools.

University Service quality, AI assimilation, and the moderating effect of gender

The link between university service quality, gender, and AI adoption is intricate, illustrating how these elements interact to shape educational experiences. Cachero et al. (2025) note that AI integration can notably enhance service quality in higher education, while gender influences perceptions and the use of AI technologies. Likewise, Balasa et al. (2025) and Al-Samarraie et al. (2024) stress that gender plays a key role in how students perceive, accept, and utilize AI in universities. Gender-related factors can affect AI adoption in educational environments, with women often feeling less confident in their AI literacy (Brown et al., 2024).

For example, Ofosu-Ampong (2023) found that male students generally report greater awareness, perceived knowledge, and more positive attitudes toward AI, often leading to higher usage than among females. Similarly, Strzelecki and ElArabawy (2024) found that gender influences AI anxiety, perceived ease of use, and enjoyment, which, in turn, affect behavioral intentions to engage with AI. In contrast, research by Sultan and Wong (2018), Russo et al. (2025), and Younes et al. (2021) found no significant gender differences in acceptance or satisfaction with AI-enabled university services, suggesting that the moderating effect of gender is not always consistent. They also observed that certain aspects of service quality, such as assurance, can affect behavioral intentions differently by gender, indicating nuanced moderation effects.

University Perceived service quality, AI integration, and student Academic level (Postgraduate vs Undergraduate)

Notably, postgraduate students are more likely to use AI tools than undergraduate students, with final-year students showing higher adoption rates than earlier-year students (Ali et al., 2024). However, significant differences exist in how undergraduate and postgraduate students perceive the importance of AI, although both groups modestly evaluate their roles in an AI-characterized future labor market (Tominc & Rožman, 2023). Students generally maintain positive attitudes toward generative AI in education, recognizing benefits for personalized learning and research assistance, while expressing concerns about accuracy, privacy, and ethical implications (Chan & Hu, 2023). These findings suggest universities should invest in AI tools while addressing student concerns to enhance service quality.

Students, particularly undergraduates, are more likely to adopt AI tools if they perceive them as beneficial for their coursework (Vázquez Parra et al., 2024). Their level of study affects this perception, as they may have different academic goals and needs compared to graduate students or professionals.

Understanding the role of student qualification level is crucial for assessing how well service quality complements the use of AI in academic settings. Students with varying qualifications possess distinct abilities in utilizing technology, which can significantly impact their educational experiences (Haleem et al., 2022). Scholars such as Chaudhary et al. (2024) and Sova et al. (2024) have observed that higher educational attainment often correlates with a better understanding of AI tools and higher expectations for service quality, which, in turn, influence the adoption and use of AI tools.

This means that educational institutions need to adjust their approaches to meet the diverse needs of their students, utilizing AI solutions that not only enhance learning but also deliver high-quality service. As the services sector continues to impact every aspect of our lives, it is essential to understand the connection between qualifications and the quality of service. This is essential for creating an environment in which students and educators can succeed, particularly as the economy shifts to a post-industrial economy.

University Service quality, AI assimilation, and the moderating effect of country of study

Integrating Artificial Intelligence (AI) into higher education significantly affects university service quality, especially for international students. Nonetheless, this effect differs based on the country where students study. The study location plays a crucial role in shaping students' experiences, mainly regarding service quality and AI adoption. Gulzar et al. (2024) pointed out that students from various nationalities adapt to and interact with their academic environments in different ways. This highlights the need for universities to customize their services to support students from various countries, promoting an inclusive environment that encourages effective AI integration throughout their educational journey.

Studies conducted by Lan and Zhou (2025) and Chan and Hu (2023) on student attitudes and AI tool usage across countries such as Slovenia, Hong Kong, and Saudi Arabia reveal that cultural, educational, and policy environments shape perceptions and the adoption of AI in higher education. Fošner (2024) and Chan & Hu (2023) also demonstrated that students in different countries express varying concerns about AI's impact on learning quality, academic integrity, and job prospects, which can influence their willingness to engage with AI-driven services. These findings suggest that the country of study may moderate how students perceive and assimilate AI, particularly regarding service quality expectations and digital readiness, which vary internationally.

Therefore, understanding the study country's impact is crucial for enhancing overall service quality. These studies demonstrate how the country influences students' perceptions of university service quality and their adaptability to AI.

