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EXPLORING STUDENTS' INTENTIONS TO REUSE CHAT AI LLMS IN LEARNING: AN S-O-R FRAMEWORK APPROACH IN INDONESIA

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ABSTRACT

Aim/Purpose	This study examined the factors influencing students' continued intention to use LLM-based AI chat systems in higher education, addressing the limited research on sustainable AI adoption in learning contexts. The model integrates the Information Systems Success Model (ISSM) within the Stimulus-Organism-Response (S-O-R) framework, with Information Quality, Service Quality, System Quality, and Time Saving as stimuli, Satisfaction and Trust as organism variables, and Intention to Reuse as the response.
Background	Artificial Intelligence (AI) has become an integral part of higher education in the era of the Fourth Industrial Revolution, primarily through Large Language Model (LLM)-based chat tools such as ChatGPT, Gemini, and Microsoft Copilot. These tools can transform the way students learn. Indonesia ranks sixth among global users of ChatGPT, indicating a strong interest in AI-based learning technologies. However, despite this rapid adoption, maintaining students' continued engagement and trust in AI chat systems remains a significant challenge. Existing studies have primarily focused on initial adoption, leaving a limited empirical understanding of the psychological and system-related factors that sustain continued usage in developing country contexts.
Methodology	This study adopted a quantitative approach using an online survey distributed to university students across three Indonesian cities: Surabaya, Makassar, and Semarang. A total of 432 valid responses were analyzed after data screening for outliers using Z-scores. Validity and reliability were tested through confirmatory

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factor analysis, Cronbach’s alpha, and composite reliability in SPSS. Structural Equation Modeling (SEM) using AMOS was then applied to examine causal relationships among constructs and assess model fit.

Contribution: This study extends the application of the Stimulus-Organism-Response (S-O-R) framework to the educational domain, specifically in the context of repeated use of LLM-based AI chat systems. The novelty of this research lies in the inclusion of System Quality and Time Saving as stimulus variables. The mediating role of Satisfaction and its influence on Trust and Intention to Reuse further supports and strengthens findings from previous studies.

Findings: The findings revealed that all four stimuli, Information Quality, Service Quality, System Quality, and Time Saving, affected Satisfaction, which subsequently enhanced Trust and strengthened students’ intention to continue using LLM-based AI chat systems. Among the observed pathways, the effect of Trust on continued use was the strongest. These results underscore that both technical quality and the psychological dimensions of student satisfaction and trust served as critical foundations for sustaining the integration of LLM-based AI chat technologies in academic settings.

Recommendations for Practitioners: Developers of LLM-based AI chat systems should ensure the provision of accurate, relevant, and easily comprehensible information that supports critical thinking skills. System quality must be enhanced through fast response times, user-friendly interfaces, and reliable access. Services should be personalized to align with students’ profiles and include time-saving features such as content summarization.

Recommendations for Researchers: Researchers examining the application of LLM-based AI chat systems are encouraged to explore a broader range of variables across the stimulus, organism, and response dimensions. Incorporating alternative theoretical frameworks and potential moderating factors could further enrich the analysis, offering a more comprehensive understanding of the determinants of sustained usage intentions toward LLM-based AI chat platforms.

Impact on Society: The utilization of LLM-based AI chat systems can enhance learning effectiveness, accelerate information access, and foster greater student independence. These benefits contribute to strengthening the quality of higher education and improving readiness for the demands of the digital era.

Future Research: Future research is recommended to include a larger proportion of postgraduate students (Master’s and Doctoral levels) to enhance academic diversity, and to expand the study area using a longitudinal design to capture long-term trends. Additionally, exploring participants from professional certification programs may offer valuable insights for further investigation into the sustained intention to use LLM-based AI chat systems.

Keywords: intention to reuse, Chat AI LLM, S-O-R, learning, university student

INTRODUCTION

The development of technologies associated with Industrial Revolution 4.0 has significantly reshaped how individuals interact with digital systems, with Artificial Intelligence (AI) emerging as a significant catalyst for innovation and human-machine collaboration (Castro et al., 2024). AI refers to the science and engineering of creating intelligent systems, particularly those capable of performing tasks that typically require human intelligence, such as reasoning, learning, and decision-making (McCarthy, 2007). The Large Language Model (LLM) is one of the most important new ideas in AI. It is a type of AI that learns to understand, create, and process human language by reading large amounts of text. LLM-based applications such as ChatGPT (Menon & Shilpa, 2023), Gemini (Islam & Ahmed, 2024), and Microsoft Copilot (Stratton, 2024) have gained widespread attention for their ability to engage in natural, human-like conversations across a range of contexts.

LLM-powered AI chat systems are increasingly utilized in diverse sectors, including e-commerce, finance, and healthcare. Recently, their application in education has also drawn considerable interest due to their potential to support learning through interactive and personalized assistance (Uspenskyi, 2025). Evidence suggests that integrating LLMs into academic environments can improve students' performance by up to 62%, particularly by offering customized learning experiences and real-time feedback (Uspenskyi, 2025). In response to these developments, Indonesia's 2024 Deputy Minister for Higher Education, Science, and Technology, Prof. Stella Christie, has encouraged the responsible use of AI in education, emphasizing the need to balance technological adoption with the cultivation of critical and analytical thinking skills (Firdaus, 2024).

Despite the promising potential of LLMs in higher education, there remains a notable lack of empirical and theory-driven studies examining the factors that influence students' continued intention to use AI chat systems for learning (Duong, 2024). Most existing research has primarily focused on initial adoption or perceived usefulness of AI tools (e.g., ChatGPT), rather than on the psychological and behavioral mechanisms that support long-term use in educational contexts (Camilleri, 2024; Ma et al., 2025). Furthermore, prior studies have primarily been conducted in Western or developed-country settings, leaving a gap in understanding how students in developing nations, such as Indonesia, perceive and sustain engagement with these systems (Almogren et al., 2024; C. Yu et al., 2024). This gap is particularly relevant given the rapid adoption of ChatGPT in Indonesia, which ranked sixth globally in user numbers by 2024 (Syaftahan, 2024). According to organizational change theory (Kotter, 1996), initial adoption does not guarantee long-term engagement. Without continuous efforts to maintain motivation and perceived value, users may gradually lose interest. Clear (2018) also emphasizes that while forming new digital habits can be relatively easy, keeping them consistently over time is far more challenging.

To address this research gap, the present study adopts the Stimulus-Organism-Response (S-O-R) framework to investigate the factors influencing students' continued intention to use LLM-based AI chat systems in higher education. The S-O-R framework has been widely used in human–computer interaction research (Duong, 2024; Xie et al., 2023). It explains user behavior as a response to external stimuli (e.g., system features or design) that affect internal psychological states (e.g., satisfaction, trust), which in turn shape behavioral outcomes. This framework has also been applied in various digital settings, including e-learning continuation in China (Zheng et al., 2023), ChatGPT usage among tourists (Pham et al., 2024), and consumer behavior in online marketplaces (Kühn & Petzer, 2018). Additionally, this study provides empirical evidence from Indonesia, contributing insights from a developing-country perspective to the global discourse. Based on this background, the study aims to answer the following research question: What are the key factors influencing Indonesian university students' intention to continue using chat-based LLM systems for academic learning?

