REVIEW OF ARTIFICIAL INTELLIGENCE IN EDUCATION
eISSN: 2965-4688

ARTIFICIAL INTELLIGENCE ASSIMILATION AND UNIVERSITY SERVICE QUALITY: THE MEDIATING ROLE OF STUDENT SATISFACTION

Phineas Sebopelo
Email: psebopelo@staff.bou.ac.bw
ORCID: https://orcid.org/0000-0001-9594-778X
Department of Quality Assurance
Botswana Open University (Botswana)

Olivia Baloyi (PhD)
Email: obaloyi@wsu.ac.za
ORCID: https://orcid.org/0000-0002-7125-2681
Walter Sisulu University (South Africa)

Nnenna Nancy Chukwuma (PhD)
Email: nnchukwuma@noun.edu.org
ORCID: https://orcid.org/0000-0002-5171-7488
National Open University of Nigeria (Nigeria)

ABSTRACT

Purpose: This study investigates how artificial intelligence (AI) assimilation influences students' perception of university service quality (USQ), considering student satisfaction (SS) as a mediating factor.

Methodology: A quantitative research design was applied. Data were collected through a Likert-scale questionnaire administered to students from Botswana Open University and the National Open University of Nigeria. Structural Equation Modelling (SEM) using Smart PLS was employed for hypothesis testing.

Findings: The results confirm that AI assimilation significantly influences students' perception of university service quality. Moreover, student satisfaction partially mediates the relationship between AI assimilation and USQ, indicating its essential role in successful AI integration in higher education.

Originality/Contribution: The study offers empirical evidence on the mediating effect of student satisfaction in the AI assimilation–USQ nexus within the context of developing countries. It contributes to theoretical understanding and provides practical insights for institutions aiming to improve service quality via responsible AI use.

Practical Implications: Universities are encouraged to invest in AI tools that enhance personalized services, administrative efficiency, and student engagement, while simultaneously addressing student concerns related to critical thinking and autonomy.

Limitations: The study is limited to two universities and adopts a cross-sectional approach, suggesting the need for longitudinal and broader studies.

Keywords: Artificial Intelligence, Service Quality, Higher Education, Student Satisfaction, Smart PLS.

Received: 30 April 2025 / **Revised:** 18 June 2025/ **Accepted:** 20 June 2025
DOI: https://doi.org/10.37497/rev.artif.intell.educ.v6ii.42

ASSIMILAÇÃO DA INTELIGÊNCIA ARTIFICIAL E QUALIDADE DOS SERVIÇOS UNIVERSITÁRIOS: O PAPEL MEDIADOR DA SATISFAÇÃO DOS ESTUDANTES

RESUMO

Objetivo: Investigar como a assimilação de inteligência artificial (IA) impacta a percepção dos estudantes sobre a qualidade dos serviços universitários, considerando a satisfação dos estudantes como fator mediador.

Metodologia: Aplicou-se uma abordagem quantitativa. Os dados foram coletados por meio de um questionário tipo *Likert*, respondido por estudantes da *Botswana Open University* e da *National Open University of Nigeria*. Utilizou-se modelagem de equações estruturais (SEM) com Smart PLS para testar as hipóteses.

Resultados: A assimilação da IA tem impacto significativo na percepção da qualidade dos serviços universitários. A satisfação dos estudantes atua como mediadora parcial nessa relação, sendo elemento chave para o sucesso da integração da IA no ensino superior.

Originalidade/Contribuição: O estudo oferece evidências empíricas sobre o papel mediador da satisfação estudantil na relação entre assimilação de IA e qualidade do serviço, especialmente em países em desenvolvimento, ampliando o conhecimento teórico e prático na área.

Implicações Práticas: Recomenda-se que as universidades invistam em ferramentas de IA que melhorem a personalização dos serviços, a eficiência administrativa e o engajamento dos estudantes, considerando também as preocupações relacionadas à autonomia e pensamento crítico.

Limitações: O estudo é limitado a duas universidades e adota um desenho transversal, sugerindo futuros estudos longitudinais e com escopo ampliado.

Palavras-chave: Inteligência Artificial, Qualidade do Serviço, Ensino Superior, Satisfação do Estudante, Smart PLS.

INTRODUCTION

AI generally refers to the capacity of machines to make predictions or solve problems using large amounts of data in complex, structured, and unstructured environments (Agrawal et al., 2018). It uses various techniques and applications, such as neural networks, speech/pattern recognition, genetic algorithms, and deep learning (i.e., machine learning and machine vision. (Jarrahi, 2018).

AI is a branch of computer science concerned with developing intelligent computers capable of doing tasks that typically need human intelligence (Zouhaier, (2023). AI has become part of the virtual world and plays a vital role in higher education. In recent years, the rapid advancement of AI technologies has not just been a trend but a transformational force across various sectors. The education sector has been a notable domain undergoing significant changes propelled by AI (Jackson, 2024).

In higher education, the use of AI has seen a significant surge with the development of AI tools designed for both students and educators (Chu et, 2022). Artificial Intelligence integration is not just about the optimal integration of AI into existing systems and processes; it is about the potential for AI to automatically process data or information using predetermined algorithms, revolutionizing how teaching and learning occur (Kineber et al., 2023). Assimilation of AI is an inevitable phenomenon. The use of AI technologies helps institutions to maintain and maintain a competitive a competitive edge but that requires assimilation of such technologies throughout business processes(Shao, 2019). According to Wamba (2022), assimilation of AI is a subject that needs investigation because there is little that has been written about it in education particularly with regards to university service quality. For instance, Al-Araj et al., (2022) argued that despite abundant research on client perceived service quality in the commercial sector such as banks, there is limited research on the impact of AI assimilation on service quality and satisfaction in the education sector. It is observed that many new generative AI tools are being launched into the education sector targeting both learners and educators. The avalanche of these tools creates a dilemma because of the rate of their introduction and the level and speed at which educators and students are expected to assimilate them.

Understanding and addressing students' perceptions of AI and their satisfaction with its integration is vital for universities developing sustainable digital strategies (Duong, et al., 2024). Positive perceptions and high satisfaction levels are linked to greater adoption and effective use of AI tools in learning, while negative perceptions can hinder progress (Vieriu, & Petrea, (2025). Universities need to proactively manage student views to ensure successful integration and maximize the benefits of AI for learning and teaching. Although the literary realm is becoming rife with research on AI digital technologies, research concerning how their assimilation and use affects student perception of university service quality, and their satisfaction remains minimal. Satisfaction is deemed critical for the improved perception of university service quality when AI is being assimilated. According to Otto et al, (2020), satisfaction is achieved when students' needs are met.

The present study posits that AI assimilation affects student perception of university service quality. The study further opines that satisfaction mediates the relationship between assimilation of AI and how students perceive university service quality

This study significantly contributes to this body of research in several ways. First, it provides an original addition to the limited literature on mediating the role of Student satisfaction in the relationship between AI assimilation (AIA), University service quality (USQ), and student Satisfaction (SS). Second, some studies have previously examined the relationship between AA, USQ, and SS. Still, these have limited applicability to education, particularly at universities in the developing world. Third, this study utilizes a sample from a developing country to explore whether the mediating role of student satisfaction in student loyalty is generalizable in this context.

Having introduced the overview of this study, the upcoming sections will address, the literature review which will be examining existing research on the topic The literature review considers the three primary constructs: (1) AIA, (2) SS, and USQ (3). The methods section will be explaining the research approach and procedures, the results section will present the findings of the study), in the discussion section, the results of the study will be interpreted and related to the literature. The conclusion section will be summarizing the main points and contributions of the research.