Theoretical Framework and Hypotheses Development

This research employs the Technology Acceptance Model (TAM), focusing on two primary aspects: perceived usefulness and perceived ease of use (Davis, 1989). Davis (1989) explains that when users perceive an IT system as both helpful and easy to use, they tend to develop a positive attitude toward it, which encourages ongoing use (Calle-Díaz et al., 2024). TAM is based on Davis's Theory of Reasoned Action (TRA), which links various components to illustrate how individuals accept and adopt new technology. It offers a solid framework for understanding how perceptions of ease and usefulness shape users' attitudes and intentions toward technology adoption (Kusuma et al., 2025). By analyzing TAM alongside perceptions of service quality, this model identifies critical factors that facilitate successful AI deployment and explores the intricate relationship between user acceptance and service quality (Darancik et al., 2025). Recent studies also emphasize the influence of demographic and contextual factors—such as age, gender, and country that moderate technology acceptance and significantly affect university students' views on AI-powered services (Kelly et al., 2022; Mariani et al., 2022). Rakya (2024) highlights TAM's value not only as a model for technology acceptance but also as a flexible framework for uncovering ethical issues in AI adoption within the education sector. Furthermore, Lai et al. (2024) emphasizes the role of TAM in understanding the use of ChatGPT for assessment support in higher education, where trust emerges as the strongest positive predictor of students' behavioral intention. In the TAM, service quality is considered an antecedent of AI assimilation because high service quality fosters trust, increasing the likelihood that users adopt AI technologies. From the users' perspective, quality services improve perceptions of AI's usefulness, encouraging adoption. Additionally, the Perceived Ease of Use of the technology makes AI tools seem simpler to operate, further promoting assimilation.

Moreover, the TAM constructs Perceived Usefulness and Perceived Ease of Use are closely tied to service quality perceptions. For instance, users' perceptions of service quality often hinge on how useful it is in achieving their goals. And when the service is easy to use, users perceive it as more reliable and high-quality. This means that if the technology is complex, it can lead to frustration and lower perceptions of service quality. Therefore, this theory enables the researchers to examine both

the moderating impact of demographic variables and students' perceptions on the adoption of AI in the diverse context of higher education.

A theoretical framework linking service quality and AI usage, based on the Technology Acceptance Model (TAM) , centers on how the perceived quality of AI-enabled services (reliability, responsiveness, personalization) shapes user attitudes, ultimately driving the intention to use and actual AI adoption. TAM provides the structure where Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) of AI act as mediators between external service factors and user behavior.

The research hypotheses describe the relationships among factors that influence the use of AI tools to enhance students' academic performance.

The literature review indicates that several scholars, including Testa et al. (2024) and Russo et al. (2025), have identified gender as a factor influencing the relationship between perceived service quality and AI usage. Iqbal et al. (2020) also found that age moderates this connection. Furthermore, the level of study impacts the link between perceived service quality and AI use (Britchenko et al., 2018; Sardesai et al., 2024). Research by Cappelli et al. (2018) shows that the country of study additionally moderates this relationship. The hypotheses for this research are: H1 suggests that university perceived service quality directly influences AI adoption among students. H2 argues that age moderates the relationship between service quality and AI use; H3 suggests gender as a moderator; H4 considers the level of study as a moderator; and H5 indicates that the country of study moderates the relationship.

These hypotheses aim to investigate how three demographic factors, age, gender, and level of study, moderate the relationship between perceived service quality and the use of AI. Based on the theoretical foundations of the study and the discussed literature, the conceptual framework depicting the influence of these demographic variables on AI usage and service quality is shown in Figure 2. The framework guided the study in answering its objectives. The framework in Figure was also applied by Fuchs (2022)