By identifying these determinants, this study aims to contribute to the theoretical understanding of sustained technology use in educational settings. Furthermore, the findings offer practical insights for AI developers, higher education institutions, and policymakers to support effective AI integration strategies. Considering that LLM-based chat systems are still in the early stages of their technological life cycle (Foster, 1986), understanding user behavior during this critical phase is essential to ensuring long-term success, optimizing the user experience, and maximizing the educational benefits of AI in a digitally connected academic environment.

LITERATURE REVIEW

CHAT AI LLM

Chat-based Artificial Intelligence (Chat AI), particularly those powered by Large Language Models (LLMs), represents a transformative advancement in Natural Language Processing (NLP), a core subfield of artificial intelligence (AI) that enables computers to interpret, analyze, and generate human language (Jurafsky & Martin, 2023; Russell & Norvig, 2020). LLMs are trained on extensive text corpora to capture linguistic patterns and contextual meanings (Brown et al., 2020). The introduction of the Transformer architecture (Vaswani et al., 2017) marked a breakthrough, allowing models to process entire text sequences in parallel through self-attention mechanisms. This capability significantly improved performance in tasks such as text summarization, question answering, and conversational dialogue.

Prominent LLM-based systems such as GPT and BERT have demonstrated exceptional ability in generating human-like text and adapting to a variety of domains through zero-shot and few-shot learning (Brown et al., 2020). Their deployment has extended to sectors such as education, healthcare, customer service, and business analytics, where they act as intelligent agents providing adaptive interaction and decision support. In higher education, Chat AI tools have shown promise in fostering personalized learning, offering immediate feedback, and enhancing student engagement (Uspenskyi, 2025). These developments form the technological stimulus within the present study's conceptual framework.

Research on the sustainable use of Chat AI systems powered by Large Language Models (LLMs) in higher education remains limited and underexplored (Duong, 2024). This paucity of research underscores the need to strengthen the theoretical foundation of this study by referring to prior works that examine the long-term use of information technologies in educational contexts. Table 1 summarizes previous studies that support the constructs and variables employed in this research, even though they do not explicitly adopt the Stimulus-Organism-Response (S-O-R) framework. The table further indicates that studies examining continued use behavior remain limited. In particular, few have explored this topic in relation to advanced technologies such as ChatGPT and LLM-based learning systems. This reinforces the importance of investigating not only initial adoption or short-term intention to use, but also the mechanisms that sustain long-term engagement and the integration of AI technologies into learning environments.

Prior research frequently utilized constructs from the Information Systems Success Model (ISSM), including Information Quality, System Quality, and Service Quality, to assess the effectiveness and success of information systems in educational and organizational contexts. These dimensions have been widely used to explain users' views of a system's reliability, performance, and service quality. These perceptions then play an essential role in shaping satisfaction and continued usage intention. In the context of Chat AI applications, these constructs act as external stimuli that influence users' internal evaluations and behavioral intentions. This relationship aligns closely with the principles of the S-O-R framework.

In addition to these quality-related factors, user satisfaction and trust have emerged as critical mediators in technology adoption and continuance studies. Satisfaction reflects users' affective evaluation of their overall experience, while trust reduces perceived uncertainty and promotes sustained interaction with AI systems. Together, these variables bridge the gap between system quality and user behavior, offering a more nuanced understanding of technology engagement. Accordingly, the theoretical foundation of this study not only draws on literature employing the S-O-R framework but also integrates robust constructs from information systems and technology adoption research. This comprehensive approach enables a deeper and more holistic understanding of the factors influencing the sustainable use of chat AI–based LLM systems in higher education.

Table 1. Studies in Chat AI LLM

Year	Topic	Variable	MF	Country	Author
2024	Factors affecting performance expectancy and intentions to use ChatGPT	Information Quality, Source Trustworthiness, Effort Expectancy, Performance Expectancy, Social Influences, Perceived Interactivity, Intentions to Use ChatGPT	–	Malta	(Camilleri, 2024)
2021	Factors of chatbot service quality that influence satisfaction and continued usage intention in online travel agencies in China	Chatbot Quality Dimensions: Understandability, Reliability, Responsiveness, Assurance, Interactivity Post-Acceptance Model of IS Continuance: Confirmation, Satisfaction, Use Continuance	Technology Anxiety	China	(L. Li et al., 2021)
2024	Sustainable usage intention of AI-based digital banking services using the Expectation Confirmation Model (ECM) approach	AI Features: Perceived Intelligence, Perceived Anthropomorphism, Interaction Quality, Confirmation, Customer Experience, Continuance Intention to Use	–	India	(Bhatnagr et al., 2024)
2024	Factors of e-government user satisfaction and their impact on continued intention and citizen trust, based on the TAM-ISSM model in India	Information Quality, System Quality, Service Quality, Perceived Usefulness, Perceived Ease of Use, Perceived Risk, User Satisfaction, Citizen Trust, Continuance Use Intention	Residential Status	India	(Kala et al., 2024)
2021	The influence of food delivery app service attributes on user satisfaction and repeat usage behavior in Thailand	Delivery Experience, Social Benefits, Ease of Use, Reviews. Food Hygiene, Time Saving, Food Rider, FDA Customer Satisfaction, Advocacy, Intention to Reuse App	–	Thailand	(Fakfare, 2021)
2021	The impact of information system quality on the sustainable intention to use cloud-based financial systems, mediated by user satisfaction and trust	ISQ: Information Quality, System Quality, Service Quality Relationship Quality: Satisfaction, Trust Continuance Intention	–	China	(Y. Li & Wang, 2021)

S-O-R Framework

The Stimulus-Organism-Response (S-O-R) model is a theoretical framework that explains how external environmental factors influence human behavior through internal psychological processes (Mehrabian & Russell, 1974). First introduced by Mehrabian and Russell in 1974, the model suggests that environmental stimuli (S) affect the organism (O) and these internal reactions lead to specific behavioral responses (R) (Asyraff et al., 2023). Compared with the earlier Stimulus–Response (S–R) theory proposed by Thorndike in 1898, the S-O-R model provides a more complete explanation by including internal mental processes as mediators. It emphasizes that people do not respond to external stimuli automatically. However, their actions are shaped by their personal perceptions, judgments, and emotions.
The S-O-R framework has been widely used in consumer behavior and technology research to study how external factors influence internal states, which then affect behavioral intentions such as purchase decisions or continued system use (S. Yu et al., 2024). The model consists of three key elements: Stimulus, Organism, and Response. The Stimulus (S) refers to external factors or environmental conditions that trigger users' psychological reactions, such as interface design, system functionality, social influence, or contextual factors (Hewei & Youngsook, 2022; Xie et al., 2023). The Organism (O) represents the users' internal thoughts and feelings in response to the stimulus, including constructs such as attitude, perception, trust, and satisfaction, which connect the stimulus to behavioral outcomes (S. Yu et al., 2024). The Response (R) refers to the users' observable behaviors, such as adopting, purchasing, or continuing to use technology. These actions arise from the users' internal psychological processes (Duong, 2024).

