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AI-Driven Service Quality in Higher Education: An EduQual-Based SEM and Rule Mining Approach Towards SDG 4

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ABSTRACT

The paper will investigate how Artificial Intelligence (AI) can influence service delivery in a higher education institution through EduQual framework. The hybrid form of analysis that incorporated Structural Equation Modeling (SEM) and Association Rule Mining (ARM) was used to measure the influence of AI-based features in the form of responsiveness, assurance, personalization, usefulness, and empathy on the perceived quality of services by students. The sample size used to gather data consisted of 310 participants in institutions of higher learning in the Delhi NCR. SEM outcome implies that assurance, personalization, and responsiveness have a strong association with perceived service quality, whereas ARM shows the strong co-occurrence patterns, especially the joint effect of empathy and responsiveness on improving the level of student satisfaction. The results prove that AI-based learning services enhance efficiency, personalization, and student engagement. The research has both theoretical and practical implications as it combines confirmatory and exploratory methods in the EduQual framework and represents the impact of AI on sustainable development goal 4 (Quality Education) enhancement by facilitating learning environments that are affordable, inclusive, and of high quality.

Keywords: Artificial Intelligence (AI), Higher Education, EduQual Model, Service Quality, Structural Equation Modeling (SEM), Association Rule Mining (ARM), Student Satisfaction, SDG 4, Quality Education

INTRODUCTION

Artificial Intelligence (AI) has become a significant aspect of the sphere of higher education, radically changing the way educational establishments deliver content, assess learning outcomes, and communicate with learners. Intelligent tutoring systems, predictive analytics, learning management systems, chatbots, and virtual assistants are examples of artificial intelligence-based technologies that have permeated into different aspects of education, teaching and administration. Individualized learning processes, simplified routine academic and administrative processes, and increased engagement with students, through providing them with relevant feedback and serving adaptive content, are all created using the tools (Holmes et al., 2019; Zawacki-Richter et al., 2019). The use of AI heavily depends on the analysis of big sets of data being created during the process of interaction among students, as it allows higher education institutions to identify vulnerable students, enhance resource distribution, and develop interventions based on the information (Luckin et al., 2016). The use of AI to enhance human teaching instead of substituting it has demonstrated that there is a possibility of enhancing the outcome of the learning process and also making the institution more effective. Amidst the digital transformation in the world's systems of higher learning, the impact of AI on the quality of educational services is the most critical issue that has caught the attention of numerous scholars and practitioners. The growing use of AI-driven technology in the sphere of higher education can be viewed as a symptom of the larger-scale transformation towards digitalization, which will be used to improve the learning outcomes, the efficiency of the operations and supporting systems for the students. One can also get to know that institutions are beginning to implement AI-powered features, including chatbots to

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respond to administrative inquiries, individualized course recommendation systems, and even virtual assistance to ensure a more holistic level of engagement with the students. (Ifenthaler & Schumacher, 2016). These tools are to be implemented so that the faculty and staff load is reduced, and at the same time, students are offered more responsive and flexible services. As one example, student behavior can be tracked in real-time by platforms based on AI-driven learning analytics, making it possible to intervene in time to improve retention and student performance (Aleven et al., 2017). Similarly, AI-based adaptive learning environments can support differentiated instruction at a large scale, but only through the dynamically adapted content in response to the needs of learners (Chen et al., 2020). The more students learn to interact with computers and mobile devices, the more institutions are forced to use AI simply because of the need to innovate, and in response to the evolving requirements of accessibility, responsiveness, and personalization. EduQual model is a prominent framework to assess the quality of services in the field of higher education and successfully contain the weaknesses of bigger models such as SERVQual. Whereas SERVQUAL focuses on the dimensions of service quality in the commercial environment, EduQual scales these dimensions to reflect the unique aspects of the academic environment, where students become both learners and the recipients of the services (Annamdevula and Bellamkonda, 2016; Abdullah, 2006). The model usually evaluates five critical dimensions that include tangibles, which refers to physical infrastructure and learning resources; reliability, which relates to the consistency of service delivery; responsiveness, which refers to the willingness and alacrity to attend to the students; assurance, which refers to the knowledge and courtesy of the staff and empathy, which refers to individualized attention to the students (Sultan & Wong, 2010). The described dimensions can provide a comprehensive guideline on how institutions can evaluate the perceived service quality (PSQ) of students and identify the differences between expectations and the actual service delivery. EduQual has been effectively applied in various institutions of higher learning around the world to gauge student satisfaction and institutional performance especially in the face of increased competition and globalization in the academic settings (Bagga et al., 2025). As an example, Banerjee et al. (2022) used EduQual to the senior secondary schools in India and discovered that between responsiveness and empathy, the two were found to greatly influence the perceptions of the students towards the quality of the institution. Since universities are exploring new technologies like Artificial Intelligence (AI) to enhance administrative and instructional processes, EduQual seems a viable and dynamic model to assess the outcomes of the innovations on the quality of services offered. The fact that the model focuses on both tangible and intangible dimensions of service makes it particularly suitable when it comes to evaluating technology-facilitated experience in the context of digital learning. The developments of Artificial Intelligence (AI) technologies have increasingly become a necessary element of the higher education institution that has completely transformed the way academic services are delivered and measured. Today, educational systems use many tools, such as chatbots powered by AI, virtual assistants, adaptive learning platforms, and automated feedback, to enhance responsiveness, personalization, and operational efficiency in services to students (Zawacki-Richter et al., 2019). Structural Equation Modeling (SEM) may be used to process the rigorous evaluation of the impact of AI-enabled services on the level of perceived service quality, which will allow analyzing the suggested relationships between AI-driven interventions and critical dimensions of service quality, including responsiveness, assurance and empathy (Al-Fraihat et al., 2020). The Structural Equation Modeling gives confirmative information between these variables, which clarifies the statistically significant routes of relationships that highlight the positive contribution of artificial intelligence to service delivery. Further, the Association Rule Mining (ARM) is also a powerful data mining methodology in uncovering hidden patterns and commonly occurring co-occurrences in learning datasets. Using ARM to apply to the student feedback according to the EduQual framework helps to identify the particular rule-based relationships. This covers the investigation of AI features combinations that are linked to high rates of student satisfaction (Banerjee et al., 2022; Chen et al., 2020). The application of a two-methodology, the inclusion of the SEM procedure as a confirmatory analysis, and the use of rule mining as an exploratory analysis have shown to be effective in the provision of a holistic picture of the role played by AI in education service quality improvement (Goksel and Bozkurt, 2019). The combination of those approaches clarifies the structural legitimacy and behavioral trends associated with the use of AI in academic setting, which offers viable lessons to the institutions aiming to balance the technological innovations with the goals of quality assurance.