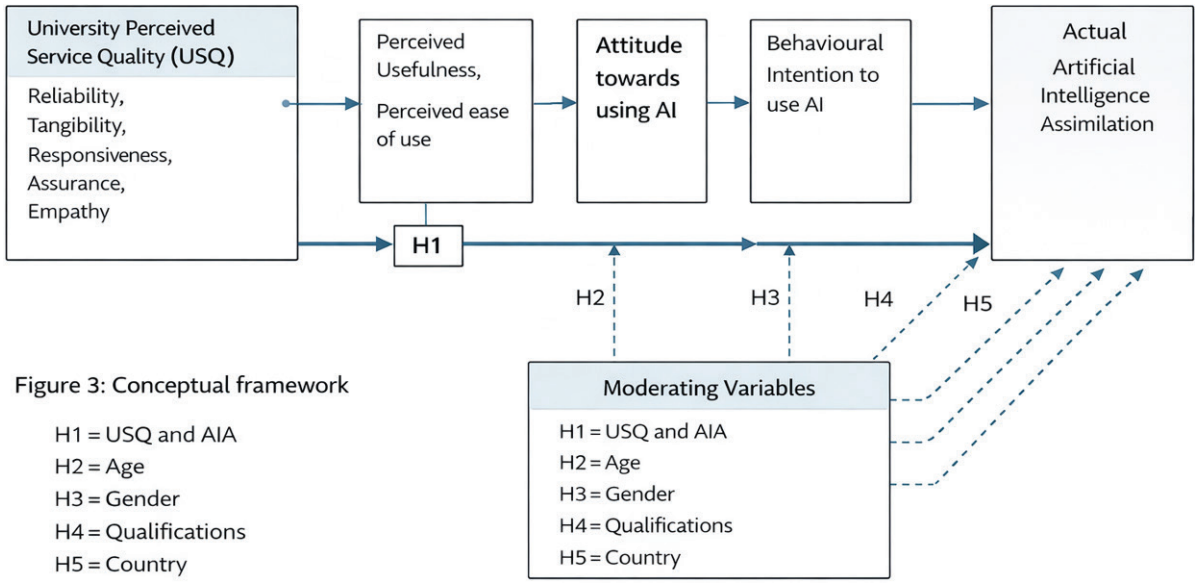

Figure 3: Conceptual framework

H1 = USQ and AIA
H2 = Age
H3 = Gender
H4 = Qualifications
H5 = Country

METHODOLOGY

Research Design

The researcher used a quantitative approach and employed a survey to collect and analyze data on the impact of AI tools on students' academic performance. The survey method was selected for its efficiency in collecting data from many respondents, providing a comprehensive view of students' opinions and experiences with AI tools in educational settings.

Research Procedure

This section outlines the systematic steps taken to investigate a research problem. It involves defining the research approach (qualitative, quantitative, or mixed methods), detailing data collection tools, justifying sampling methods, describing analysis techniques, and addressing ethical considerations.

Survey instrument design

The researchers developed an online survey using Google Forms by creating a new form, incorporating different question types such as multiple-choice and Likert scales, organizing questions into sections, and customizing the appearance. Important settings included response limits, login requirements, and validation rules to maintain data quality before sharing the survey via link or email. All questions were rated on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Sampling process

This study recruited 398 students registered at the Botswana Open University and the National Open University of Nigeria. The participants were selected using a purposive sampling approach because it was deemed simpler and less costly. This non-probability sampling technique enables researchers to select participants most knowledgeable about the topic of interest, thereby enhancing the relevance and depth of the data collected (Bell et al., 2022).

Data collection procedure

Data for this research were collected through an online survey using Google Forms, which featured a message encouraging participation. Google Forms is a popular, user-friendly platform that streamlines survey distribution and response collection (Lim et al., 2023). Its use enhances data-collection efficiency and enables rapid-response analysis, providing immediate feedback and adjustments. Data were gathered in November and December 2024, after the widespread adoption

of generative AI (GenAI) tools, marked by the launch of ChatGPT on November 30, 2022, and a period during which AI tools became widely used by students.

Data cleaning and validation.

SPSS was used to clean the data entries by ensuring that survey responses were complete, accurate, consistent, and correctly formatted for analysis. This included removing duplicates, handling incomplete responses (dropouts), coding open-ended answers, detecting invalid responses, and cleaning missing data. The validity of the survey questions was evaluated using Cronbach 's alpha reliability coefficient.

Statistical analysis steps

In this study, SPSS 28.0 was employed for data analysis, mainly for descriptive statistics. Jamovi was also used for moderation analysis and other inferential tests, such as ANOVA and independent T-tests. Jamovi software was employed to analyze the moderating effect, supporting various statistical modules used for moderation analysis. This software enables researchers to explore how the relationship between two variables varies across different levels of a third variable (Breuninger, 2023).