1.1. Theoretical underpinnings

In this study, the constructivist theory of learning was referred to. The theory emphasizes the importance of active engagement and knowledge construction by learners (Blinkstein and Worsley,2016; Siemens, 2012; Sablić, et al., (2025). According to this theory, learning is not passive reception of information but an active process where learners engage in critical thinking, problem solving and knowledge construction (Almulla, 2023). Thus, knowledge is an inter subjective interpretation. The learner must consider the information being taught and, based on past experiences, personal views, and cultural background - construct an interpretation (Brau, 2020). According to Huang, et al., (2024) the rise of artificial intelligence technologies in higher education brings new possibilities to the process of learning.

1.2 Problem statement

A gap in the literature is the lack of comprehensive understanding of the critical factors that contribute to the impact of AI assimilation on business outcomes. Previous research has not adequately explored the relationships between AI assimilation and learner experience, and learner performance. This study aimed to address this gap in the literature by exploring these critical factors in depth. Thus, there is a gap in the current literature concerning the effect. The current study intends to fill this gap by interrogating the effects of AI on perceived service quality, thereby contributing to the literature scarcity on AI discourse in the higher education sector.

1.3 Objectives of the study.

The study wants to achieve the following objectives

a) To determine the effect of AI Assimilation on University Service Quality.

b) To investigate the mediating effect of Student satisfaction on the relationship between AI Assimilation and University Service Quality.

2. Literature Review

2.1. AI assimilation.

AI assimilation has become crucial in modern businesses and customer service landscapes (Hariguna & Ruangkanjanases, 2024). The assimilation of AI technology into organizational business processes has brought benefits such as enhanced customer experience, reduced waiting time, and improved business efficiency (Bughin et al., 2018)

AI assimilation is described as the integration of technology throughout an organisation dimensions of work and project procedures as well as the routinisation of technologies in those activities (Wahab, & Radmehr, 2024). AI assimilation therefore refers to the integration of AI technologies into various sectors with a focal point on research. Sydoruk, (2024), notes that the successful assimilation of AI is contingent upon the readiness of an institution and the alignment of AI capabilities with strategies that emphasise the need for a cultural shift within organisations to embrace these technologies effectively. Wahab and Redmehr (2024), highlight that the adoption of AI can embrace operational efficiency, and decision-making processes, yet they caution that the lack of skilled personnel poses significant barrier to effective implementation of AI technologies. Chen et al., (2024), further elaborate that on the importance of data quality and infrastructure in facilitating assimilation of AI, noting that organisations must invest in robust data management systems to leverage the full potential of AI. Kelly and Pottast (2024), suggested that organisations must navigate challenges posed by AI to foster trust and acceptance among stakeholders and users. Pervaiz et al., (2025), argued that AI has the potential to affect students critical thinking and writing skills. They noted that some students worried that over-reliance on AI might hinder their ability to develop independent thought and original ideas.

2.2. Student Satisfaction.

AI applications for education are being developed and adopted for use at an increasing rate. The assimilation of AI technologies is meant to enhance student learning experience and their satisfaction with their engagement during their learning (Rodway & Schepman, 2023). AI technologies used in education therefore have the potential to improve learning outcomes that enhance student satisfaction levels. The impact of AI assimilation on satisfaction is revealed by Grájeda, et al., (2024) who revealed that there is a significant positive impact of AI tools on student academic experiences, including enhanced comprehension, creativity, and productivity. Research findings from several scholars attest to the idea that University service quality influences student satisfaction. This is demonstrated by Al-yozbakey and Esmaeel (2024) who proved that effective service delivery in Universities enhance student satisfaction. Suyafi et al. (2024) found that dimensions of service quality such as empathy, and reliability correlate with student satisfaction levels suggesting that student value personalised and dependable services. This idea is further supported by Supriyanto et al. (2024) who demonstrated that high service quality leads to increased student loyalty through their positive word of mouth, resulting in enhanced institutional reputation. However, Rahman et al. (2024) cautions that while service quality is essential, it must be maintained consistently across all departments to avoid discrepancies that could negatively impact student perceptions. Thin et al. (2024) emphasize the role of feedback mechanism in continuously improving service quality thereby enhancing student satisfaction overtime.

Alemu, 2023) argued that it is crucial to evaluate the level of service offered by universities because that will make them recognise the role of service upgrades on their competitiveness and in increasing student satisfaction.

A study by Gupta, and Kaushik, (2018) revealed that students experience of service quality had significant direct effect on their satisfaction levels, which implied that higher education authorities should improve on service quality to enhance student satisfaction. Htang, (2021) conducted a study on university service quality and student satisfaction and found out that all service quality dimensions were significantly correlated with student satisfaction. The study concluded that the students' perceived service quality dimensions resulting from that study could be applied by universities to evaluate their performance.

2.3 University service quality

The concept of service quality in higher education is borrowed from business companies and is applied to denote (Leonardo, 2018), Service quality is considered as a customer's reaction to a service (Amoako, et al., 2023). Therefore Berry et al., (1990) regard customers as judges of service quality by virtue of their ability to evaluate the service by contrasting their expectations with the actual performance of the service. This view is shared by Kandeepan, et al., (2019), who emphasised that service quality pertains to the extent to which a service meets customer demands or expectations. In the context of higher education service quality is the comparison between students expectations and their perception of the institutions performance , which ultimately used to gauge their level of satisfaction (Dugenio-Nadela et al.,2023).This study focus in on University Service Quality and it strongly emphasises perceived student quality which is determined by contrasting student anticipation for service with their performance assessments, (Zeithaml, et al.,2018).

University service quality is a multifaceted concept that encompasses various dimensions impacting student satisfaction and institutional effectiveness (Seitova, et al., (2024). Various dimensions, such as academic service quality, perceived service quality, and specific service attributes, play crucial roles in shaping students' experiences and satisfaction levels. In higher education service quality attributes relating to staff responsiveness, assurance and their empathy to students. The attributes also cover such areas as reliability of the service and tangibility. These factors directly correlate with student perception of value and satisfaction (Al-Yozbakey and Esmaeel, 2024). Furthermore, the integration of AI in service delivery has been proven to enhance accessibility, and efficiency thus thereby improving the overall University Service Quality (Ramseook-Munhuran and Numdlall, 2010). Nocosia and Sialza(2024), contends that while strides have been taken to enhance university ongoing evaluation and adaptation are critical for meeting evolving student expectations.

2.4 AI Assimilation and University Service Quality.

Assimilation of Artificial intelligence in higher education enhances service quality in across various dimensions of the university. It has been proven by various scholars that utilisation of AI technologies streamlines and nurture processes leading to improved efficiency and responsiveness in student services, which in turn boosts satisfaction levels (Rahiman and Korkdal, 2024). Moreover, AI driven analytics facilitate personalised learning experiences, allowing institutions to tailor services according to individual learner needs, thereby enhancing engagement and academic performance (Wang et al., (2022). However, the integration of AI is not without challenges. For instance, there is concern regarding data privacy and the potential for algorithmic bias which can undermine trust AI systems thus negatively impacting student perceived service quality. Despite these limitations the consensus is that if AI assimilation is well managed it can lead to marked improvement in in university service quality thus fostering a more supportive educational learning environment.

Based on the foregoing, it is s postulated that AI Assimilation has a positive and linear relationship with university service quality (H1).