Many empirical studies have used the S-O-R model to explain different kinds of behaviors, especially in technology adoption and continuance research, as seen in Table 2. However, the definitions of stimulus and organism differ across studies. For example, organismic factors may include perceived ease of use, perceived usefulness, attitude toward the technology, trust, or satisfaction.

Table 2. Research on the S-O-R framework

Year	Topic	Variable	MF	Country	Author
2024	Students' continued intention to use ChatGPT using the S-O-R approach, along with UTAUT factors, attitude, and trust.	**Stimuli:** Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions **Organism**: Attitude, Trust **Response**: Continuance Usage Intention	-	Vietnam	Duong (2024)
2024	An analysis of the influence of information quality and ChatGPT services on students' trust, satisfaction, and continued usage intention.	**Stimuli:** Information Quality, Service Quality **Organism**: Trust in ChatGPT, Satisfaction **Response**: Continuance Usage Intention	-	Vietnam	Duong et al. (2024)
2024	The influence of short video advertisements on consumers' purchase intention for furniture using the S-O-R model approach.	**Stimuli:** Effort Expectancy, Social Influence, Performance Expectancy, Facilitating Conditions, Media Richness, Perceived Enjoyment, Perceived interactivity **Organism**: Flow Experience, Telepresence **Response**: Consumption Intention	-	China	S. Yu et al. (2024)

Year	Topic	Variable	MF	Country	Author
2024	Adoption of AI-based customer service in Malaysia by integrating the Stimulus–Organism–Response (S-O-R) theory and Task-Technology Fit (TTF).	**Stimuli:** Social Influence, Anthropomorphism, Communicative Competence, Technology Characteristics, Task Characteristics, Perceived Intelligence **Organism**: Emotional Trust, Task-technology Fit **Response**: AI Readiness, Initial Trust, AI Customer Service Adoption	-	Malaysia	Vafaei-Zadeh et al. (2024)
2023	The influence of e-learning service quality on students' continued intention using the S-O-R approach.	**Stimuli:** System Quality, Information Quality, Service Quality, Instructor Quality, Learning Community, Personalization **Organism**: Perceived ease of use, Perceived usefulness **Response**: Continuance Intention	-	China	Zheng et al. (2023)
2022	Factors influencing users to continue using mobile services in Jordan using the S-O-R approach.	**Stimuli:** Mobile Network Quality, Service Content Quality, Customer Service Quality **Organism**: Perceived Value, Customer Satisfaction **Response**: Continuance Intention	-	Yordania	Al-Debei et al. (2022)
2020	Repurchase intention of Generation Y in Thailand on e-commerce platforms using the S-O-R approach.	**Stimuli:** Website Appearance, Security, Promotion **Organism**: Trust **Response**: Repurchase Intention	-	Thailand	B. Zhu et al. (2020)
2020	The influence of online reviews on consumers' purchase intention in e-commerce using the S-O-R framework.	**Stimuli:** Perceived Information Quality, Social Presence **Organism**: Trust, Satisfaction **Response**: Purchase Intention	Emotional Polarity	China	L. Zhu et al. (2020)

However, stimuli are often derived from theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT), the Information Systems Success Model (ISSM), or the Technology Acceptance Model (TAM). This flexibility makes the S-O-R model a practical integrative framework that connects system features, psychological mechanisms, and user behavior. It is particularly relevant for understanding continued engagement with emerging technologies such as AI-based learning systems.

ISSM

The Information Systems Success Model (ISSM) was first introduced by DeLone and McLean in 1992 and later revised in 2003. It is one of the most influential frameworks for evaluating the effectiveness of information systems (DeLone & McLean, 1992, 2003). The model was developed to address the fragmented approaches previously used to measure system success. It introduces an integrated structure that captures multiple dimensions of system performance and impact. In 2003, DeLone and McLean refined the model to reflect the evolution of information systems, particularly with the rise of web-based services and enterprise applications. The revised version added service quality as a new dimension. This highlights the importance of technical support and user assistance in shaping the overall user experience. The original constructs of individual impact and organizational impact were also combined into a single construct called net benefits. This construct reflects the overall positive outcomes that result from using the system.

The ISSM outlines three interrelated dimensions that provide a comprehensive view of system success. The first is information quality, which refers to the relevance, accuracy, and timeliness of the system's information. The second is system quality, which includes aspects such as reliability, performance, and ease of use. The third is service quality, which relates to the responsiveness, empathy, and technical support provided to users. These three quality dimensions together influence system use or the intention to use it. System use reflects the level of user engagement with the system. User satisfaction represents the users' overall evaluation of their interaction with the system. In the end, these factors lead to net benefits, including both tangible and intangible outcomes such as higher productivity, better decision-making, and improved organizational efficiency.

The model further posits that improvements in system, information, and service quality foster greater user satisfaction and system usage, which, in turn, lead to increased net benefits. Importantly, these relationships are dynamic and cyclical: perceived benefits can reinforce continued use and satisfaction over time, creating a positive feedback loop that sustains system success. Because of its comprehensive and adaptable structure, the ISSM has been widely applied across diverse sectors, including healthcare, education, business, and public administration. It continues to serve not only as a robust theoretical framework for academic research but also as a practical tool for organizations seeking to evaluate and optimize the performance and value of their information systems.

CONCEPTUAL MODEL AND HYPOTHESIS

INFORMATION QUALITY

Information Quality refers to the degree of accuracy, completeness, relevance, and timeliness of information provided by an information system, which in turn affects decision-making and the utility of the information (DeLone & McLean, 2003). In the context of this study, Information Quality pertains specifically to the level of accuracy, relevance, completeness, and clarity of the information generated and delivered by AI-based large language model (LLM) chat systems to users. High-quality information enables users to obtain accurate and useful answers that align with their needs. Prior studies (Kala et al., 2024; Y. Li & Wang, 2021) have shown that Information Quality has a significant impact on user Satisfaction. For example, Kala et al. (2024), in their research on continued usage intention of India's e-government services, found strong support for the relationship between the constructs of the Information Systems Success Model (ISSM), namely information quality, system quality, and service quality, and user satisfaction.

H1: Information Quality (IQ) positively influences user Satisfaction (S) in the use of Chat AI LLM systems.

SYSTEM QUALITY

System Quality refers to the technical performance of an information system, including its reliability, ease of use, efficiency, flexibility, and response time (DeLone & McLean, 2003). In the context of this study on AI-based large language model (LLM) chat systems, system quality refers to the chatbot's technical capability to operate reliably and responsively, its user-friendliness, its ability to comprehend user queries (natural language understanding), and its adaptability to conversational context. Prior studies (Kala et al., 2024; Y. Li & Wang, 2021) have found that system quality significantly influences user Satisfaction. Based on this, the following hypothesis is proposed in this study:

H2: System Quality (SYQ) positively influences user Satisfaction (S) in the use of Chat AI LLM systems.