Ethical Considerations

To address ethical concerns, researchers provided a clear introduction to the study, informing participants that participation was voluntary and that data would not be shared without their consent. They assured secure data storage, offered options to withdraw, and emphasized the protection of participant confidentiality.

RESULTS

In this study, the results refer to the key findings and outcomes derived from the data analysis. The results demonstrate the measurable effects of AI assimilation in university settings. In particular, the results examine the moderating effects of demographic variables, such as age, gender, level of study, and country of study, on the relationship between students' perceptions of service quality and their adoption of AI tools.

Profile of respondents

Table 1 presents the demographic characteristics of the study respondents. The analysis revealed that the sample was predominantly female (76.4%) and that a slightly higher percentage of respondents were over 35 years old (60.5%). Most respondents were undergraduate students

(53.8%), with postgraduates making up the remaining 46.2% of the sample. Most respondents in this study were from Nigeria (76.4%), while 23.6% were from Botswana.

Table 1. Sample of Study

Demographic characteristics	Number of respondents	Frequencies	Percentage
Gender	Male	94	23.6
	Female	304	76.4
Age	<20	25	6.3
	21-30	112	28.1
	31-40	132	33.2
	41-50	102	25.6
	51-60	25	6.3
	61-70	2	.5
	Over 71	0	-
Level of study	Postgraduate	184	46.2
	Undergraduate	214	53.8
Country of study	Nigeria	304	76.4
	Botswana	94	23.6

Descriptive statistics

Artificial intelligence assimilation descriptive statistics

The average response to the artificial intelligence assimilation items was 3.66, indicating that respondents generally agreed with the questions. The standard deviation of the responses is 1.131, which falls within the accepTable range. The results of the descriptive analysis for the Artificial Intelligence assimilation variable are reflected in Table 2.

Table 2. AI Assimilation descriptive statistics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AIA1	394	3.27	1.157	-.292	.123	-.560	.245
AIA2	395	3.71	1.153	-.673	.123	-.277	.245
AIA3	392	3.58	1.173	-.454	.123	-.617	.246
AIA4	392	3.65	1.143	-.544	.123	-.469	.246
AIA5	392	3.80	1.096	-.736	.123	-.107	.246
AIA6	392	3.94	1.065	-.958	.123	.457	.246
Valid N (listwise)	385						

University Perceived Service Quality Descriptive Statistics

The average response to the University Perceived Service Quality items was 3.18, indicating that respondents generally agreed with the questions. The standard deviation of the responses is 1.050, which falls within the accepTable range. The results of the descriptive analysis are reflected in Table 3.

Table 3. Service quality descriptive statistics

Descriptive Statistics							
	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Tangiability	398	3.3844	.82782	-.412	.122	-.068	.244
Reliability	397	2.7448	.68806	-.049	.122	-.438	.244
Responsiveness	397	3.5401	.99150	-.572	.122	-.242	.244
Assurance	396	3.6534	.91582	-.739	.123	.515	.245
Empathy	397	3.4546	.88448	-.543	.122	.231	.244
Valid N (listwise)	395						

Reliability

The reliability of study variables was evaluated using Cronbach's Alpha (α), as presented in Table 4. This method helps determine whether the questionnaire items consistently measure the same construct. Calculating alpha values yields a range that indicates the questionnaire's reliability (Butt & Yazdani, 2023). The scores are interpreted as follows: $\alpha > 0.9$ indicates excellent reliability, $\alpha > 0.8$ very good, $\alpha > 0.7$ good, $\alpha > 0.6$ acceptable, $\alpha > 0.5$ questionable, and $\alpha < 0.5$ unacceptable. The internal consistency of the constructs is above 0.7, indicating strong reliability.

Table 4. Reliability

Reliability Statistics		
Variable Name	Cronbach's Alpha	N of Items
AI Assimilation	.875	6
Service Quality	.854	13

Correlations

Spearman's rank correlation was computed to assess the correlation between AI Assimilation and Service Quality. As can be seen in Table 5, there is a positive correlation between AI Assimilation and Service Quality (p = .001).

Table 5. correlations

Associations	Coefficient	P value	Conclusion
AI Assimilation and Service Quality	.322	<001	significant

Notes. **. Correlation is significant at the 0.01 level (2-tailed).

Validity Test

The data collected from the questionnaires it was processed using SPSS (Statistical Package for Social Science) for Windows. The first step is to assess the validity and reliability of the questionnaires.