2.5. AI Assimilation and University Service Quality, the mediating role of Student satisfaction

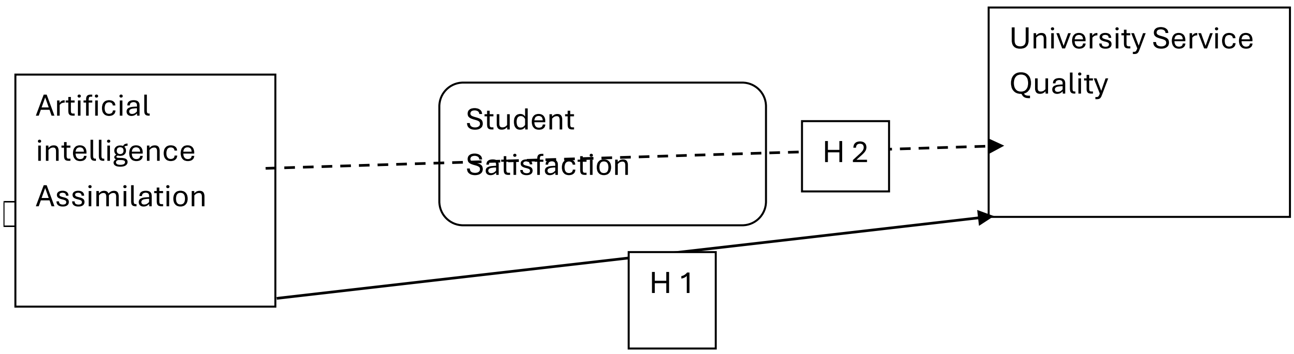
The assimilation of AI in a University setting significantly impacts service quality, with student satisfaction playing a crucial mediator role. Research indicates that AI technologies enhance administrative efficiency and personalised learning experiences which directly contribute to improved service quality in higher education institutions. (Rodrigues, et al., 2022; Rahiman, and Kodikal, 2024). Moreover, the integration of AI tools has been shown to foster engagement and satisfaction among students as they receive tailored support and resources that meet their individual needs (Moch et al., 2024). However, the effectiveness of

AI applications in enhancing service quality is contingent upon student perceptions and their acceptance of these technologies (Farhan, et al., 2024). This suggests that if students feel that AI applications are intrusive their satisfaction may diminish, ultimately undermining the individual benefits. Thus, fostering positive student experience through assimilation of AI requires careful consideration of both technological implementation and feedback from students (Namjoo, et al.,2023). This means that while AI can enhance university service quality, its success hinges on student satisfaction as a mediating factor.

Based on the foregoing, the study postulates that student satisfaction mediates the relationship between AI Assimilation and University Service Quality (H2).

2.6 Research Framework.

Based on the perused literature and the identified relationships, the study proposes the framework depicted in Figure 1.



3. Methodology

3.1 Research design

The study adopts a quantitative design approach.

3.2 Measurement instrument development

This study employs the use of a survey questionnaire based on a five -point Likert scale. This is a widely used instrument for data collection based on research design in educational technology research. The measurement items used in this study have been adopted from previous research works with proven reliability and validity. The data collection document is written in English language to ensure that students can understand the instrument comprehensively.

3.3 Population and Sampling.

The population for this study is registered students at the Botswana open University and National open university of Nigeria. Students forming the sample were selected based on their access and use of AI tools.

The current study has opted for application of non-probability sampling technique. A purposive sampling approach was used to sample the study respondents. This approach is found to be simpler and less costly. The approach is deemed appropriate since it will ensure that data collected included only those students using AI tools. The survey instrument will be distributed on-line using a Goggle Forms questionnaire with a message embedded to complete the forms. The measurement instrument items will be checked compulsorily to reduce the chances of respondents skipping some questions. Data collection was undertaken in approximately three months.

3.4 Data analysis

In this study, collected data was analyzed using SPSS 28.0. The results will be presented using tables to clarify trends and patterns. The analysis stage included testing the hypothesis and interpreting results using statistical tests of significance to determine the validity of the results.

Confirmatory Factor Analysis through the application of Smart PLS4 was used to assess the paths in the proposed study model and to test for mediation between independent variables on the dependent variable.

4. Results.

4.1 Demographic Analysis

Demographic analysis is essential for understanding the characteristics of research population. Social sciences emphasize that demographic information provides significant insights into the observed population, by their gender, age, education level, income, and occupation. Such information varies on the type of the study being conducted. The results in Table 1 shows that most of the respondents were from Nigeria (76%) and Botswana (24%). The gender differentials showed that males made (56.5%) of the sample, while females were (and most of the respondents were of postgraduate level of study (65.6%) and 37.4% being at undergraduate level. The table also shows that mostly the respondents had bachelor's degree (46.25) qualifications followed by those with master's degree, (26.1%) and only 2,35 had a PhD qualification. The samples can be seen as good representation of the population, as the data in Table 2 show a good coverage in terms of categories and the respondent numbers of each category. The samples consist of both types of gender, all age groups and educational background. However it can be seen from the table that Nigeria has the largest number of respondents however the samples are spread well across the levels of demographic categories in the study. A more even spread of demographic categories within a study sample can indeed reduce the concern for potential bias, particularly demographic bias, by ensuring the sample more closely reflects the diversity of the broader population (Tao, et al.,2020).

Table 1 Demographic characteristics of respondents

Variables		Frequency	Percentage
Level of study	Undergraduate	149	37.4.0%
	Postgraduate	259	65.6%
	Total	398	100
Gender	Male	225	56.5
	Female	173	43.5
	Total	398	100.0
Qualifications	Certificate	2	.5
	Diploma	99	24.9
	Bachelor's degree	184	46.2
	Master's degree	104	26.1
	PhD	9	2.3
	Total	398	100.0
Country	Nigeria	304	76.4
	Botswana	94	23.6
	Total	398	100.0

4.1 Descriptive analysis

Table 2 is representing the descriptive analysis of data. It is a summary of data that represent, how much variation exists in data. This includes mean, median, standard deviation, skewness and kurtosis of data. Table 2 depicts that the mean of the overall satisfaction scale is 3.8, standard deviation is 7.9. The value of Skewness -809, which means the distribution of the student satisfaction score is negatively skewed, kurtosis is 1.2, for AI Assimilation the mean is 3.6, Standard deviation 8.8, Skewness, -741and kurtosis .48. For University service quality scores, the standard deviation 6.5, Skewness, -945 and kurtosis .89. The table shows that the means the distribution of the student satisfaction, AI Assimilation, Service quality scores are negatively skewed, whereas the kurtosis are higher than the kurtosis's normal value which means the distribution of the study variables score is Platykurtic, which indicates a flatter, more spread-out distribution compared to a normal distribution, with fewer extreme values or outliers (Akoglu, & Özbek, 2021). This means that the data points are more evenly distributed, and the tails of the distribution are thinner.

Table 2: Descriptive of study statistics

Variables	minimum	maximum	Mean	Standard deviation	skewness	kurtosis
Student satisfaction	1.00	5.00	3.8	7.9	-809	1.2
AI Assimilation	1.00	5.00	3.6	8.8	-741	.48
Service Quality	1.00	4.77	3.3	6.5	-945	.89

4.2 **Reliability Analysis**

To check the internal consistency of data Cronbach alpha is measured. This is the most common way to measure the consistency of data Table 2 shows, the average alpha of the study variables measurement tool consisting of 3 items has been tested has an overall α=0.889, which is very appropriate for the reliability of internal consistency. A Cronbach's alpha value of 0.70 or higher is generally considered an acceptable threshold for internal consistency reliability in research (Farahani, et al., 2024).