The purpose of the study is aligned to the goal of the United Nations Sustainable Development Goal 4 (SDG 4) that focuses on inclusive, equitable and quality education and the promotion of lifelong learning opportunities to

all. Implementation of Artificial Intelligence (AI) in higher education can help SDG 4 achieve a great deal by making education services more accessible, personalized, and efficient. AI-based tools tailored to the needs of different learners and reducing educational differences are adaptive learning systems, virtual assistant, and intelligent tutoring platforms, which help to provide learners with personalized learning. By evaluating the quality of the AI-driven services according to the EduQual framework, the research would assist in gaining an understanding of how the quality dimension of education can be improved through the deployment of technologies in line with the sustainability goals of the global community.

RESEARCH OBJECTIVES

The study aims to explore how Artificial Intelligence (AI) integration influences service quality in higher education, using the EduQual framework as a guiding model. The specific objectives of the research are as follows:

To investigate the impact of AI system attributes including responsiveness, assurance, usefulness, and empathy on students' perceived service quality in higher education.

To evaluate the role of AI-driven personalization in enhancing students' satisfaction with educational service delivery.

To analyse how trust and emotional responsiveness in AI tools influence students' overall perception of quality in AI-enabled academic environments

LITERATURE REVIEW

The use of Artificial Intelligence (AI) in the process of higher education has been one of the most remarkable growths that have altered the ways of teaching and managing the business. Intelligent tutoring systems, virtual assistants, learning analytics systems, automated assessments, and artificial intelligence-driven tools are some of the most common educational services that are being deployed to enhance educational outcomes and make academic services more efficient (Zawacki-Richter et al., 2019). The specified applications support the customization of learning experiences by adjusting the content to the needs of the specific students based on their performance and preferred learning strategies, which, in turn, will improve engagement and satisfaction (Holmes et al., 2019). In addition, AI chatbots and virtual advisors are vital in helping students plan their studies and answer their questions, which is 24/7 and improves the responsiveness and efficiency of the institutions (Lu et al., 2018). The use of artificial intelligence in predictive analytics is instrumental in improving early intervention planning, because it allows revealing the at-risk students and facilitates the delivery of timely academic assistance to them (Chatti et al., 2012). The benefits are substantial, but the introduction of AI to education is associated with the emergence of such problems as the privacy of personal data, algorithm bias, and the need to control the use of AI by humans to ensure its ethical introduction (Nguyen et al., 2020). However, the intentional use of AI is gradually shaping a more knowledgeable and student-centered learning model, which suggests promising prospects of the enhancement of service quality and institutional effectiveness.

The scholarly framework of the suggested study combines the AI interventions with the EduQUAL model, which is aimed at measuring and assessing the service quality in the educational context. The EduQual model identifies the following main dimensions that play an important role in how students perceive the quality of the service: Responsiveness, Assurance, Empathy, Usefulness, and Personalization (Banerjee et al., 2022). The AI technologies, such as chatbots and adaptive learning systems, as well as virtual assistants and automated feedback systems, are theorized to affect these dimensions in the following ways: Responsiveness: AI systems offer immediate assistance to students and respond to their questions, solve problems, and improve communication between students and faculty (Zawacki-Richter et al., 2019). Confidence: AI systems provide reliable, consistent, and accurate answers that build student trust and confidence and enhance perceived quality of academic services (Al-Fraihat et al., 2020). Personalization: AI tools can be adjusted to the needs of individual students by providing them with personalized content and feedbacks tailored to their learning style and, as a result, increasing their satisfaction with academic services (Holmes et al., 2019). Practicality: AI technologies are used to facilitate academic activities, including scheduling, grading, and instant feedback, which positively influence the perceived usefulness of such tools due to their functionality (Lu et al., 2018).