SERVICE QUALITY

Service Quality refers to the quality of services provided by an information system provider, including responsiveness and the ability to support user needs (DeLone & McLean, 2003). In the context of this study on AI chatbot systems, service quality encompasses the chatbot's ability to deliver responsive, empathetic, and personalized support that meets individual user needs. Previous studies (Kala et al., 2024; Y. Li & Wang, 2021) have demonstrated that service quality significantly impacts user Satisfaction. Therefore, the following hypothesis is proposed in this study:

H3: Service Quality (SQ) positively influences user Satisfaction (S) in the use of Chat AI LLM systems.

TIME SAVING

In the context of the Information Systems Success Model (ISSM) (DeLone & McLean, 2003), Time Saving refers to the net benefits perceived by users due to the reduction in time required to complete tasks or achieve specific goals through the use of an information system. It reflects the system's operational efficiency, such as faster information access, quicker task completion, and overall reduced process time. Time is a highly valuable resource for both individuals and organizations; thus, significant time savings can enhance user productivity and reinforce the perceived value of adopting an information system. Previous research (Fakfare, 2021) has shown that Time Saving (TS) has a significant impact on user Satisfaction (S). Based on these insights, the following hypothesis is proposed:

H4: Time Saving (TS) positively influences user Satisfaction (S) in the use of Chat AI LLM systems.

SATISFACTION

Satisfaction is defined as a subjective condition in which a users' needs and expectations regarding a product or service are perceived to be met, based on a comparison between expectations and the actual performance (Bhattacherjee, 2001; Tseng, 2015). In the context of AI LLM chatbots, satisfaction refers to the positive emotional response experienced by users after interacting with the chatbot, based on their evaluation of expectations versus the quality of the interaction received. Satisfaction is influenced by factors such as answer accuracy, information relevance, response speed, contextual understanding, and the overall user experience. When the chatbot consistently delivers accurate, useful, and contextually appropriate responses, users are more likely to feel satisfied, leading to increased trust and long-term usage. Previous studies (Kala et al., 2024; Y. Li & Wang, 2021) have shown that Satisfaction positively affects Trust (T). In addition, prior research (Kala et al., 2024; Y. Li & Wang, 2021; Pham et al., 2024) has found that Satisfaction (S) significantly influences Intention to Reuse (CI). Hence, the study also proposes the following hypothesis:

H5: Satisfaction (S) positively influences Trust (T) in the use of Chat AI LLM systems.

H6: Satisfaction (S) positively influences Intention to Reuse (CI) in the use of Chat AI LLM systems.

TRUST

Trust is the perceived belief in the reliability of technology and its ability to deliver promised services. In the context of Chat AI LLM systems, trust encompasses the users' perception that the chatbot can be relied upon to deliver benefits (Duong, 2024) consistently. A high level of trust reduces user hesitation, fosters confidence, and promotes continued usage. Prior studies (Duong, 2024; Pham et al., 2024) support a positive relationship between Trust and Intention to Reuse. Therefore, the following hypothesis is proposed:

H7: Trust (T) positively influences Intention to Reuse (CI) in the use of Chat AI LLM systems.

Intention to Reuse

In this study, Intention to Reuse is conceptualized as a key response variable, referring to an individual's willingness to continue using a system based on their prior experience (Bhattacherjee, 2001). It is often synonymous with Continue Intention, and its inclusion as a dependent construct is supported by previous studies (Al-Debei et al., 2022; Duong, 2024; Duong et al., 2024; Pham et al., 2024; Zheng et al., 2023). This study specifically focuses on the continued use of Chat AI LLM systems within the context of student learning in higher education.

Research Model

The research model adopts the Stimulus-Organism-Response (S-O-R) framework. The proposed hypotheses illustrate the relationships among constructs within the research model, which comprises several constructs designed to address the research background and literature review (Figure 1). The Stimulus component includes elements from the ISSM group, namely information quality, system quality, service quality, and time saving. The Organism component consists of satisfaction and trust. Finally, the Response component refers to the intention to reuse, specifically the students' intention to continue using AI-powered large language models (LLMs) in the context of higher education learning.

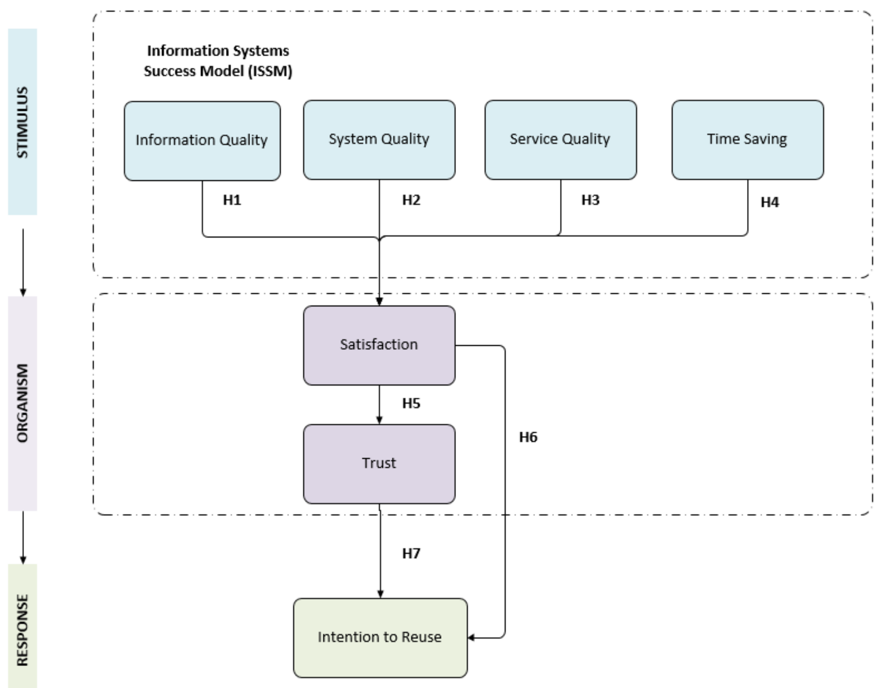

Figure 1. Conceptual model and hypotheses

The S-O-R framework posits that external stimuli influence user behavior solely via internal psychological states (Mehrabian & Russell, 1974). In this study, the model assumes that quality factors (information, service, system quality, and time saving) affect the behavioral outcome (intention to reuse) indirectly by first influencing user satisfaction and trust. Therefore, direct paths from stimulus to response were excluded, following prior evidence that such effects are fully mediated (Jiang et al., 2024; Wang & Men, 2025). Rahmawati and Kuswati (2022) revealed that higher service or system quality often enhances users' satisfaction, which in turn strengthens their loyalty or reuse intention, without a significant direct effect from quality to intention. Similarly, research on online reviews found that information quality and social presence improved trust and satisfaction, which then increased purchase intention, supporting the indirect stimulus-organism–response pathway (L. Zhu et al., 2020). A study combining the IS Success Model with the S-O-R framework also showed that system, service, and information quality act as stimuli shaping user perceptions (satisfaction, perceived value), which subsequently drive continuance or reuse intention (Gunawan et al., 2025).