The validity of the questionnaires is established through a correlational analysis (Sekaran &

Bougie (2016). The indicators can be considered valid when they are strongly correlated with the concept.

Construct Validity

Through factor analysis, this study confirmed construct validity by examining the internal structure of a scale to determine whether its observed variables (items) grouped as expected, forming underlying latent factors that matched the theoretical construct being measured.

The results of the construct validity testing are shown in the Table. 7. The results of the factor analysis show that the service quality and Artificial Intelligence items load together into the same underlying factors, providing enough evidence of construct validity.

Table 6. Rotated factor matrix

Rotated Component Matrix					
	Component				
	1	2	3	4	5
T1				.698	
T2				.747	
T3				.724	
T4				.775	
R1					.660
R2					.733
R3					.681
R4					.769
R5					.660
RP1	.611				
RP2	.755				
RP3	.803				
RP4	.794				

Rotated Component Matrix					
	Component				
	1	2	3	4	5
AS1	.752				
AS2	.585				
AS3	.730				
AS4	.748				
E1			.623		
E2			.700		
E3			.664		
E4			.683		
E5			.681		
AIA1		.745			
AIA2		.860			
AIA3		.841			
AIA4		.868			
AIA5		.857			

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

Discriminant Validity

For this study, we used the correlational analysis approach to assess discriminant validity. This method helps determine how distinct different theoretical constructs are from one another. Discriminant validity was evaluated using the correlation matrix by checking whether correlations between unrelated constructs were low, typically below 0.85. As shown in Table 7, discriminant validity was supported, as correlations between unrelated constructs were weak, with values less than 0.4.

Table 8. Correlational analysis

Correlations							
		Tangiability	Reliability	Responsiveness	Assurance	Empathy	Assimilation
Tangiability	Pearson Correlation	1	.304**	.491**	.484**	.498**	.164**
Reliability	Pearson Correlation	.304**	1	.348**	.309**	.278**	.043
Responsiveness	Pearson Correlation	.491**	.348**	1	.727**	.610**	.150**
Assuranced	Pearson Correlation	.484**	.309**	.727**	1	.646**	.178**
Empathy	Pearson Correlation	.498**	.278**	.610**	.646**	1	.317**
Assumilation	Pearson Correlation	**.164****	**.043**	**.150****	**.178****	**.317****	1

**. Correlation is significant at the 0.01 level (2-tailed). N=394

Moderating Analysis

Gender Effect on Service Quality and AI Assimilation

A moderation analysis was conducted to explore how gender affects the relationship between service quality and AI adoption. The findings indicate that gender plays a moderating role in this relationship. Table 8 presents the results of our moderation tests, which investigate the impact of gender on service quality and AI adoption (p-value = 0.015. However, the Z-score of 2.424 demonstrates that the effect size of Age as a moderating factor is minimal.

Table 9. Gender Effect on Service Quality and AI Assimilation

Moderation Estimates				
	Estimate	**SE**	**Z**	**p**
Service Quality	0.4297	0.0643	6.684	<.001
Gender	0.0327	0.0845	0.387	0.698
Service Quality ✻ Gender	0.3140	0.1295	2.424	0.015

Age Effect on Service Quality and AI Assimilation

A moderation analysis was conducted to explore how age affects the relationship between service quality and AI adoption. The moderating effect of age proved to be insignificant, with a p-value of 0.511. Moreover, the Z-score of 0.657 signifies that the effect size is insignificant. The findings indicate that age does not moderate this relationship. Table 9 presents the results of the moderation tests, which examine whether age affects service quality and AI adoption.

Table 10. Age Effect on Service Quality and AI Assimilation

Moderation Estimates				
	Estimate	**SE**	**Z**	**p**
Service Quality	0.4281	0.0652	6.564	<.001
Age	0.0280	0.0403	0.695	0.487
Service Quality ✻ Age	0.0418	0.0636	0.657	**0.511**

Level of study: Effect on Service Quality and AI Assimilation

A moderation analysis was conducted to explore how the level of study affects the relationship between service quality and AI adoption. The moderating effect of the level of study proved insignificant with a p-value of 0.276. The Z-score of -1.090 signifies that the effect size is insignificant. The findings suggest that the level of study does not moderate this relationship. Table 10 presents the results of the moderation tests, which examine whether the level of study affects service quality and AI adoption.