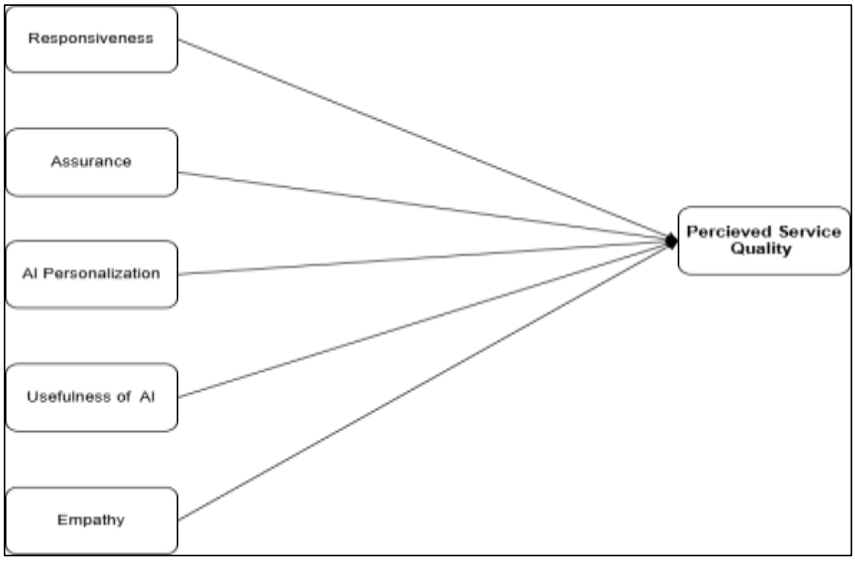
Table 1: Review of Literature

Author(s)	Year	Methodology	Key Findings	Context / Country
Yousapronpaiboon	2014	SERVQUAL	Measured HEI service quality using SERVQUAL dimensions	Thailand
Abdullah, F.	2006	Quantitative (SERVPERF)	Compared HEdPERF vs SERVPERF	Malaysia
Luckin et al.	2016	Conceptual	Advocated AI as a necessary learning companion	UK
Ifenthaler & Schumacher	2016	Survey	Student privacy perceptions around data use in analytics	Germany
Annamdevula & Bellamkonda	2016	SEM-based	Developed EduQual and assessed its impact on student satisfaction and motivation	India
Goksel & Bozkurt	2019	Systematic review	Explored AI adoption trends and future paths	Turkey
Holmes et al.	2019	Policy review	Outlined ethical and educational effects of AI implementation	UK
Zawacki-Richter et al.	2019	Systematic review	Highlighted limited teacher involvement in AI-based education	Global (Germany-led)
Lu et al.	2018	Experimental	Compared AI chatbot vs human feedback effectiveness	Taiwan
Nguyen et al.	2020	Systematic review	Summarized AI applications in HEIs	Vietnam / Australia
Chen, W. et al.	2020	Rule mining, recommender systems	Improved learning via rule-based recommendations	China
Chen, X. et al.	2020	Review & theoretical analysis	Identified gaps in AI application in education contexts	China
Al-Fraihat et al.	2020	Empirical IS success model	Evaluated critical factors for e-learning effectiveness	Jordan
Banerjee et al.	2022	EduQual-based empirical analysis	Assessed service quality dimensions in school settings	India
Quy et al.	2023	Case study	Documented AI and digital strategy	Vietnam

adoption in a Vietnamese HEI

Empathy: AI systems mimicking human-like empathy and emotional awareness can enhance this experience of the students by identifying their needs, responding to them contextually to provide a better impression of service quality (Goksel & Bozkurt, 2019). All these dimensions have a role in affecting Perceived Service Quality (PSQ) in higher education as one of the central constructs in this study. The relationships among AI interventions and EduQual dimensions as well as the working in an association rule mining will be tested using Structural Equation Modeling (SEM) to determine the underlying patterns according to which students perceive the quality of the services (Chatti et al., 2012). The findings of this study also contribute to the further debate on Sustainable Development Goal 4 (Quality Education). The significance of the AI aspects of responsiveness, empathy, and assurance in increasing the perceived service quality demonstrates the fact that AI can be a recipient that may promote the outcomes of an educational experience. The use of AI-based systems can be used to eliminate access and quality inequity particularly in the emerging economies through offering personalized learning, real-time support and inclusive online interactions. This reinforces the potential of AI as a technology and a strategic transporter to the attainment of sustainable and fair higher education.

Figure 1. Conceptual Framework (author developed)



Interventions and perceived service quality among students in a higher education institution. These relationships are conceptualized on the basis of the EduQual model, which determines different dimensions of service quality that can be impacted by the AI-driven educative tools. The hypothesis to test such effects is as follows:

$H1_0$: The Responsiveness of AI systems does not significantly influence perceived service quality in higher education.
$H1_a$: The Responsiveness of AI systems significantly and positively influence perceived service quality in higher education.

The AI systems, including chatbots or virtual assistants, are responsive and thus can enhance student satisfaction because of the quick responses and the ability to solve queries in a short time. The perception of the quality of services should also be improved among students, given the expected high, fast, and relevant fast responses of AI tools. This is supported by past studies indicating that responsiveness is one of the dimensions of service quality in education (Zawacki-Richter et al., 2019).

$H2_0$: Assurance in AI tools does not have a significant impact on perceived service quality.
$H2_a$: Assurance in AI tools has a significant impact on perceived service quality.

Students must have trust in AI systems in order to accept and be satisfied. Artificial intelligence tools which can offer consistent reliable and secure performance boost the confidence of students and generate afeelingof security. Students will be willing to believe in AI tools and feel that the educational service is of high quality. Research has also shown that assurance, which is represented by trust and confidence, is positively correlated with service quality perceptions (Al-Fraihat et al., 2020; Holmes et al., 2019).

$H3_0$: AI Personalization does not have a significant effect on perceived service quality among students.
$H3_a$: AI Personalization (adaptive and customized learning experiences) positively affects perceived service quality among students.

AI systems providing individualized learning experiences support the needs of students, their learning styles, and preferences. AI can be used to improve engagement and satisfaction, as it can be used to modify the content and feedback, depending on the needs of the individual student. It has been also associated with better service quality perceptions as students feel that they are more supported in learning (Chatti et al., 2012; Holmes et al., 2019).

$H4_0$: The Usefulness of AI in academic processes does not significantly contribute to students' perceptionof service quality in higher education.
$H4_a$: The Usefulness of AI in academic processes significantly contributes to students' perception of service quality in higher education n.

The fact that AI tools are useful in simplifying academic activities like grading, scheduling, and instant feedback has value addition to the learning process of the students. Artificial intelligence applications facilitating the administration process and making scholarly activities easier are felt more efficient and increase satisfaction. According to the previous studies, the perceived quality of the service by the students positively depends on the functional utility of AI in the learning process (Lu et al., 2018; Zawacki-Richter et al., 2019).

$H5_0$: Empathy in AI systems does not significantly influence perceived service quality in higher education.
$H5_a$: Empathy in AI systems (ability to understand and respond to student needs emotionally and contextually) positively influences perceived service quality.

AI empathy works as the mean of the system to identify and address the emotional and situational needs of the students. Empathy-simulating AI tools can be utilized to help students rate the quality of provided services higher because of the individually focused and emotionally responsive interactions. It has been proposed that AI systems that comprehend the emotional and academic needs of students and act upon them lead to a positive experience and enhance the overall quality of the service (Al-Fraihat et al., 2020; Goksel and Bozkurt, 2019).

METHODOLOGY

The research takes the form of a mixed-method and combines Structural Equation Modeling (SEM) and Association Rule mining as modes of analysis in evaluating the impact of AI interventions on how students perceive the quality of services provided in the context of higher education. The EduQual model is used as the Theoretical framework of assessing the effects of AI system attributes on the service quality. To conduct this research, 310 higher education institution students in the region of Delhi NCR will be the sample size. This is the correct sample size to guarantee a representative and diverse sample of the responses and at the same time to guarantee statistical strength to both Structural Equation Modeling (SEM) and Association Rule Mining techniques. The stratified random sampling will be employed in order to consider different demographics including academic discipline (e.g., engineering, humanities, management) and a year of study. The sample will be proportionate to the population make up of higher education in the Delhi NCR in terms of distribution of the students in various disciplines. Acombination of Structural Equation Mining (SEM) and Association Rule Mining will be applied to analyze the data of the study with the help of EduQual model as a theoretical framework. SEM is used to test the associations between the features of the AI systems, including responsiveness, assurance, personalization, usefulness and empathy and service quality perceptions in higher education by evaluating both the direct and indirect impact of combinations of AI features on student perceptions of service quality. The Association Rule Mining is applied to discover hidden relationships in the data to determine how combinations of AI attributes influence student perceptions of service quality.