METHODS

RESEARCH VARIABLES

This section outlines the measurement instruments used in the study, as presented in Table 3. Specifically, it describes the questionnaire designed to assess each construct within the research model. The questionnaire was developed based on indicators that have been validated in previous studies and are relevant to the constructs under investigation. Each item in the questionnaire used a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree," to facilitate respondents in providing their answers. The questionnaire was used to collect accurate quantitative data, which were then analyzed using Structural Equation Modeling (SEM)

This study employed a quantitative cross-sectional design. As shown in Table 3, the measurement items were adapted from previously validated instruments. Specifically, the Information Quality construct was adapted from Duong et al. (2024), System Quality and Service Quality from Zheng et al. (2023), Time Saving from Fakfare (2021), Satisfaction from Kala et al. (2024), and both Trust and Intention to Reuse from Duong (2024). All adapted indicators were then reviewed by two experts in Structural Equation Modeling (SEM) to ensure their conceptual and measurement validity, followed by a pilot study involving ten respondents to refine item clarity and content. SEM was employed for hypothesis testing because the study used a large dataset and aimed to confirm theoretically grounded relationships. This approach was considered more appropriate than PLS-SEM, which is typically used for exploratory or predictive purposes. Prior to SEM analysis, data were screened for missing values, outliers, and normality. Participants were informed about the study's purpose and provided consent before participation.

Table 3. Measurement items

Variable	Code	Indicators	Source
Information Quality	IQ1	The information provided by the Chat AI LLM is clear.	(Duong et al., 2024)
	IQ2	The information provided by the Chat AI LLM is accurate.	
	IQ3	The information provided by the Chat AI LLM is up to date.	
	IQ4	The information provided by the Chat AI LLM is reliable for use in university-level learning.	
System Quality	SYQ1	The Chat AI LLM is capable of quickly delivering both textual and visual information.	(Zheng et al., 2023)
	SYQ2	The Chat AI LLM is accessible at any time without significant issues.	
	SYQ3	The user interface of the Chat AI LLM is well-designed.	
Service Quality	SEQ1	The Chat AI LLM responds promptly to my requests.	(Zheng et al., 2023)
	SEQ2	The Chat AI LLM provides personalized attention.	
	SEQ3	The Chat AI LLM provides accurate solutions to my queries.	
Time Saving	TS1	The Chat AI LLM enables quick comparisons of the information I need from various online sources.	(Fakfare, 2021)
	TS2	The Chat AI LLM helps save time by offering inspiration or assisting in developing learning concepts in university courses.	
	TS3	The Chat AI LLM benefits me by accelerating my learning process in university settings.	

Satisfaction	S1	I am satisfied with the ease of access to Chat AI LLM anytime and anywhere.	(Kala et al., 2024)
	S2	I am satisfied with the features and services provided by Chat AI LLM.	
	S3	Overall, I am satisfied with Chat AI LLM.	
Trust	T1	The Chat AI LLM is honest and trustworthy.	(Duong, 2024)
	T2	The Chat AI LLM is capable of addressing my problems.	
	T3	The responses and suggestions from Chat AI LLM meet my learning expectations.	
	T4	Overall, I trust the advice and recommendations provided by Chat AI LLM.	
Intention to Reuse	CI1	I intend to continue using the Chat AI LLM in the future.	(Duong, 2024)
	CI2	I will consistently make use of the Chat AI LLM to support my daily learning activities in university.	
	CI3	I would highly recommend the Chat AI LLM to other students.	

DATA COLLECTION

Data collection was conducted using a quantitative cross-sectional design through an online survey. The survey was distributed to the target respondents using Google Forms. The target population consisted of active diploma, undergraduate, and master's students enrolled in Indonesian universities, including those currently on academic leave. The selected universities represented both public and private institutions in major cities such as Surabaya, Semarang, and Makassar. Respondents Participants were required to have prior experience using at least one Large Language Model (LLM)-based AI chatbot, such as ChatGPT, Gemini, or Microsoft Copilot.

To achieve a 95% confidence level with a 5% margin of error, as suggested by Israel (1992), a minimum sample size of 400 respondents was required. This was based on the total population of active higher education students in Indonesia at the end of 2024, as reported by Pusat Data dan Teknologi Informasi, Kementerian Pendidikan Tinggi, Sains, dan Teknologi (n.d.). The total number reached 9,211,997 students, comprising 544,937 diploma students, 8,287,504 undergraduates, and 379,556 master students (Figure 2). A purposive sampling technique was employed to select respondents who met the criteria.

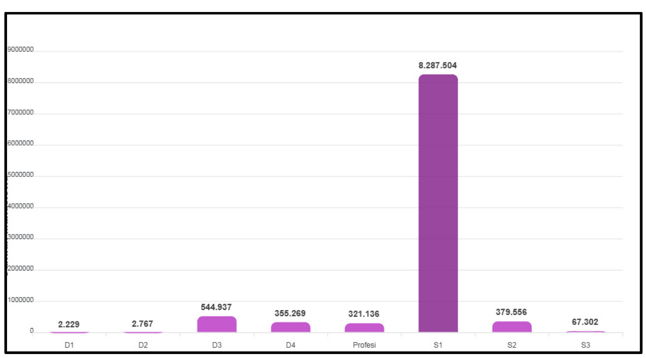

Figure 2. Number of university students in Indonesia, 2024

The online survey was structured into two main sections. The first section focused on respondent characteristics, including gender, the specific AI chatbot used during academic activities, educational level, city, and whether their faculty was categorized as STEM or non-STEM. The second section comprised measurement items developed based on validated scales from previous research studies.

VALIDITY AND RELIABILITY

This study employed SPSS version 27 to evaluate the validity and reliability of the measurement instrument and AMOS (Byrne, 2016) to conduct Structural Equation Modeling (SEM) on validated data. Prior to any analysis, the dataset was cleaned in SPSS by removing outliers, specifically responses with Z-scores outside the acceptable range of -3 to +3, following the guidelines of Hair et al. (2010). This data preprocessing step was essential to ensure the robustness and accuracy of subsequent statistical procedures.

Construct validity was assessed through Confirmatory Factor Analysis (CFA) using SPSS. The evaluation focused on ensuring that each indicator had a factor loading of at least 0.4, indicating a sufficient correlation between the observed variable and its underlying latent construct. Additionally, for a latent factor to be retained in the model, its corresponding eigenvalue had to be equal to or greater than 1.0 (Lisana, 2023; Straub et al., 2004). Factor loadings reflect the strength of the relationship between observed indicators and latent variables, where higher values signify stronger contributions to the factor being measured. Eigenvalues, on the other hand, represent the amount of variance accounted for by each factor. A factor with an eigenvalue below 1.0 is considered insufficiently explanatory and therefore excluded from the model.