Table 2: Cronbach's Alpha of study variables

Name of Variable	Cronbach's Alpha	N of Items
Student satisfaction	.886	5
AI Assimilation	.859	5
University Service Quality	.921	21
Total	.889	31

Table 3: Psychometric Properties of Study variables.

Table 3 shows that the inter item correlations for AI Assimilation ranged between .35 to .48, for student satisfaction .38 to .55 and University service quality was .45 to .64. Durairatnam, Chong, and Jusoh, (2020), recommend the acceptable range of inter item correlation to be from 0.3 to 0.9.

Variable	Inter-Item Correlation	Cronbach's Alpha	N of Items
Assimilation	.35 to .48	.91	6
Student satisfaction	.38 to .55	.89	5
Service Quality	.45 to .64	.91	21

4.3 Correlations

Table 4 presents correlation results. The Pearson's correlation test was used to test the relationship among the AI Assimilation, and perceived university service quality. It shows the relationship between the two variables to have a weak coefficient of 0.322. Kelly, et al., 92024), considered correlations between 0.70–0.89 as strong, between as 0.40–0.69 moderate and 0.10–0.39, as weak. This means that as AI Assimilation changes, perceived service quality also changes. It implies that while there is a discernible relationship, but it's rather weak.

Table 4: correlations

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

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

4.4 multi-collinearity.

Table 5 presents the collinearity statistics. Collinearity diagnostic test is run to prove that this multicollinearity is not affecting research results. Following liner regression test is proved that this multicollinearity is not affecting the results of this data and coefficients are well calculated. It is generally believed that any variance inflation factor (VIF) exceeds 10 and tolerance value lower than 0.10 indicates a potential problem of multicollinearity (Larsen, et al., 2025). The result in Table 5, shows that multicollinearity does not exist among all independent variables because the Tolerance values are more than 0.10 and VIF values are less than 10. The result indicates that the study does not have any multicollinearity problem.

according to the results.

Table 5: collinearity statistics.

Variable	Tolerance	VIF
AI Assimilation	.995	1.005
Student Satisfaction	.995	1.005

Note, Dependent variable: university Perceived Service Quality

4.5 Confirmatory Factor Analysis (CFA)

The measurement model was examined first under two step technique proposed by J. C. Anderson and Gerbing (1988). Confirmatory factor analysis is employed to measure the validity and, fitness of framework. Partial least squares version 4 was used to run the model fitness test.

4.6. Measurement model

The hypothesized empirical measurement model was developed using Partial least squares version 4, and CFA was performed to estimate and test the measurement model. In this stage of model testing, all the latent constructs were considered and the strength of the paths between the factors and their observed variables were deemed important. The initial measurement model is shown in figure 1.

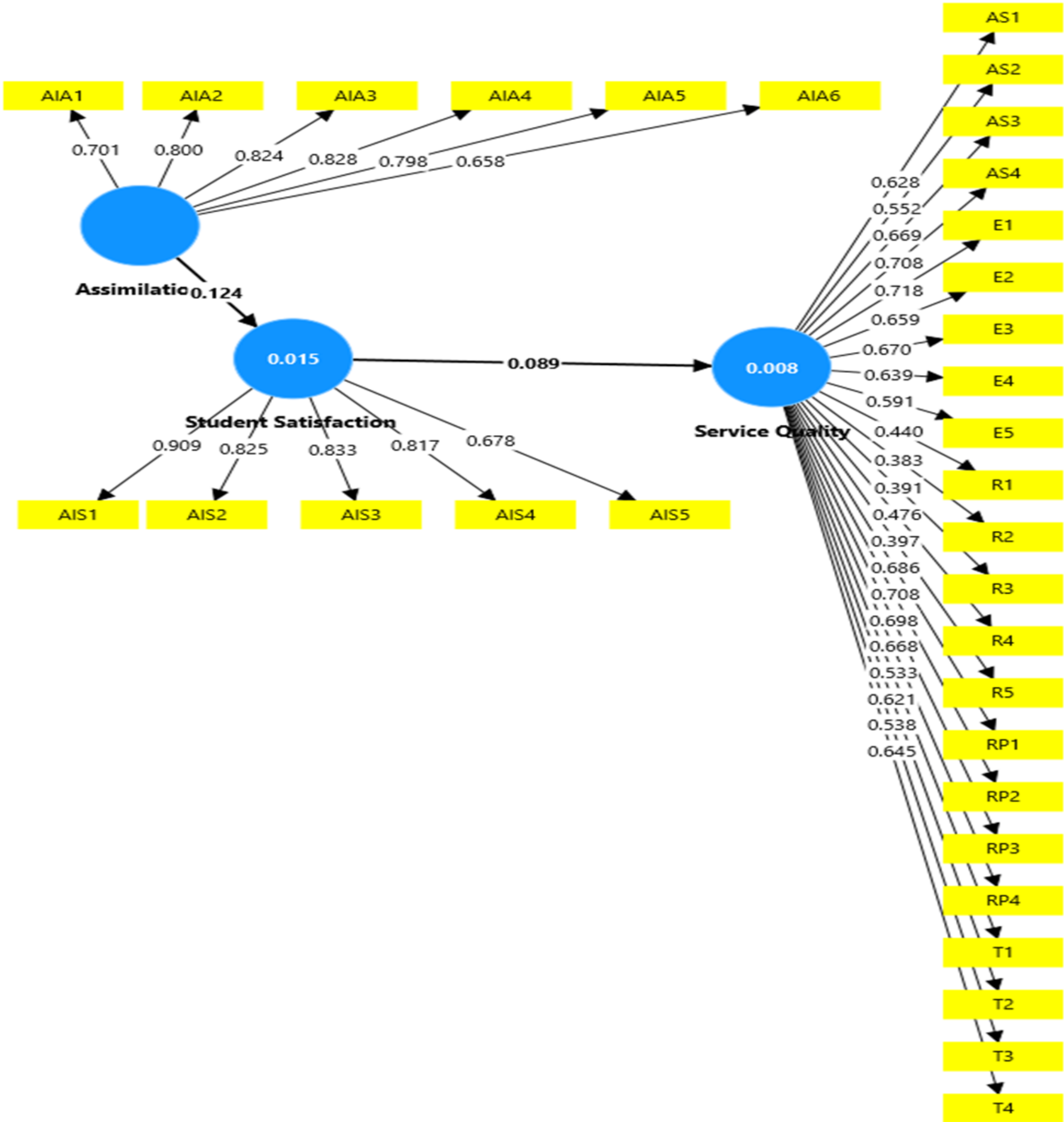


Figure 1: Original Model

4.7 Model Modification.

To improve the validity of a measurement model, the researcher modified it by examining modification indices, ensuring discriminant validity, and removing or adjusting items The model was assessed since the initial model did not display a sound goodness fit, tangibility indicators were removed to attain model fitness. If modification indices suggest high redundancy between items, one or more items might be redundant and can be removed or constrained as free parameters (Kim, et al., (2021). In this study tangibility variable had indicators with low factor loadings which were below 0.50. Güvendir, and Özkan, (2022), stated that indicators with very low loadings (e.g., below 0.50 or 0.40) on a factor may not be strongly related to the underlying construct and can be removed. After their removal the model displayed sound fitness. In a Partial Least Squares (PLS) model, path coefficients represent the strength and direction of relationships between latent variables (Fauzi, 2022). In this study as shown in figure 2, the outer loads ranged from 0.63 to 0.910. This shows that more than 50 percent of the variance of the indicator is explained by the structure, thus giving acceptable item reliability.