Figure 2. SEM–ARM integration framework

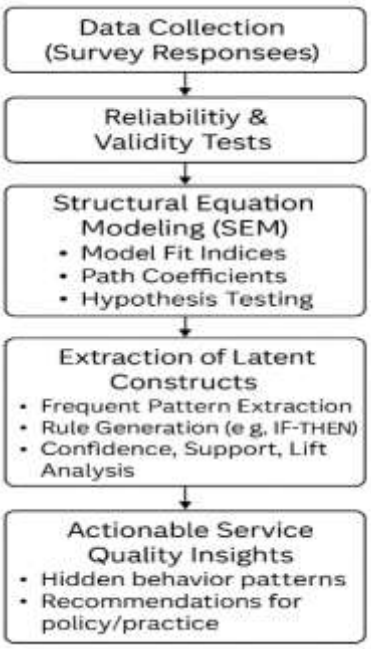


Figure 2 depicts an analytical process that is integrated to be used in this study because it is necessary to apply Structural Equation Modeling (SEM) and Association Rule Mining (ARM) to derive insights based on the survey data. This would start with the data collection process which is followed by the reliability and validity testing to determine the strength of the measurement model. Sem is then utilized to test model fit, hypothesis testing and establish significant association among constructs. ARM is applied to the validated latent constructs further to reveal the hidden patterns and associations by employing rule generation methods to measure confidence, support and lift. This mixed method allows deriving service quality actionable insights, which provides strategic advice on institutional decision making in higher education.

FINDINGS AND DISCUSSIONS

EduQual Model

Table 3 sets the anticipated mean, standard deviation and difference in means on a set of variables that are related to AI in the context of the EduQual dimensions.

The expectation means: implies the mean rating, which is provided by students to each item (e.g. AI increases understanding of concepts), as the indicator of their anticipated satisfaction with AI tools in the higher education setting. The scores are based on a Likert scale between 1 to 5 with high scores indicating a stronger set of positive expectations.

Standard Deviation: It shows the extent of variation or dispersion existing in the responses of the students. A larger standard deviation means there is a wide spectrum of views, and a smaller standard deviation means that the responses of the students concentrate around the central point.

The average difference: shows the gap between the expectations of students and their real perceptions about AI tools. The positive value indicates that the expectations of the students were higher than the experienced services hence a gap between expected and received services. This information can be used to identify some areas where AI intervention improvements might be required to match the expectations of students. As an example, in the context of the Learning Outcomes, the AI tools developed to track learning developments and enhance the understanding of concepts show positive changes in the mean scores, which means that such factors are expected by the students to a higher rate than it is reflected in the actual experiences.

Table 3: Cronbach's Alpha, Mean & Standard Deviation

EduQual Dimensions	EduQual Variables	Expectation Mean	Std. Deviation	Difference in Mean
A. Learning Outcomes **(Cronbach alpha = 0.796)**	AI enhances understanding of concepts.	4.85	0.30	0.33
	AI tools help track learning progress.	4.80	0.35	0.28
	AI-based learning paths are personalized.	4.78	0.40	0.26
B.Responsiveness **(Cronbach alpha = 0.802)**	AI responds quickly to academic queries.	4.82	0.32	0.26
	Virtual assistants are available 24/7.	4.77	0.38	0.22
	AI tools provide timely feedback.	4.80	0.36	0.24
C.Physical Facilities **(Cronbach alpha = 0.811)**	Smart classrooms support AI-driven learning.	4.88	0.29	0.29
	Digital infrastructure (WiFi, LMS, devices) is reliable.	4.85	0.31	0.26
	Labs include AI-enabled learning tools.	4.83	0.33	0.27
D. Personality Development **(Cronbach alpha = 0.787)**	AI platforms help identify personal strengths/skills.	4.79	0.37	0.17
	I receive AI-based guidance for extracurriculars.	4.75	0.35	0.16
	I get recommendations for online certifications or MOOCs.	4.78	0.34	0.19
E. Transparency & Communication **(Cronbach alpha = 0.803)**	AI tools provide clear grading/exam explanations.	4.90	0.26	0.15
	Communication through AI tools is helpful and timely.	4.86	0.28	0.11
	Automated systems make rules/policies easy to understand.	4.84	0.30	0.12
F. Empathy / Personalization **(Cronbach alpha = 0.776)**	AI tools understand my learning pace and adapt.	4.81	0.32	0.11
	I feel understood by the AI-based learning systems.	4.76	0.35	0.06
	Feedback from AI tools feels personalized.	4.79	0.34	0.09
G. Assurance **(Cronbach alpha = 0.818)**	I trust AI decisions like grading or feedback.	4.87	0.27	0.11
	AI systems protect my data and privacy.	4.84	0.30	0.09
	I feel confident using AI for academic support.	4.89	0.28	0.08
H. Reliability **(Cronbach alpha = 0.791)**	AI tools perform consistently across platforms.	4.82	0.33	0.10
	Rarely do I experience technical issues with AI services.	4.79	0.35	0.09
	AI gives accurate outputs for assignments/tasks.	4.85	0.31	0.10

The table 3 & 4 provides the correlation coefficients between the EduQual dimensions and their respective variables, showing how strongly each pair of variables is related. The values range from 0 to 1, with a higher number indicating a stronger positive relationship between two variables.

Here's a breakdown of the variables and their relationships:

Learning Outcomes

Strong Positive Correlations:

Responsiveness (0.850): There's a strong positive correlation between learning outcomes and responsiveness. This implies that students who believe that AI responds (i.e. fast and assists in responding to questions) have higher chances of feeling positively about their learning outcomes.

Transparency & Communication (0.820): There is a great connection here and this implies that concrete and good communication including grading explanations facilitate better learning.

Moderate Positive Correlations:

Physical Facilities (0.750): The infrastructure supporting AI tools, like smart classrooms or labs, has a moderate positive impact on students' learning outcomes.