In addition to construct validity, the internal consistency of the measurement instrument was evaluated using Cronbach's alpha (α). The interpretation of α values followed the widely accepted benchmarks established by George and Mallery (2003): $\alpha \geq 0.90$ is categorized as excellent, 0.80–0.89 as good, 0.70–0.79 as acceptable, 0.60–0.69 as questionable, 0.50–0.59 as poor, and values below 0.50 as unacceptable. These reliability tests ensured that the indicators within each construct were consistently measuring the same underlying concept.

Through this rigorous validation and reliability testing, the study ensured that all measurement instruments met the required psychometric standards before use in the SEM analysis.

ANALYSIS AND RESULTS

DEMOGRAPHIC PROFILE OF RESPONDENTS

The measurement instrument was distributed to a total of 459 respondents via an online platform. During the data cleaning process, 27 responses were identified as outliers and subsequently removed, resulting in a final dataset of 432 valid responses. The demographic profile of the respondents was presented in Table 4, covering variables such as gender, city of educational institution, level of education, type of institution, academic discipline (faculty), and the AI chatbot application used by each respondent.

In terms of gender distribution, the sample was nearly balanced, with 47% male and 53% female respondents. The majority of participants were from the target cities, namely Surabaya, Semarang, and Makassar, as representative urban centers in Indonesia. Specifically, 46% of respondents were from Surabaya, 26% from Semarang, 22% from Makassar, and the remaining 6% from other cities across Indonesia.

Figure 2 shows that most respondents (74%) were undergraduates, followed by master's students (13%), diploma students (12%), and doctoral students (1%). A relatively even distribution was also observed in the type of higher education institution, with 53% of respondents enrolled in private universities and 47% in public universities. Regarding academic discipline, 60% of respondents were from STEM (Science, Technology, Engineering, and Mathematics), while the remaining 40% were from non-STEM fields. Lastly, with respect to the use of AI chatbot applications based on Large Language Models (LLMs), ChatGPT emerged as the most commonly used tool, reported by 46% of respondents. This was followed by Gemini (34%), Microsoft Copilot (16%), and other applications (4%).

Table 4. Preliminary data analysis

	Freq.	%		Freq.	%
Gender:			**Type of Institution:**		
Male	202	47	Public Universities	203	47
Female	230	53	Private Universities	229	53
Total	432	100	Total	432	100
City:			**Faculty:**		
Surabaya	199	46	Non-STEM	169	39
Semarang	113	26	STEM	263	61
Makassar	96	22	Total	432	100
Others	24	6	*Note: STEM = Science, Technology, Engineering, and Math*		
Total	432	100			
Education Level:			**Type of Chat AI LLM apps:**		
Diploma (D1/D2/D3)	51	12	ChatGPT	335	46
Undergraduate	321	74	Gemini	249	34
Master	56	13	Microsoft Copilot	114	16
Doctoral	4	1	Others (Deepseek, Blackbox, Perplexity, etc.)	32	4
Total	432	100	Total	730	100

ASSESSMENT OF THE DATA AND THE MODEL

The assessment of the data and the proposed model was conducted following the recommendations of Neuman (2014). After the removal of outliers, the data underwent validity testing through factor analysis. Reliability was then evaluated using Cronbach's alpha, while the distribution of the data was examined based on skewness and kurtosis values. In addition, model fit was assessed to determine the appropriateness of the measurement model. Once these steps were completed, the dataset was deemed suitable for further analysis of the relationships among variables using the AMOS software.

The results of the factor analysis were presented in Table 5. These findings showed that each indicator correctly loaded onto its intended construct, with all factor loadings exceeding the minimum threshold of 0.4 (Lisana, 2023; Straub et al., 2004). After six iterations, a total of seven components were extracted, matching the number of constructs proposed in the study, using the SPSS "Equamax with Kaiser Normalization" method.

Model fit statistics were presented in Table 6 to evaluate whether the proposed causal model was adequately supported by the data. The assessment of model fit followed the threshold criteria recommended by Kline (2023). The reported indices include CMIN/DF, GFI (Goodness of Fit Index), AGFI (Adjusted GFI), CFI (Comparative Fit Index), NFI (Normed Fit Index), IFI (Incremental Fit Index), RMR (Root Mean Square Residual), and RMSEA (Root Mean Square Error of Approximation). A satisfactory fit is indicated when the normed chi-square (CMIN/DF) is ≤ 3, GFI, AGFI, NFI, IFI, and CFI are ≥ 0.95, and RMR is close to 0. An RMSEA value ≤ 0.05 further indicates a close fit, reflecting minimal approximation error per degree of freedom. Overall, the results across all fit indices demonstrated that the model fit the data well and was statistically sound, confirming the adequacy of the specified structural model.

Table 5. Factor analysis results

Rotated component matrix							
	Component						
	1	2	3	4	5	6	7
IQ2	.844						
IQ3	.839						
IQ4	.821						
IQ1	.811						
CI1		.902					
CI2		.898					
CI3		.857					
TS1			.927				
TS2			.926				
TS3			.909				
T1				.783			
T2				.755			
T4				.732			
T3				.728			
SEQ1					.837		
SEQ2					.833		
SEQ3					.821		
SYQ2						.863	
SYQ3						.833	
SYQ1						.804	
S3							.779
S1							.760
S2							.674
Extraction Method: Principal Component Analysis *Rotation Method: Equamax with Kaiser Normalization.a*							
a. Rotation converged in 6 iterations							

Table 6. Model fit statistics

Fit index	Score	Interpretation
CMIN/DF	1.044	Good Fit
GFI (Goodness of Fit Index)	0.957	Good Fit
AGFI (Adjusted GFI)	0.946	Good Fit
CFI (Comparative Fit Index)	0.998	Good Fit
NFI (Normed Fit Index)	0.951	Good Fit
IFI (Incremental Fit Index)	0.998	Good Fit
RMR (Root Mean Square Residual)	0.013	Good Fit
RMSEA (Root Mean Square Error of Approximation)	0.01	Close Fit

Table 7 presents the reliability results based on Cronbach's alpha, calculated using SPSS. Following the interpretation guidelines proposed by George and Mallery (2003), the constructs SYQ (System

Quality), SEQ (Service Quality), S (Satisfaction), and T (Trust) all yielded Cronbach's alpha values above 0.7, indicating acceptable internal consistency. The construct IQ (Information Quality) achieved an alpha value above 0.8, which reflects good reliability. Furthermore, the constructs TS (Time Saving) and CI (Intention to Reuse) recorded alpha values above 0.9, demonstrating excellent internal consistency.