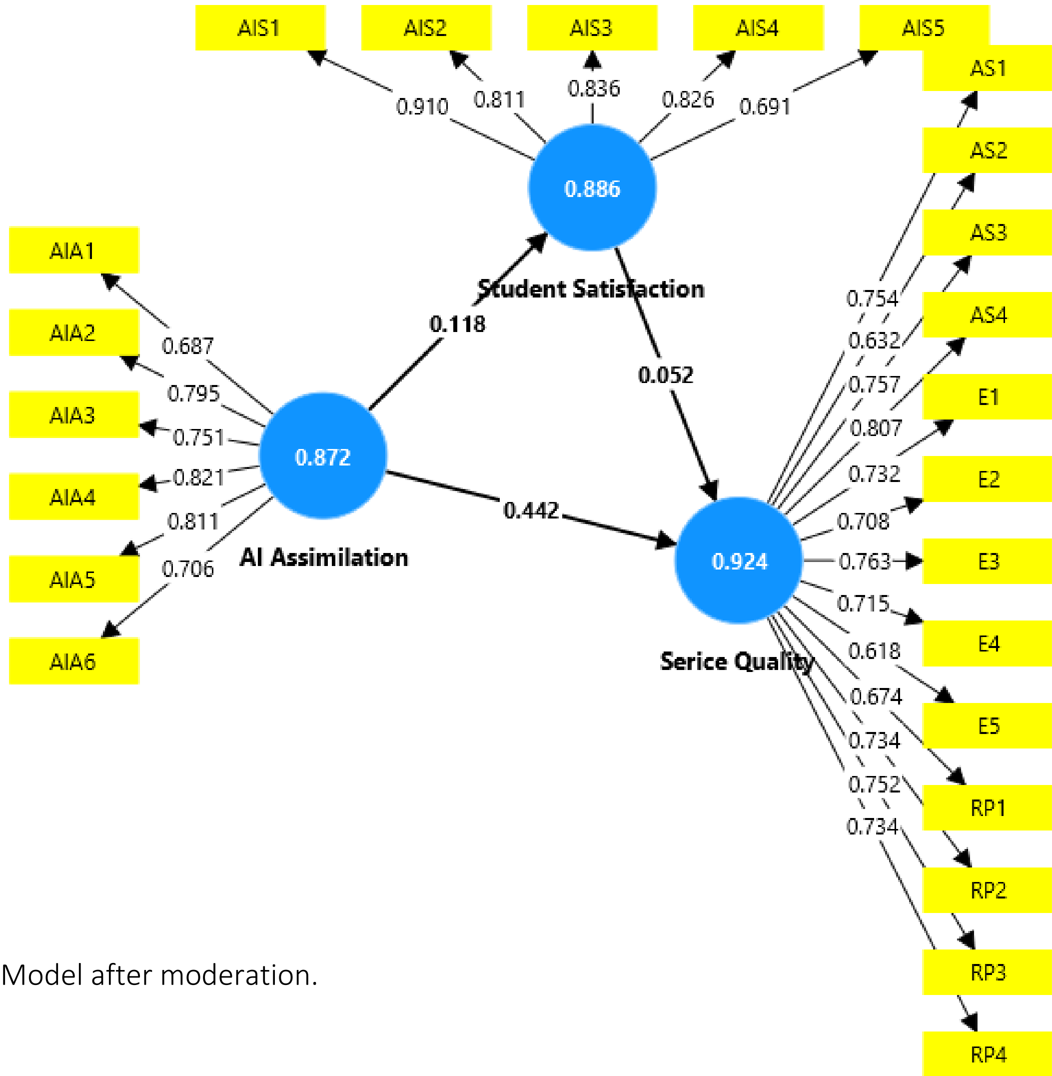


Figure 2. Model after moderation.

4.8. Assessing Model Fitness.

The standard values of Chi-square and SRMR d_G and d_ULS were used to assess model fitness A lower SRMR value generally indicates a better model fit, with values below 0.08 often considered acceptable (Pinedaa, et al., 2022). For d_G**,** Values less than 0.10 (or 0.08, in some more conservative approaches) are generally considered indicative of a good model fit. NFI ranges between 0 and 1, and a value of NFI close to 1 means a good fit (Dash, & Paul, 2021). According to the results in Table 6, the values are fulfilling the model fitness threshold.

Table 6: CFA Model fit

Parameters	Saturated model	Estimated model
SRMR	0.09	0.09
d_G	0.593	0.6
Chi-square	1354.98	1354.98
NFI	0.772	0.8

4.9 Test for Validity

In this study two types of validity being, discriminant and construct validity ere tested. Discriminant validity tests that construct that should have no relationship do, in fact, not have any relationship (Cheung, et al.,2024). The results for discriminant validity are reflected in Table 8, whilst for construct validity are shown in Table 9. The results of the tests show that both discriminant and construct validity were attained.

4.9.1 Discriminant Validity.

In this study discriminant validity test was conducted. It ensures that a test designed to measure a specific concept or trait doesn't inadvertently measure something else entirely different. As shown in Table 7, the square root of each construct’s AVE was greater than its correlations with other constructs. This means that no problem was identified regarding, discriminant validity, as shown by the FornellLarcker criterion.

Table 7: Discriminant Validity

	AI Assimilation	Service Quality	Student Satisfaction
AI Assimilation	0.764		
service Quality	0.442	0.723	
Student Satisfaction	0.118	0.052	0.818

4.9.2 Construct Validity

Construct validity is crucial for ensuring that measures accurately represent the intended constructs. In this study observed pattern of correlations in a convergent-discriminant validity matrix matches the theoretically predicted pattern of correlations which affirms construct validity.

Table 8: Construct Validity

Variables	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
AI Assimilation	0.872	0.893	0.583
Service Quality	0.924	0.934	0.523
Student Satisfaction	0.886	0.909	0.669

4.10. Testing for mediation.

In this study Mediation analysis was conducted to understand the mechanism through which an AI Assimilation influences a university perceived service quality via student satisfaction as a mediator. The outcome of the mediation analysis is shown in Table 9. After conducting test on indirect effect relationship (mediation hypothesis) (Table 5) involving AI assimilation (AIAS) →Student Satisfaction (SS)→University service quality USQ), the coefficient value of the indirect effect is 0.052 with p-value of 0.002 (p<10%). The result indicates that student satisfaction significantly mediates to the effect of AIAS on USQ. Direct effect relationship (direct path) involving AIAS→USQ was also tested and the obtained value of 0.442 which was significant at level of <0.001. The results revealed that student satisfaction has a partial mediation effect on the relationship between AI assimilation and University Service quality.

Table 9: mediation

Type of effect	Association	Path coefficient	P value.	Conclusion
Direct	Assimilation (AIAS) Student Satisfaction (SS), University service quality (USQ)	**0.052**	001	significant
Indirect	AI assimilation (AIAS), Student satisfaction (SS), and University service quality(USQ)	0.442	001	Significant

- Partial mediation

4.11. Hypothesis Testing.

The aim of this research was to assess the impact of AI Assimilation, on perceived service quality, and the mediating effect of student satisfaction on the relationship between AI Assimilation, on university service quality,

All of the two tested hypothesis were supported by the results. The first hypothesis posited that AI assimilation have a positive and significant influence on the university service quality, whereas the second hypothesis posited that student satisfaction mediated the relationship between AI assimilation and University Service quality. The overall results of hypothesis testing are shown in Table 10.