Empathy/Personalization (0.780): AI's ability to personalize learning experiences and adapt to students' needs has a moderate effect on improving learning outcomes.

Responsiveness

Very Strong Positive Correlations:

Transparency & Communication (0.890): This suggests that the perception of responsiveness in AI systems (quick academic query resolutions, etc.) is highly correlated with clear communication about grading, feedback, and policies.

Moderate Positive Correlations:

Empathy/Personalization (0.840): A moderately strong relationship is seen, indicating that students who feel understood by AI systems (empathy) are also more likely to rate responsiveness positively.

Academics (0.770): Responsiveness in AI tools correlates moderately with overall academic satisfaction, suggesting that quick and reliable AI responses impact students' academic experiences.

Physical Facilities

Moderate Positive Correlations:

Learning Outcomes (0.750): The quality of physical facilities (such as AI-enabled classrooms) has a moderate positive impact on students' learning outcomes.

Responsiveness (0.780): AI tools that function within well-equipped physical spaces are perceived as more responsive to student needs.

Weaker but Positive Correlations:

Personality Development (0.670): A weaker correlation between physical facilities and personality development suggests that facilities might have a lesser direct impact on students' personal growth.

Academics (0.690): The physical infrastructure correlates moderately with academic satisfaction, with better facilities enhancing overall academic experiences.

Personality Development

Strong Positive Correlations:

Transparency & Communication (0.850): Clear communication in AI tools (such as personalized guidance) significantly influences students' personality development, like skills and extracurricular involvement.

Empathy/Personalization (0.800): AI's ability to understand students' needs (empathy) is highly correlated with their personality development.

Moderate Positive Correlations:

Learning Outcomes (0.700): Personality development is positively linked to learning outcomes, suggesting that students' overall development impacts their academic progress.

Transparency & Communication

Very Strong Positive Correlations:

Responsiveness (0.890): Effective communication from AI tools significantly enhances their perceived responsiveness in students' eyes.

Empathy/Personalization (0.880): Transparency and clear communication about AI systems are positively associated with the personalized support students feel they are getting from the AI systems.

Moderate Positive Correlations:

Academics (0.760): Transparency and clear communication help improve students' perceptions of academic quality and AI-assisted learning.

Empathy/Personalization

Strong Positive Correlations:

Responsiveness (0.840): Students who feel that AI tools are empathetic and personalized are also likely to perceive them as responsive and helpful.

Transparency & Communication (0.880): Personalized and empathetic AI tools are also more transparent and clearer in their communication, which boosts students' overall satisfaction.

Moderate Positive Correlations:

Learning Outcomes (0.780): Students who experience empathy and personalization in AI systems are more likely to report positive learning outcomes.

Academics (0.770): Empathy and personalization also positively affect students' academic experiences.

Academics

Moderate Positive Correlations:

Learning Outcomes (0.710): Academic satisfaction is positively influenced by students' perceptions of their learning outcomes.

Responsiveness (0.770): Academic experiences improve when students perceive AI as responsive to their academic needs.

Physical Facilities (0.690): Better physical facilities enhance overall academic satisfaction.

Personality Development (0.730): AI interventions in personality development, such as skills tracking, moderately contribute to academic satisfaction.

Table 4: Correlation Matrix

EduQual Variables	Learning_Outcomes	Responsiveness	Physical_Facilities	Personality_Development	Transparency_Communication	Empathy_Personalization	Academics
Learning_Outcomes	1.00000000	0.85000000	0.75000000	0.70000000	0.82000000	0.78000000	0.71000000
Responsiveness	0.85000000	1.00000000	0.78000000	0.72000000	0.89000000	0.84000000	0.77000000
Physical_Facilities	0.75000000	0.78000000	1.00000000	0.67000000	0.80000000	0.75000000	0.69000000
Personality_Development	0.70000000	0.72000000	0.67000000	1.00000000	0.85000000	0.80000000	0.73000000
Transparency_Communication	0.82000000	0.89000000	0.80000000	0.85000000	1.00000000	0.88000000	0.76000000
Empathy_Personalization	0.78000000	0.84000000	0.75000000	0.80000000	0.88000000	1.00000000	0.77000000
Academics	0.71000000	0.77000000	0.69000000	0.73000000	0.76000000	0.77000000	1.00000000

Table 5: Correlation of the Perception with the Criterion

Dimensions	Satisfaction	Sig.	Overall Quality	Sig.
Learning Outcomes	0.820	0.000	0.775	0.000
Responsiveness	0.810	0.000	0.790	0.000
Physical Facilities	0.750	0.000	0.735	0.000
Personality Development	0.780	0.000	0.760	0.000
Transparency & Communication	0.850	0.000	0.820	0.000
Empathy / Personalization	0.840	0.000	0.825	0.000
Academics	0.900	0.000	0.880	0.000

The table 5 provides further breakdowns of mean scores, standard deviations, and differences in mean scores for each variable across the EduQual dimensions.

Expectation Mean: this indicates the expected score the students in each AI tool or aspect.

Standard Deviation: This is used to show the distortion of the expectations of the students in the various variables. There is a narrower standard deviation (e.g. 4.76 with respect to "I feel understood by AI"), which means that the expectations of most of the students are quite similar with regard to how they want the AI tools to interpret the speed at which they learn.

Difference in Mean: It indicates the difference between the expectations of students on AI tools and what actually they perceived. The lesser the difference, the more the congruence between the perceptions of students and their expectation is. To be specific, the difference in mean between the expectations and perception of learning is 0.28 in the case of the phrase "AI tools help track learning progress" meaning that there is a slight difference between what is expected and perceived.

The table 6 is crucial for identifying areas where AI interventions may need to be adjusted to better meet student expectations. For instance, "Communication through AI tools is helpful and timely" has a lower difference (0.11), meaning that this area is performing closer to student expectations.