Table 7. Cronbach's alpha results

Variable	Indicator	CA	Inter-pretation	Variable	Indicator	CA	Inter-pretation
Information Quality	IQ1, IQ2, IQ3, IQ4	0.857	Good	Satisfaction	S1, S2, S3	0.701	Acceptable
System Quality	SYQ1, SYQ2, SYQ3	0.799	Acceptable	Trust	T1, T2, T3, T4	0.797	Acceptable
Service Quality	SEQ1, SEQ2, SEQ3	0.797	Acceptable	Intention to Reuse	CI1, CI2, CI3	0.917	Excellent
Time Saving	TS1, TS2, TS3	0.914	Excellent				

Skewness and kurtosis values were also calculated using SPSS to assess the shape of the data distribution, particularly for normality testing. The thresholds used were based on the criteria recommended by Kline (2023), where skewness values should be less than 2 and kurtosis values less than 7. As shown in Figure 3, all values fell within these acceptable ranges, indicating that the data distribution met the assumptions of normality and was suitable for further analysis.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
avIQ	432	3.50	5.00	4.4821	.49399	-.322	.117	-1.440	.234
IQ1	432	3	5	4.47	.609	-.691	.117	-.480	.234
IQ2	432	3	5	4.48	.597	-.665	.117	-.510	.234
IQ3	432	3	5	4.49	.570	-.577	.117	-.664	.234
IQ4	432	3	5	4.49	.586	-.650	.117	-.539	.234
avSYQ	432	2.33	4.67	3.5185	.54889	.031	.117	-1.222	.234
SYQ1	432	2	5	3.53	.649	.169	.117	-.257	.234
SYQ2	432	2	5	3.48	.649	-.348	.117	-.275	.234
SYQ3	432	2	5	3.55	.652	.122	.117	-.259	.234
avSEQ	432	2.33	5.00	3.5910	.53728	-.062	.117	-1.139	.234
SEQ1	432	2	5	3.61	.641	.146	.117	-.336	.234
SEQ2	432	2	5	3.59	.629	.190	.117	-.370	.234
SEQ3	432	2	5	3.57	.642	-.015	.117	-.228	.234
avTS	432	3.00	5.00	4.0795	.58609	-.015	.117	-.378	.234
TS1	432	3	5	4.07	.634	-.055	.117	-.512	.234
TS2	432	3	5	4.11	.619	-.071	.117	-.427	.234
TS3	432	3	5	4.06	.650	-.064	.117	-.633	.234
avS	432	3.00	5.00	3.9846	.33336	-.452	.117	3.514	.234
S1	432	3	5	3.99	.433	-.038	.117	2.373	.234
S2	432	3	5	3.98	.411	-.116	.117	2.957	.234
S3	432	3	5	3.98	.419	-.150	.117	2.713	.234
avT	432	2.25	4.75	3.6001	.55337	-.135	.117	-1.201	.234
T1	432	2	5	3.56	.657	-.035	.117	-.205	.234
T2	432	2	5	3.59	.692	.024	.117	-.247	.234
T3	432	2	5	3.66	.715	-.056	.117	-.259	.234
T4	432	2	5	3.58	.742	.096	.117	-.362	.234
avCI	432	3.00	5.00	4.2407	.73344	-.464	.117	-1.247	.234
CI1	432	3	5	4.20	.802	-.380	.117	-1.349	.234
CI2	432	3	5	4.22	.816	-.429	.117	-1.368	.234
CI3	432	3	5	4.30	.756	-.557	.117	-1.056	.234
Valid N (listwise)	432								

Figure 3. Results of skewness and kurtosis

HYPOTHESIS TESTING RESULT AND DISCUSSION

Several important statistical indicators were looked at in the context of SEM analysis. The unstandardized estimate (β) represents the magnitude of the direct effect of an independent variable on a dependent variable in its original measurement units. The p-values generated by AMOS indicate the statistical significance of each estimated effect. These are classified as *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$), and NS (not significant) ($p > 0.05$) (Lisana, 2023). In addition, the standardized effect is reported in parentheses, accompanied by its magnitude classification according to Cohen (1988): small (S) for values below 0.1, medium (M) for values between 0.1 and 0.5, and large (L) for values of 0.5 or greater. The results of all hypotheses are summarized in Table 8 and illustrated in Figure 4.

Table 8. Hypotheses testing results

Hypothesis	Flow	Unstandardized	p	Standardized	Magnitude	Result
H1	KS " "U	0.135	***	0.216	Medium	Significant
H2	U[S " "U	0.198	***	0.345	Medium	Significant
H3	UGS " "U	0.18	***	0.308	Medium	Significant
H4	V U" "U	0.08	**	0.166	Medium	Significant
H5	U" "V	0.895	***	0.491	Medium	Significant
H6	U" "E K	0.535	**	0.203	Medium	Significant
H7	V " "E K	0.667	***	0.461	Medium	Significant

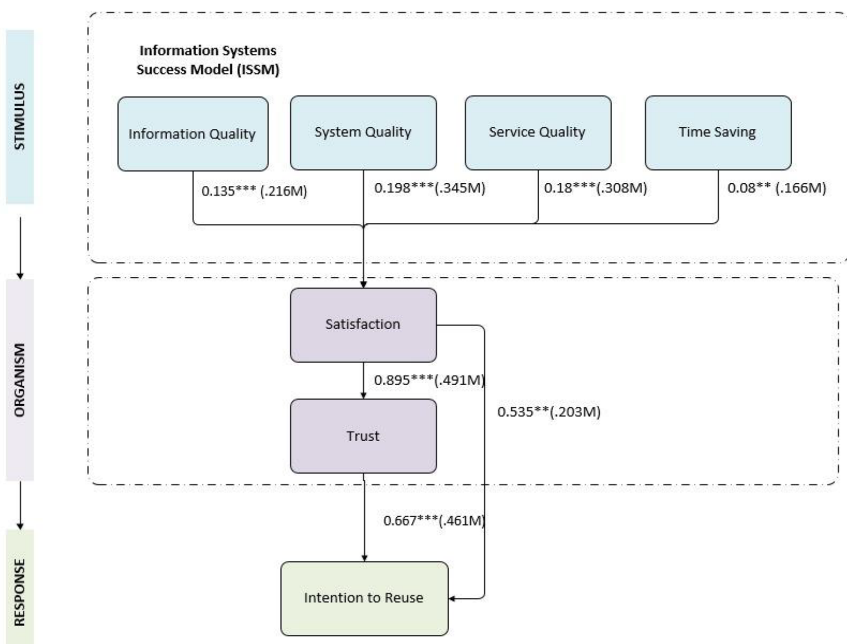

Figure 4. SEM results

The SEM analysis revealed that all four stimulus-related hypotheses (H1, H2, H3, and H4) had significant effects on Satisfaction, representing the "organism" component in the S-O-R framework. Specifically, Information Quality positively influenced Satisfaction, with an unstandardized estimate of 0.135 and $p < 0.001$. This indicated a statistically significant (***) positive relationship between Information Quality and student satisfaction in Indonesia. This finding was consistent with previous studies, such as Duong et al. (2024), which found that Information Quality and Service Quality played key roles in enhancing Satisfaction. Accurate, clear, and up-to-date information provided by LLM-based chat AI tools (ChatGPT, Gemini, and Microsoft Copilot) contributed to higher satisfaction among university students. Furthermore, information that effectively supported problem-solving processes further strengthened student satisfaction. Presenting the information clearly and comprehensively was crucial. This approach enabled students from diverse academic and cultural backgrounds to engage more effectively with the learning content delivered by AI chatbots.