Table 10: Summary of hypothesis results

Hypothesis	Narration	P-Value	Conclusion
H1	AI Assimilation and Service quality	<001	supported
H2	Student satisfaction mediates the link between AI assimilation and service quality	0.001	Supported

5. Discussion

The current study explored the direct impacts of AI assimilation on university service quality. The research also investigated the mediating role of student satisfaction on the relationship between AI assimilation and university service.

The research findings validated (H1), indicating that AI assimilation was a positive determinant of university perceived service quality. These findings support the conclusions of Alalwany, et al (2023), and Wang, et al., (2024), regarding the effect of AI Assimilation in enhancing student perception of university perceived service quality These studies suggest that AI assimilation enhances university perceived service quality through improved personalized learning experiences, content quality, and perceived utility, while also addressing challenges related to technological and pedagogical limitations. The findings of this study therefore support the constructivist theory that that integrating AI into learning environments foster active learning and critical engagement. The findings validate Sablić, et al., 2025) assertion that the constructivist learning theory emphasizes that learners actively build their own understanding and knowledge, rather than passively receiving information. Thus in this study it was further demonstrated that AI-powered tools can personalize learning experiences, promote deeper understanding, and encourage students to actively construct knowledge through interaction and experience

The findings of the study supported (H2), implying that student satisfaction mediate the link between AI assimilation and university service quality. This means that , student satisfaction does not play a significant mediating role in this context. These results are in affirmation with the findings of studies conducted by Namjoo, et al.,(2023), and Moch et al., (2024), who concluded that the integration of AI tools fosters engagement and satisfaction among students as they receive tailored support and resources that meet their individual needs. While students generally accepted the use of AI tools, many expressed concerns about their satisfaction with these tools, particularly regarding the potential impact on critical thinking, communication skills, and overall learning experience. This is in line with results of the study conducted by Pervaiz et al., (2025), on the impact of AI on critical thinking and writing Skills in Higher Education. Specifically, some students worried that over-reliance on AI might hinder their ability to develop independent thought and original ideas.

5.1 Implications

5.1.1Theoretical implications

In putting forth a mediation model, the current research offers crucial contributions to the comprehension of AI assimilation by linking it with university service quality and student satisfaction outcomes, particularly in the context of higher education.

The exploration of the mediating role of student satisfaction on the relationship between AI Assimilation and University service quality in a developing country, constitutes an essential addition to the emerging knowledge on AI assimilation in the existing literature. By offering empirical evidence on the crucial role of AI assimilation in enhancing university service quality in higher education, particularly in developing countries, the study fills a seemingly existing void in the literature stream that is marked by a paucity of empirical evidence resulting from the limitations in data availability.

5.1.2 Managerial implications.

The findings offer important practical implications for educational administrators and higher education institutions that seek to assimilate AI tools and systems in their business operations. Most of universities in developing countries are faced with challenges of resource constraints making it difficult for them to implement advanced technologies such as Artificial intelligence. This study provides educators and administrators with recommendations for maximizing the utilization of AI. Consequently, educators can realize the importance of service quality if they invest in AI assimilation in the university by taking full cognisance of ensuring student satisfaction.

5.1.3 Practical implications

The practical implications of this study are paramount for higher education institutions that aspire to embrace AI in their day-to-day teaching and learning operations. This study demonstrates that effective AI assimilation positively enhances students' perception of university service quality. As higher education institutions navigate the dynamic landscape of AI implementation, understanding the key factors that influence successful assimilation becomes imperative. This study identified critical determinants, including reliability and trustworthiness of AI, perceptions around its usefulness, and ease of use. This information empowers education practitioners to formulate strategic AI adoption plans that not only consider technological aspects but also address student satisfaction attributes and their perceived service quality.

From a practical point of view the study also emphasizes the importance of responsible AI integration in education by promoting ethical considerations, equitable access, and student agency. This involves carefully considering potential biases, ensuring fair access to AI tools, and empowering students to critically engage with and shape the use of AI in their learning.

5.2 Limitations

Like all studies, this research also has some limitations. The research study was limited interns of accessing a large pool of respondents and it was conducted within a short space of time. During this period the researcher experienced slow and low response from participants. This is attributed to participants unwillingness to respond to the online survey questionnaire used to gather data. The study was also confined to two universities, one in Nigeria and the other from Botswana. A combination of low response rates and limited geographical coverage makes confident generalisation of study findings a little problematic.

6. Conclusion.

This study investigates how the AI assimilation or adoption affected the university service quality, with student satisfaction acting as a mediating variable. A research framework was designed to examine the relationships among the variables, and utilized two research variables associated with AI assimilation, university service quality and student satisfaction. The results strongly indicate a significant relationship between AI assimilation and university service quality, suggesting that assimilation of AI in universities is correlated with enhanced perceived service quality. This research offers concrete evidence that effective AI adoption not only improves operational efficiency for companies but also provides students with an assurance to feel safe when they perform any transactions with university employees.

Moreover, this study uncovered the mediating role played by student satisfaction in the link between AI assimilation and university service quality. This implies that higher education institutions must provide satisfactory AI services for students to have a positive perception of service quality. This inclination is grounded on the notion that the effectiveness of AI applications in enhancing service quality depends on student perceptions and their acceptance of these technologies. The fundamental conclusion drawn from this study was that the ability to promote AI adoption to enhance student perception of service quality can be affectively achieved by ensuring student satisfaction. The study also notes the significance of AI assimilation in promoting perceived service quality by ensuring that university staff is responsive when dealing with students queries and questions. Therefore, institutions planning to adopt AI should optimize their service provision practices before entering into AI integration.

However, it is important to acknowledge the limitations of the present study. First, the cross-sectional design limited the ability to draw causal conclusions about the relationships between variables. Future research may benefit from adopting a more suitable longitudinal design to gain insight into the longitudinal impact of AI assimilation. Second, the scope of this study is confined to the impact of AI assimilation on students at two universities and does not cover more institutions of higher learning. Future research could broaden the scope of investigating the impact of AI assimilation on job satisfaction, productivity, and employee well-being. Subsequent research can provide more detailed insights into AI applications, including the most effective features and algorithms for improving customer satisfaction.

Furthermore, this study offers a general analysis of AI assimilation without exploring the impact of various types of AI applications on student satisfaction. Future research could delve into the impact of different AI applications, such as chatbots, voice assistants, and recommendation systems, and identify the types that are most effective in enhancing perceived service quality.

6.1 Study Contribution.

a) AI is a relatively new technology in Africa particularly as applied in the higher education landscape. This means that a lot of ground needs to be covered in exploring the viability and potential benefits of AI by tapping on the experiences of students.

b) The findings of this study serve as useful feedback to decision makers in higher education and sponsors such as governments on the need to embrace AI to enhance the quality of education.

c) The findings from this study also serve as a basis of future research by addressing students' perceptions and utilisation of AI in higher education.

d) The information contained in this study provides additional knowledge of students' perception in the use of technologies in education by focusing on their perception on the knowledge and use of AI tools in education.

Declarations

Conflict of Interest: There are no conflicts of interest regarding the publication of this article.

Informed Consent: Participants were informed about the study's objectives, procedures, and potential risks. They were informed that participation was voluntary and that they could withdraw from the study at any point if they felt reluctant without any consequences. All personal information was anonymized to protect participants' confidentiality.