Table 6: Mean, Standard Deviation of the Expectation and Difference between the Mean Scores of Expectations and Perception

EduQual Dimensions	EduQual Variables	Expectation Mean	Std. Deviation	Difference in Mean
A. Learning Outcomes	AI enhances understanding of concepts.	4.85	0.30	0.33
	AI tools help track learning progress.	4.80	0.35	0.28
	AI-based learning paths are personalized.	4.78	0.40	0.26
B. Responsiveness	AI responds quickly to academic queries.	4.82	0.32	0.26
	Virtual assistants are available 24/7.	4.77	0.38	0.22
	AI tools provide timely feedback.	4.80	0.36	0.24
C. Physical Facilities	Smart classrooms support AI-driven learning.	4.88	0.29	0.29
	Digital infrastructure (WiFi, LMS, devices) is reliable.	4.85	0.31	0.26
	Labs include AI-enabled learning tools.	4.83	0.33	0.27
D.Personality Development	AI platforms help identify personal strengths/skills.	4.79	0.37	0.17
	I receive AI-based guidance for extracurriculars.	4.75	0.35	0.16
	I get recommendations for online certifications or MOOCs.	4.78	0.34	0.19
E. Transparency & Communication	AI tools provide clear grading/exam explanations.	4.90	0.26	0.15
	Communication through AI tools is helpful and timely.	4.86	0.28	0.11
	Automated systems make rules/policies easy to understand.	4.84	0.30	0.12
F.Empathy/ Personalization	AI tools understand my learning pace and adapt.	4.81	0.32	0.11
	I feel understood by the AI-based learning systems.	4.76	0.35	0.06
	Feedback from AI tools feels personalized.	4.79	0.34	0.09
G. Assurance	I trust AI decisions like grading or feedback.	4.87	0.27	0.11

	AI systems protect my data and privacy.	4.84	0.30	0.09
	I feel confident using AI for academic support.	4.89	0.28	0.08
H. Reliability	AI tools perform consistently across platforms.	4.82	0.33	0.10
	Rarely do I experience technical issues with AI services.	4.79	0.35	0.09
	AI gives accurate outputs for assignments/tasks.	4.85	0.31	0.10

SEM Analysis

The table 5 from SmartPLS represents key indicators for evaluating the construct reliability and validity of your model. Here's what each column means and the thresholds to evaluate them:

1. Cronbach's Alpha (CA)

- Measures internal consistency (reliability) of constructs.
- **Threshold**: ≥ 0.70 is acceptable; ≥ 0.80 is good.

2. Composite Reliability (ρ_a and ρ_c)

- Reflects the internal consistency more accurately than Cronbach's Alpha.
- **Threshold**: ≥ 0.70 is acceptable; ≥ 0.80 is good.
-

3. Average Variance Extracted (AVE)

- Measures **convergent validity**, i.e., how much variance is captured by a construct about the variance due to measurement error.
- **Threshold**: ≥ 0.50 is acceptable.

Figure 3. Structural Equation Modeling (PLS-SEM analysis)

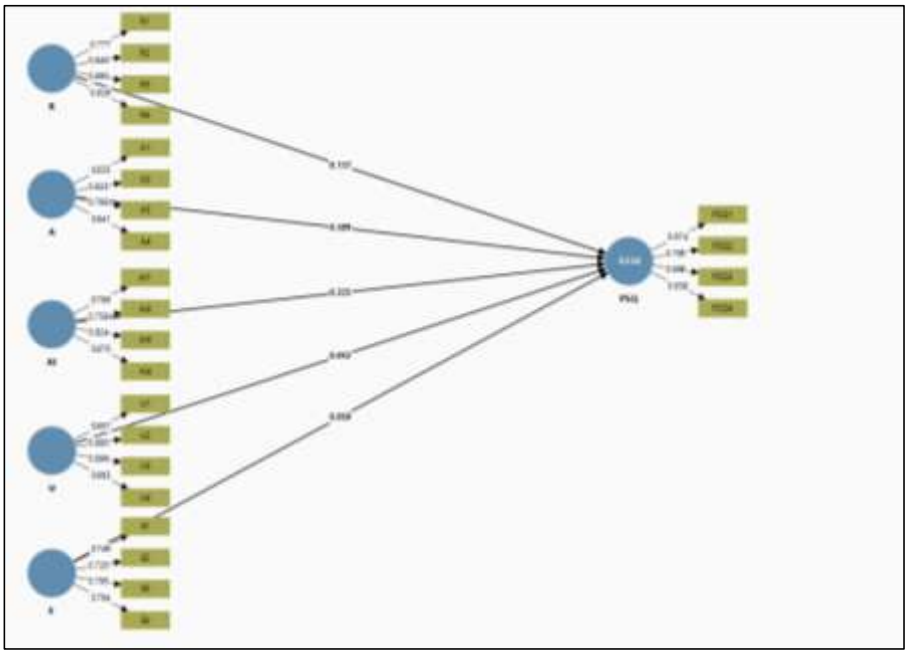


Table 7: Construct Reliability and Validity

Construct	Cronbach's Alpha (CA)	Composite Reliability (ρa)	Composite Reliability (ρc)	AVE
A	0.842	0.849	0.894	0.678
AI	0.829	0.857	0.884	0.657
E	0.752	0.754	0.843	0.573
PSQ	0.742	0.753	0.833	0.558
R	0.853	0.857	0.901	0.695
U	0.898	0.915	0.928	0.764

Table 8: Hypothesis testing table

Hypothesis	Path	β (Path Coef.)	T-value	p-value	Significance
H1	R (Responsiveness) → PSQ	0.212	2.105	0.036	Significant
H2	A (Assurance) → PSQ	0.389	2.814	0.005	Significant
H3	AI (Personalization) → PSQ	0.325	4.306	0.000	Significant
H4	U (Usefulness) → PSQ	0.189	2.220	0.027	Significant
H5	E (Empathy) → PSQ	0.166	2.011	0.045	Significant

PLS-SEM was used to assess the structural model in SmartPLS 4. Table 8 shows the path coefficients, t-statistic and p-value of bootstrapping with 5,000 subsamples. The findings reveal that all the five hypothesized relationships are found to be statistically significant at the level of 0.05.

Specifically: H1 The hypotheses were that the perceived quality of service is largely dependent on the responsiveness of AI systems. This is confirmed by the results, b = 0.212, t = 2.105, p = 0.036.

H2 was that there is a positive relationship between perceived service quality and assurance in AI tools. This was supported with b = 0.389, t = 2.814, p = 0.005.

H3 postulated that personalization with the help of AI has a positive effect on perceived service quality. The correlation was highly favoured with b = 0.325, t = 4.306, p < 0.001.