Table 11. Level of study: Effect on Service Quality and AI Assimilation

Moderation Estimates				
	Estimate	**SE**	**Z**	**p**
Service Quality	0.4274	0.0652	6.555	<.001
Level of Study	0.0513	0.0615	0.834	0.404
Service Quality ✻ Level of Study	-0.1260	0.1156	-1.090	0.276

Country of study: Effect on Service Quality and AI Assimilation.

A moderation analysis was conducted to explore how the Country of study affects the relationship between service quality and AI adoption. The findings suggest that the country of study does not moderate this relationship. Table 11 presents the results of the moderation tests, which examine whether the country of study affects service quality and AI adoption. The moderating effect of the country of study proved insignificant with a p-value of 0.841. The Z-score of -0.2003 signifies that the effect size is insignificant.

Table 12. Country of study: Effect on Service Quality and AI Assimilation.

Moderation Estimates				
	Estimate	**SE**	**Z**	**p**
Service Quality	0.43567	0.0651	6.6918	<.001
Country	-0.00243	0.0991	-0.0245	0.980
Service Quality ✻ Country	-0.03285	0.1640	-0.2003	0.841

Hypothesis test

The results of the hypothesis tests are presented in Table 12, indicating that only H1 and H2 were accepted, while the remaining hypotheses (H3, H4, and H5) were rejected.

Table 13. summary of hypothesis tests.

Hypothesis	Description	Significance level	Decision
H1	There is a significant direct relationship between the university's perceived service quality and students' assimilation of AI tools.	<001	Accepted
H2	Gender moderates the relationship between AI assimilation and service quality.	0.015	Accepted
H3	Age moderates the relationship between AI assimilation and service quality.	0.511	Rejected
H4	Level of study moderates the relationship between AI assimilation and service quality.	0.276	Rejected
H5	The country of study moderates the relationship between AI assimilation and service quality.	0.841	Rejected

DISCUSSION

The discussion is provided for each research construct examined.

One objective of this study was to investigate how service quality impacts students' ability to adopt AI. The correlation analysis revealed that students' perception of service quality is associated with their adoption of AI. This aligns with findings from Vázquez-Parra et al. (2024), which demonstrated that positive student perceptions significantly affect motivation and learning commitment, underscoring the importance of creating a positive environment for the use and learning of AI.

This study also aimed to investigate the moderating effects of age, gender, level of study, and country of enrollment on the relationship between university service quality and AI adoption. The assessment of the moderating effects of age on the relationship between University Service quality and AI assimilation proved that age did not moderate this relationship. This was confirmed by the moderation analysis using Jomavi software. The results contradict those of Iqbal et al. (2020), who also found that age moderates this relationship.

The assessment of the moderating effects of gender on the relationship between University Service quality and AI assimilation proved that gender moderates this relationship. Gender moderates the relationship between university service quality (USQ) and artificial intelligence (AI) assimilation because male and female students differ significantly in their attitudes, adoption, confidence, and ethical concerns regarding technology. Female students tend to approach AI with greater caution, prioritizing ethical implications, privacy, and accuracy over efficiency, whereas male students often prioritize practical utility and career benefits. Consequently, high-quality AI services may be readily adopted by males, whereas females may require more evidence of reliability (Matobobo, 2026). The finding confirms results by scholars such as Testa et al. (2024) and Russo et al. (2025), who have shown that gender influences the relationship between perceived service quality and AI usage.

The study also sought to assess the hypothesis that the student level of study, i.e., postgraduate or undergraduate, moderates the relationship between university service quality and students' use of AI tools. The results of the moderation analysis revealed that the level of study does not moderate the relationship between students' perception of university service quality and their uptake of AI. Research by Sebopelo et al. (2025) shows that the level of study does not moderate the relationship between perceived university service quality and AI uptake. Instead, findings indicate that AI assimilation directly boosts perceptions of service quality, with student satisfaction acting as a mediator, suggesting that service improvements are universally valued regardless of study level. This finding contradicts those of Fošner (2024), who found that the frequency and manner of AI tool use varied significantly by academic level, with postgraduate students often engaging more deeply or critically with AI tools than undergraduates.