Data Availability: The data are not publicly available due to privacy or ethical restrictions.

References

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines: the simple economics of artificial intelligence. Harvard Business Press.

Alalwany, W., & Yonan, J. (2023). Role of Artificial Intelligence (AI) in Improving Educational Quality and Networking for Students and Faculty. *Babylonian Journal of Networking*. https://doi.org/10.58496/bjn/2023/008.

Al-Araj, R. E. E. M., Haddad, H. O. S. S. A. M., Shehadeh, M. A. H. A., Hasan, E., & Nawaiseh, M. Y. (2022). The effect of artificial intelligence on service quality and customer satisfaction in Jordanian banking sector. *WSEAS Transactions on Business and Economics*, *19*(12), 1929-1947. DOI: 10.37394/23207.2022.19.173.

Alemu, A. (2023). Assessing service quality in tertiary Education using adapted SERVQUAL scale. Cogent Education, 10(2), 2259733. https://doi.org/10.1080/2331186X.2023.2259733.

Almufarreh, A. (2024). Determinants of Students' Satisfaction with AI Tools in Education: A PLS-SEM-ANN Approach. *Sustainability*, *16*(13), 5354. http://dx.doi.org/10.3390/su16135354.

Almulla, M. A. (2023). Constructivism learning theory: A paradigm for students' critical thinking, creativity, and problem solving to affect academic performance in higher education. Cogent Education, 10(1), 2172929. https://doi.org/10.1080/2331186X.2023.2172929.

Alshahrani, A., Dennehy, D., & Mäntymäki, M. (2022). An attention-based view of AI assimilation in public sector organizations: The case of Saudi Arabia. *Government Information Quarterly*, *39*(4), 101617. http://dx.doi.org/10.1016/j.giq.2021.101617.

Al-Yozbakey, E. A., & Esmaeel, R. I. (2024). The Role of Educational Service Quality in Enhancing Student Satisfaction/an Exploratory Study of the Opinions of a Sample of Students of the Department of Industrial Management. Journal Port Science Research, 7(issue), 523-544. https://doi.org/10.36371/port.2024.special.41.

Amoako, G. K., Ampong, G. O., Gabrah, A. Y. B., de Heer, F., & Antwi-Adjei, A. (2023). Service quality affecting student satisfaction in higher education institutions in Ghana. Cogent Education, 10(2), 2238468. http://dx.doi.org/10.1080/2331186X.2023.2238468.

Annuš, N. (2023). Chatbots in education: The impact of artificial intelligence based ChatGPT on teachers and students. *International Journal of Advanced Natural Sciences and Engineering Research*, *7*(4), 366-370. http://dx.doi.org/10.59287/ijanser.739.

Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics*, *3*(2), 220-238. http://dx.doi.org/10.18608/jla.2016.32.11.

Brau, B. (2020). Constructivism. In R. Kimmons, & S. Caskurlu (Eds.), The Students' Guide to Learning Design and Research (pp. 33-43).

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018, September). Notes from the AI Frontier: Modeling the Impact of AI on the World Economy. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/artificial-intelli-gence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy#/.

Chen, K., Chen, T., Ye, P., Chen, H., Chen, K., Han, T., ... & Bai, L. (2024). FNP: Fourier Neural Processes for Arbitrary-Resolution Data Assimilation. arXiv preprint arXiv:2406.01645.

Chu, H.C., Hwang, G.H., Tu, Y.F. and Yang, K.H., 2022. Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. Australasian Journal of Educational Technology, 38(3), pp. 22-42. https://doi.org/10.14742/ajet.7526.

Dugenio-Nadela, C., Cañeda, D. M., Tirol, S. L., Samillano, J. H., Pantuan, D. J. M., Piañar, J. C., ... & Decena, E. (2023). Service Quality and Student's Satisfaction in Higher Education Institution. Journal of Human Resource and Sustainability Studies, 11(04), 858-870. http://dx.doi.org/10.4236/jhrss.2023.114049.

Durairatnam, S., Chong, S. C., Jusoh, M., & Dharmaratne, I. R. (2021). Does people-related total quality management "work" for people? An empirical study of the Sri Lankan apparel industry. *The TQM Journal*, *33*(6), 1183-1200. https://doi.org/10.1108/TQM-06-2020-0140.

Farhan, N. D., Sadiq, B. H., Zwayyer, M. H., & Arnout, B. A. (2024). The impact of using artificial intelligence techniques in improving the quality of educational services/case study at the University of Baghdad. *Frontiers in Education*, *9*. https://doi.org/10.3389/feduc.2024.1474370.

Grájeda, A., Burgos, J., Córdova, P., & Sanjinés, A. (2024). Assessing student-perceived impact of using artificial intelligence tools: Construction of a synthetic index of application in higher education. Cogent Education, 11(1), 2287917. http://dx.doi.org/10.1080/2331186X.2023.2287917.

Gupta, P., & Kaushik, N. (2018). Dimensions of service quality in higher education–critical review (students' perspective). International journal of educational management, 32(4), 580-605. http://dx.doi.org/10.1108/IJEM-03-2017-0056.

Hariguna, T., & Ruangkanjanases, A. (2024). Assessing the impact of artificial intelligence on customer performance: A quantitative study using partial least squares methodology. *Data Science and Management*, *7*(3), 155-163. https://doi.org/10.1016/j.dsm.2024.01.001.

Htang, L.K. (2021), "A look at university student service quality and satisfaction", Quality Assurance in Education, Vol. 29 No. 2/3, pp. 101-115. https://doi.org/10.1108/QAE-09-2020-0108.

Huang, Z., Mao, Y., & Zhang, J. (2024). The Influence of Artificial Intelligence Technology on College Students' Learning Effectiveness from the Perspective of Constructivism—Taking ChatGPT as an Example. Journal of Education, Humanities and Social Sciences, 30, 40-46. http://dx.doi.org/10.54097/y1x3jj43.

Jackson, E. A. (2024). The Evolution of Artificial Intelligence: A Theoretical Review of its Impact on Teaching and Learning in the Digital Age. Available at https://hdl.handle.net/10419/280893

Jarrahi, M.H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organisational decision making. Business Horizons, 61(4), 577-586.

Kandeepan, V., Vivek, R., & Seevaratnam, T. (2019). Impact of Organizational Citizenship Behaviour on Service Quality in Banking Sector, Vavuniya District. Management, 7, 1-13. https://doi.org/10.34293/management.v7i2.636.

Keller, J. D., & Potthast, R. (2024). AI-based data assimilation: Learning the functional of analysis estimation. arXiv preprint arXiv:2406.00390.

Vieriu, A. M., & Petrea, G. (2025). The impact of artificial intelligence (AI) on students' academic development. *Education Sciences*, *15*(3), 343.

Khedrane, S. (2024). The Role of Artificial Intelligence in Distance Education. http://dx.doi.org/10.53284/2120-011-001-006.

Kineber, A. F., Othman, I., Oke, A. E., Chileshe, N., & Zayed, T. (2023). Value management implementation barriers for sustainable building: A bibliometric analysis and partial least square structural equation modeling. *Construction Innovation*, *23*(1), 38-73. http://dx.doi.org/10.1108/CI-05-2021-0103.

Maddy, E. S., & Boukabara, S. A. (2021). MIIDAPS-AI: An explainable machine-learning algorithm for infrared and microwave remote sensing and data assimilation preprocessing-Application to LEO and GEO sensors. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *14*, 8566-8576. http://dx.doi.org/10.1109/JSTARS.2021.3104389.