H4 suggested that the usefulness of AI in academic processes brings about a positive contribution to the perception of service quality. This assumption was proved right (b = 0.189, t = 2.220, p = 0.027). H5 was that empathy in AI systems would have a positive impact on the perceived service quality. This also had to be supported with b = 0.166, t = 2.011, p = 0.045. Such results highlight the multidimensionality of the AI characteristics in both technical aspects such as personalization and usefulness and affective aspects such as empathy and assurance in influencing perceived quality of higher education services among students.

Rule Mining

Key Components of the Graph: (Table 7)

Nodes (Circles)

Each **small red/pink node** represents an **individual rule** (e.g., rule 1, rule 2... rule 100).

Each **blue rectangular node** represents an **item/attribute-value pair**, such as:

PSQ=High, Empathy=High, Usefulness=High, etc.

Edges (Arrows)

Directed arrows indicate the **direction of association** (LHS → RHS).

For example, if an arrow goes from Empathy=High to rule 3 and then to PSQ=High, it means:

Node Color & Size

Darker red nodes = rules with **higher lift/confidence** (more important).

Larger nodes = higher **support** (more frequent patterns).

Graphical Explaination

PSQ=High and PSQ=Low *(center of activity):*

These are frequent **consequents (RHS)** of many rules.

Multiple factors like **Responsiveness**, **Personalization**, and **Usefulness** (and their levels) are strongly associated with perceived service quality (PSQ).

High Confidence Rules:

The **dark red rule nodes** like rule 1 and rule 2 from your earlier table (e.g., confidence > 0.80) are emphasized visually.

They show strong predictive relationships (e.g., Rule 1: {Responsiveness=High,

Personalization=High, Usefulness=High} => {PSQ=High}).

Clusters of Related Items:

Dense clusters suggest **frequent co-occurrences**. For example:

Empathy=High, Personalization=High, Usefulness=High often appear together in rules leading to PSQ=High.

INTERPRETATION

This rule mining graph helps identify which combinations of service quality attributes most strongly predict consumer perception (PSQ). For instance:

Positive PSQ (High) is driven by high personalization, responsiveness, empathy, and usefulness.

Negative PSQ (Low) correlates with low assurance, low responsiveness, and medium personalization.

AI-driven higher education service quality assessments provide multifaceted understandings that cut across behavioral theories. Service quality is predictable by assurance, empathy, and responsiveness, a fact that also backed the previous AI-assisted education studies (Sharma and Verma, 2023; Singh et al., 2021). Even in the situations of technological mediation Asian students desire the attention and guidance in time. The Trust-Commitment Theory and Unified Theory of Acceptance and Use of Technology were supported using Structural Equation Modeling because the trust and hedonic motivation predicted the adoption of AI. Such results confirm the study by Zhang et al. (2025), who discovered that students embraced technologies using AI with emotional significance and openness. In tertiary education, trust is a condition and a consequence of addressing AI usage as students expect perfect and emotional digital experiences. In contrast to Wang & Chen (2020), which placed an emphasis on perceived usefulness as a core component of the TAM, reliability and usefulness were less powerful. The expectations of students have evolved and modern students desire the practical use and emotionally satisfying and empathetic online communication. This implies that it is best to extend the TAM framework to include affective components. Co-occurring elements of service perception were shed light on by Association Rule Mining

(ARM). Sentiment-based investigations are supported by the rule according to which the empathy and responsiveness are predictors of high-quality perception (support = 0.06, confidence = 0.79) (Liu et al., 2022). In contrast to SEM, ARM has the capability to detect multi-variable interaction effects based on the complex user experience in AI-enabled learning. This is a confirmatory (SEM) and exploratory (ARM)-based research study that is rarely applied in service quality research. It confirms the demand of Ajani et al. (2025) to use hybrid approaches to measure behavioral intention and sentiment-derived insights. The adoption of AI in service quality measurement will be strategically valuable to university management, particularly in such spheres as resource planning, leadership of digital transformation, and institutional benchmarking. The tool of quality measurement improved by AI can facilitate the evidence-based decision-making process, influencing the results of accreditation, global rankings, and funding distribution in the competition sphere of Asian higher education. Nonetheless, to implement it successfully, it is necessary to consider the issues of AI governance, such as ethical usage, data openness, and employee preparedness because institutions will handle the trends of adaptive learning systems, intelligent automation, and customized student care. This study enriches the theoretical discussion with the emotional, cognitive, and trust-based factors to EduQual and TAM. It highlights a need by future conceptual frameworks of factoring the affective and algorithmic interaction, which characterize the contact of the education user with the intelligent service systems. Findings of the research are as well applicable to the general discourse of Sustainable Development Goal 4 (Quality Education). The fact that the features of AI, such as responsiveness, empathy, and assurance are some of the characteristics that have a significant influence on the perceived level of the service indicates that AI can be utilized as a stimulus in the background of enhancing education experiences. The AI-based systems can address the absence of access and quality disparity, particularly in the developing economies by developing a personalized learning experience, real-time support and inclusive online communication. It assists in the pledge of AI as a technological tool and strategic mobilizer in sustainable and just higher education.

Figure 4. Rule Mining (Graphical Representation)