The other hypothesis examined was whether students' country of study moderates their perception of service quality and their use of AI digital tools. The moderation analysis showed that the students' country of enrolment does not influence the relationship between their perception of university service quality and their use of AI tools. This is because students worldwide are motivated to use AI for similar reasons, such as improving writing skills, increasing productivity, and gaining

personalized feedback, rather than adhering to specific national educational standards. The trend of integrating AI into learning is widespread, and Singh (2025) notes that students at leading institutions globally encounter similar technological advances and face comparable pressures to adopt AI tools to succeed academically. Therefore, the country of study appears not to affect perceptions of service quality or AI adaptation. However, the results of this study indicated that a student's country of study does not moderate the link between perceived service quality and AI adoption. This contrasts with findings from Patimah et al. (2024) and Utami et al. (2023), who reported that the country significantly impacts students' experiences, especially regarding service quality and AI acceptance. This suggests that AI is becoming a common feature in universities across different countries.

CONCLUSION

The objectives of the research were to assess the relationship between university service quality and the adoption of AI tools. The study also sought to provide additional insight into the moderating roles of age, gender, level of study, and country of study in the relationship between perceived university service quality and the adoption of AI tools.

Based on the study findings, it is concluded that students' perceptions of service quality at their university influence their willingness to adopt AI tools.

The study also confirmed the hypothesis that gender plays a significant moderating role in the relationship between service quality and adoption of AI within the two universities. The results lead the researcher to recommend that, when university administrators consider introducing technology-enhanced learning strategies, particularly the adoption of AI tools, they should seriously consider students' gender as a significant factor.

The study also aimed to provide additional insight into the moderating role of age in perceptions of service quality and the adoption of AI tools. It is concluded that one's age does not determine one's appetite for using AI tools. The results suggest that age restrictions or considerations should not limit the implementation of AI strategies within universities.

The study also aimed to gain further understanding of how students' level of study influences their perspectives. Based on the results of this study, it is therefore concluded that whether students are postgraduate or undergraduate, their interest in adopting AI tools remains unaffected.

The study also aimed to investigate how a student's country of origin influences their engagement with AI tools. It concludes that students in Nigeria and Botswana show similar levels of interest in using AI tools. This highlights the changing perceptions and adoption of AI across various countries and educational institutions.

The findings have valuable pedagogical implications for educators and institutions. Students' use of AI is likely heavily influenced by how teachers integrate AI into their teaching. Additionally, the study suggests that AI policies and guidelines should be tailored rather than uniform; support strategies should consider student characteristics, such as gender and age, to ensure that teaching methods match different demographic and social contexts.

LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Like any empirical research, this study has limitations. First, resource constraints restricted the researchers to examining only two universities, which limits the generalizability of the results. Second, the study assumes that age, gender, study level, and country of study act as moderators in the relationship between students' perceptions of university service quality and their adoption of AI tools, thereby restricting the scope to these factors.

Additionally, the cross-sectional design means it did not track changes over time through a longitudinal approach. Relying on a quantitative method also limited insights into respondents' perceptions that qualitative methods could provide. These limitations highlight areas for future research, including including more universities from diverse countries beyond Nigeria and Botswana, conducting longitudinal studies to examine how time influences AI adoption, considering additional variables such as cultural background, and possibly adopting a mixed-methods approach for more comprehensive insights. This study also used self-reported survey data. Reliance on participants to report their own behaviors or attitudes introduces several forms of response bias. This study used a non-probability sampling**.** The primary drawback is the lack of representativeness, as participants are not selected randomly. Results from nonprobability sampling cannot be reliably generalized to the broader population because the selection probability for everyone is unknown.

More research is needed to examine the roles of the moderating variables in the study, providing clarity and a better understanding of how these variables may influence the bespoke design of the learning environment to meet students' needs across these variations.

This study was primarily quantitative. Future research could incorporate mixed methods and expand sampling across different geographical zones to achieve more comprehensive and robust results.

Future research studies of this nature should include more than two higher education institutions from more than two countries with a larger sample size to enhance the generalizability and credibility of the findings.

As previously noted, this was a cross-sectional study; therefore, future researchers are recommended to conduct a longitudinal survey to observe trends in participants' responses and variability over time.

The study recommends that future studies investigate the use of generative AI tools in learning environments to assess how they affect student performance, and how they educators adapt to AI assisted learning.

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