Namjoo, F., Liaghat, E., Shabaziasl, S., Modabernejad, Z., & Morshedi, H. (2023). Students' experience on self-study through AI. *AI and Tech in Behavioral and Social Sciences*, *1*(3), 35-42. http://dx.doi.org/10.61838/kman.aitech.1.3.6.

Necosia, R. I. M. T., & Sealza, I. S. (2024). Service Quality Assessment Tool in a State University in Northern Mindanao. Journal of Interdisciplinary Perspectives, 2(3), 1-1. https://doi.org/10.69569/jip.2024.0036.

Otto, A.S.; Szymanski, D.M.; Varadarajan, R. Customer satisfaction and firm performance: Insights from over a quarter century of empirical research. J. Acad. Mark. Sci. 2020, 48, 543–564. http://dx.doi.org/10.1007/s11747-019-00657-7.

Rahiman, H. U., & Kodikal, R. (2024). Revolutionizing education: Artificial intelligence empowered learning in higher education. Cogent Education, 11(1), 2293431. http://dx.doi.org/10.1080/2331186X.2023.2293431.

Ramseook-Munhurrun, P., Naidoo, P., & Nundlall, P. (2010). A proposed model for measuring service quality in secondary education. International Journal of Quality and Service Sciences, 2(3), 335-351. http://dx.doi.org/10.1108/17566691011090062.

Rodrigues, C. D., Gonçalves, R. B., Neto, F. L. A., & Camargo, R. Z. (2022). Enhancing Administrative Efficiency in Higher Education with AI: A Chatbot Solution. Review of Artificial Intelligence in Education, 3(00), e023-e023. http://dx.doi.org/10.37497/rev.artif.intell.educ.v3i00.23.

Rodway, P., & Schepman, A. (2023). The impact of adopting AI educational technologies on projected course satisfaction in university students. Computers and Education: Artificial Intelligence, 5, 100150. https://doi.org/10.1016/j.caeai.2023.100150.

Seitova, M., Temirbekova, Z., Kazykhankyzy, L., Khalmatova, Z., & Çelik, H. E. (2024). Perceived service quality and student satisfaction: a case study at Khoja Akhmet Yassawi University, Kazakhstan. *Frontiers in Education*. https://doi.org/10.3389/feduc.2024.1492432.

Güvendir, M. A., & Özkan, Y. Ö. (2022). Item removal strategies conducted in exploratory factor analysis: A comparative study. *International Journal of Assessment Tools in Education*, *9*(1), 165-180.

Shao, Z. (2019). Interaction effect of strategic leadership behaviors and organizational culture on IS-Business strategic alignment and Enterprise Systems assimilation. *International journal of information management*, *44*, 96-108. https://doi.org/10.1016/j.ijinfomgt.2018.09.010.

Siemens, G. (2012, April). Learning analytics: envisioning a research discipline and a domain of practice. In Proceedings of the 2nd international conference on learning analytics and knowledge (pp. 4-8). http://dx.doi.org/10.1145/2330601.2330605.

Supriyanto, A., Burhanuddin, B., Sunarni, S., Rochmawati, R., Ratri, D. K., & Bhayangkara, A. N. (2024). Academic service quality, student satisfaction and loyalty: a study at higher education legal entities in Indonesia. The TQM Journal. https://www.emerald.com/insight/content/doi/10.1108/TQM-10-2023-0334/full/html.

Syafi'i, M., Yulisetiarini, D., & Sukarno, H. (2024). The influence of service quality, word of mouth, and brand image on loyalty with Ibrahimy Situbondo University student satisfaction mediation. *Lisan Al-Hal: Jurnal Pengembangan Pemikiran dan Kebudayaan*, *18*(1), 113–125. https://doi.org/10.35316/lisanalhal.v18i1.113-125

Sydoruk, T. (2024). How AI Can Reduce Unemployment Rate Among Vulnerable Population of New Immigrants: Assimilation Issues Resolved with AI. Economics & Education, 9(2), 20-25. http://dx.doi.org/10.30525/2500-946X/2024-2-3.

Thin, D. B., & Le Anh Tuan, N. T. L. The Student Satisfaction on Education Service Quality: Case Study at Hong Duc University. http://dx.doi.org/10.47191/jefms/v7-i4-02.

Wahab, M. D. A., & Radmehr, M. (2024). The impact of AI assimilation on firm performance in small and medium-sized enterprises: A moderated multi-mediation model. Heliyon, 10(8). http://dx.doi.org/10.1016/j.heliyon.2024.e29580.

Wamba, S. F. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management*, *67*, 102544. http://dx.doi.org/10.1016/j.ijinfomgt.2022.102544.

Wang, L., & Li, W. (2024). The Impact of AI Usage on University Students' Willingness for Autonomous Learning. *Behavioral Sciences*, 14. https://doi.org/10.3390/bs14100956.

Zouhaier, S. (2023). The impact of Artificial intelligence on higher education: An empirical study. *European Journal of Educational Sciences*, *10*(1), 17–33. http://dx.doi.org/10.19044/ejes.v10no1a17.

Larsen, E., Barton, G., Turner, K., & Garvis, S. (2025). Enablers and constraints to teacher educator wellbeing amidst institutional accountability cultures: a PERMA perspective. *The Australian Educational Researcher*, *52*(1), 721-741.

Pinedaa, A. J. M., Mohamadc, A. N., Solomon, O., Bircob, C. N. H., Superioe, M. G., Cuencof, H. O., & Bognot, F. L. (2022). Exploring the standardized root mean square residual (SRMR) of factors influencing e-book usage among CCA students in the Philippines. *Indonesian Journal of Contemporary Education*, *4*(2), 53-70.

Kim, M., Winkler, C., & Talley, S. (2021). Binary item CFA of behavior problem index (BPI) using Mplus: A step-by-step tutorial. *The Quantitative Methods for Psychology*, *17*(2), 141-153.

Pervaiz, H., Ali, K., Razzaq, S., & Tariq, M. (2025). The Impact of Ai on Critical Thinking and Writing Skills in Higher Education. *The Critical Review of Social Sciences Studies*, *3*(1), 3165-3176.

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, *41*(2), 745-783.

Akoglu, H. E., & Özbek, O. (2021). The effect of brand experiences on brand loyalty through perceived quality and brand trust: a study on sports consumers. *Asia Pacific Journal of Marketing and Logistics*, *34*(10), 2130-2148.

Farahani, M. A., Nargesi, S., Saniee, N., Dolatshahi, Z., Heidari Beni, F., & Shariatpanahi, S. (2024). Factors affecting nurses retention during the COVID-19 pandemic: a systematic review. *Human Resources for Health*, *22*(1), 78.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*, 121092.

Duong, N. H., Tran, K. L., Do, B. N., & Duong, T. T. Q. (2024, November). The Relationship between Students' Perceptions of AI Applications and Intention to Use, Mediating Role of Satisfaction. In *The 2nd International Conference: Resiliency by Technology and Design (RTD 2024)* (pp. 245-271). Atlantis Press.

Sablić, M., Mirosavljević, A., & Bogatić, K. (2025). Multigrade education and the montessori model: A pathway towards inclusion and equity. *International journal of educational research*, *131*, 102600.

Tao, D., Yang, P., & Feng, H. (2020). Utilization of text mining as a big data analysis tool for food science and nutrition. *Comprehensive reviews in food science and food safety*, *19*(2), 875-894.