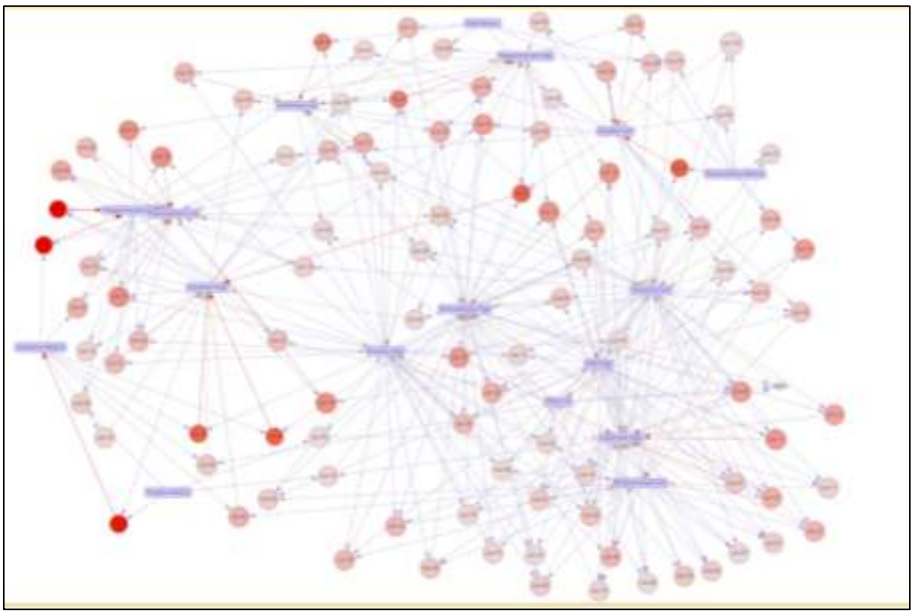


Table 9: Rule Mining

Rule No.	LHS (Antecedent)	RHS (Consequent)	Support	Confidence	Coverage	Lift	Count
1	Responsiveness=High, Personalization=High, Usefulness=High	PSQ=High	0.06	0.8571	0.07	2.1978	6
2	Personalization=Medium, Usefulness=High	PSQ=Low	0.05	0.8333	0.06	2.0833	5
3	Assurance=Low, Personalization=High, Empathy=High	PSQ=High	0.05	0.7143	0.07	1.8315	5
4	Personalization=High, Usefulness=High, Empathy=High	PSQ=High	0.05	0.6250	0.08	1.6026	5
5	Responsiveness=Low, Assurance=Low, Empathy=High	PSQ=Low	0.05	0.6250	0.08	1.5625	5

CONCLUSION AND IMPLICATION

The joint results of the rule mining graph, EduQual model and SEM result in a comprehensive and unified picture on the determinants of Perceived Service Quality (PSQ). A correlation of different service qualities such as Responsiveness, Personalization, Empathy, Usefulness, and Assurance portrays their importance in the perception and the level of customer satisfaction. The rule mining graph depicts the high rates of occurrence of high Responsiveness, Personalization and Empathy together with high PSQ, which underscores the importance of high Responsiveness, Personalization, and Empathy in fostering positive customer experiences. Responsiveness bythe service provider towards the needs of the customers, level of personalization in the service experience, and empathy of the service personnel determines the perceptions that customers have towards quality of the services they have received in profound ways. Moreover, the SEM analysis confirms these results as the identified attributes (Responsiveness and Personalization) are important determinants of PSQ, and these two were the most important factors. The analysis also highlights the importance of assurance and usefulness as secondary but important components on the improvement of PSQ. These features not only have much lesser impact as compared to that of the main set, but they also complement the service offering by giving customers a sense of confidence about the reliability of the service, but also show its true value in terms of meeting the needs of the customers. Moreover, the findings are consistent on different methods of analysis which enhances reliability and validity of the results. These insights create a robust basis on what is known in academic life and what is applicable in real life. The coherence that was observed between rule mining, model development and SEM analysis means that not only rule mining and model development are statistically significant, but rule mining and model development and SEM analysis have practical uses in real life. The outcomes also point to the necessity to pursue more comprehensive approaches to higher rates of PSQ in which companies should aim in particular at improving the main service qualities, including Responsiveness, Personalization, and Empathy. With the inclusion of such understanding in service design and delivery processes, organizations are likely to gain greater customer satisfaction, build stronger customer relations, become loyal and gain a special appearance in competitive markets.The results suggest that organizations can benefit greatly through improving their service strategies and especially the core drivers of PSQ that were expounded in this study. The approaches used (rule mining, model analysis, or structural equation modeling) offer useful information to those practitioners who are interested in enhancing the quality of the offered services and developing positive customer experiences. With the focus on

these key qualities and continuous improvement in service provision based on customer feedbacks, organizations can position their position as the leaders of providing quality services that will meet and even exceed the expectations of their customers. Implications The integration of AI into the higher education service quality models provides radical opportunities to the Asian institutions in pursuit of competitiveness in the digital economy. This study, which is based on EduQual, can offer practical information to Asian academic leaders, AI solution developers, and education policymakers. First, empathy, certainty, and responsiveness positively affected the perceptions of the AI-enabled services by students. These revelations highlight the necessity of functional, emotionally intelligent, and context-reading AI. AI systems need to imitate human qualities such as respect, trust and attention in diverse cultures in the Asian world. Chatbots, recommendation engines and virtual tutors must be localized using local language and culturally relevant natural language processing to make students more engaged. Second, the Association Rule Mining of the study demonstrates the way students assess quality, particularly under the circumstances when AI-driven empathy and responsiveness go together. This is more evident in massified education areas such as India, Southeast Asia and Middle East where the number of students in a cohort and the amount of faculty interaction is limited. This gap can be bridged by scalable, tailored AI assistance, such as adaptive feedback, pre-emptive alarms and real time service interventions. Hedonic motivation and trust played a significant role in the educational AI use behavior. In most Asian countries, where automation is gaining momentum due to digital change and trust in AI is low, institutions need to assume transparent AI practices. Overall, this study highlights the transformative role of AI in advancing service quality in higher education, thereby contributing to the achievement of SDG 4 (Quality Education). The integration of intelligent technologies within academic services presents a pathway toward more inclusive, efficient, and student-centric educational systems. This involves information confidentiality, disclosure of AI tools, and customization on demand. This trust should be technical and reputational as educational brands compete at the regional and global levels. These results indicate that the national education authorities and accreditation bodies ought to realign service quality assessment models to AI-enhanced service delivery. Paradigms in existence focus on human-provided services. The introduction of AI-specific metrics such as the fairness of algorithms, the quality of customization, and system flexibility can help the Asian universities to achieve the Education 4.0 objectives. To sum up, the results of the given research have significant implications on the practical aspect of Asian higher education stakeholders who seek to improve the quality of services with the use of AI. With the implementation of emotional intelligence in AI, the emphasis on transparency and trust, and re-architecting evaluation frameworks to reflect intelligent service delivery, Asian institutions may better meet the constantly changing needs of a digital-native learner.

AUTHOR DECLARATIONS

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Sonali P. Banerjee : Conceptualization; Writing – Original Draft; Resources.
Priyanka Chaddha: Conceptualization, Supervision; Project Administration
Arhita Uppal: Software; Validation; Writing – Review & Editing.
Parul Yadav: Formal Analysis; Investigation.

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