The relationship between System Quality and Satisfaction was found to be positive and significant, with an unstandardized estimate of 0.198 and $p < 0.001$. This indicated a strong (***) effect of System Quality on Satisfaction. This finding was supported by prior studies on cloud-based financial information systems (Y. Li & Wang, 2021) and e-government services (Kala et al., 2024). Features such as the system's ability to generate text and images quickly, real-time usability, and user-friendly interface played an important role in improving student satisfaction. Clear input fields, response areas, and simple conversation history further enhanced the learning experience of Indonesian university students.

Likewise, Service Quality was shown to positively influence Satisfaction, with an unstandardized estimate of 0.180 and $p < 0.001$. This finding also confirmed a statistically significant (***) effect. Previous research supported this result, highlighting the importance of Service Quality in shaping user satisfaction (Al-Debei et al., 2022; Duong et al., 2024; Kala et al., 2024; Y. Li & Wang, 2021). In the context of higher education, a system that responded quickly to students' learning queries and offered personalized support greatly improved their satisfaction. Tailored content based on students' interests or individual needs further enhanced their experience with AI chatbot usage.

Meanwhile, the relationship between Time Saving and Satisfaction was positive and statistically significant, with an unstandardized estimate of 0.080 ($p = 0.002$). This indicates a statistically significant (**) effect of Time Saving on Satisfaction. This result supported Fakfare's (2021) findings, which showed that Time Saving significantly influenced customer satisfaction in the context of food delivery applications. Students in Indonesia perceived that the AI chatbot helped them save time by quickly comparing academic information from various sources. Moreover, the chatbot's ability to accelerate the ideation process and assist students in developing academic concepts further enhanced their satisfaction.

In the organism section of the model, the SEM results from AMOS revealed that Satisfaction positively influenced Trust, with a strong estimate of 0.895 and $p < 0.001$. This finding indicated that students' satisfaction after using chat AI-based LLM chatbots played a crucial role in building trust in the system. Indicators S1 to S3 captured both the emotional and functional dimensions of Satisfaction. The result aligned with previous research in higher education using ChatGPT (Duong et al., 2024) and cloud-based financial systems in China (Y. Li & Wang, 2021), both emphasizing the central role of Satisfaction in shaping Trust and promoting continued use. Therefore, within the context of sustainable use of Chat AI LLMs among students, Satisfaction functioned not only as an outcome but also as a foundation for fostering Trust and long-term engagement.

In the response stage of the model, the path from Trust to Intention to Reuse was found to be significantly positive (*), with an estimate of 0.667 and $p < 0.001$. This was followed by a positive relationship from Satisfaction to Intention to Reuse, with an estimate of 0.535 and $p < 0.01$. These results indicated that both Satisfaction and Trust had statistically significant positive effects on the intention to continue using AI chatbots. This finding was consistent with previous studies showing that Satisfaction and Trust jointly influence sustainable usage in higher education (Duong et al., 2024). In cloud-based financial systems, both variables were validated as key mediators between System Quality and long-term system adoption (Y. Li & Wang, 2021). Similarly, a study in the tourism sector demonstrated that Satisfaction and Trust mediated users' willingness to continue using ChatGPT for travel-related services (Pham et al., 2024). In conclusion, the sustainability of Chat AI LLM usage among university students in Indonesia was highly dependent on two key psychological mediators:

Satisfaction and Trust. The more effectively these chat systems generated satisfaction and built trust among Indonesian students, the greater the likelihood of continued and long-term use in higher education contexts.

The study also analyzed the indirect effects from stimuli to response (Table 9). Among the stimulus variables, System Quality (SYQ) demonstrated the largest indirect effect (0.2239), followed by Service Quality (SEQ) (0.2036), Information Quality (IQ) (0.1527), and Time Saving (TS) (0.0906). Although none of the stimulus variables had a direct effect on CI, all exerted significant indirect effects through Satisfaction and Trust. These findings supported the Stimulus–Organism–Response (S-O-R) mechanism, indicating that the perceived qualities of Chat AI LLMs (IQ, SYQ, SEQ, TS) stimulate Satisfaction and Trust. Then, Satisfaction and Trust drive Intention to Reuse, indicating a full mediation effect in students' continued use of Chat AI LLMs in higher education.

Table 9. Direct, indirect, and total effects analysis

Variable	Direct effect	Indirect effect	Total effect
IQ	0	Rcvj "3"? ""KS " "U' "E K """"""""""""? "20357,,, ""™"20757,, "? "202944,, " Rcvj "4"? "KS " "U' "V " "E K = 0.135*** × 0.895*** × 0.667*** = 0.0805*** Total = 0.1527**	0.1527**
SYQ	0	Rcvj "3"? "U[S " "U' "E K = 0.198*** × 0.535** = 0.1059** Rcvj "4"? "U[S " "U' "V " "E K = 0.198*** × 0.895*** × 0.667*** = 0.1180*** Total = 0.2239**	0.2239**
SEQ	0	Rcvj "3"? "UGS " "U' "E K = 0.180*** × 0.535** = 0.0963** Rcvj "4"? ""UGS " "U' "V " "E K = 0.180*** × 0.895*** × 0.667*** = 0.1073*** Total = 0.2036**	0.2036**
TS	0	Rcvj "3"? "V U' "U' "E K = 0.080** × 0.535** = 0.0428** Rcvj "4"? ""V U' "U' "V " "E K = 0.080** × 0.895*** × 0.667*** = 0.0478** Total = 0.0906**	0.0906**
S	0.535**	U' "V " "E K? 20; 7,,, ""™"20889,,, "? "2065; ,,,	0.974**
T	0.667***	0	0.667***
The direct effect (IQ, SQ, SEQ, TS) is zero due to no direct path.			

IMPLICATIONS

THEORETICAL IMPLICATIONS

This study makes three key theoretical contributions to the development of sustainable usage models for Large Language Model (LLM)-based chat AI in higher education. First, it contributes to the limited body of research on the intention to reuse LLM chatbots for learning purposes. It also extends the application of the Stimulus-Organism-Response (S-O-R) framework, which has been widely used in business contexts such as e-commerce (B. Zhu et al., 2020), online websites (L. Zhu et al., 2020), online retail (Kühn & Petzer, 2018), mobile services (Al-Debei et al., 2022), and short video-driven purchase intentions (S. Yu et al., 2024).

Second, this study refines the conceptualization of the stimulus construct in the context of LLM chatbot usage among university students by incorporating System Quality and Time Saving, both of which showed significant effects on Satisfaction. This finding extends prior research by Duong et al. (2024), which included only Information Quality and Service Quality as antecedents of Satisfaction among Vietnamese students.

Third, this study reinforces earlier evidence from other domains, particularly cloud-based financial information systems (Y. Li & Wang, 2021), that confirmed the significant positive influence of Satisfaction on Trust. In this research, Satisfaction functioned not only as a direct outcome of stimuli but also as a mediating variable linking stimuli to Trust, which subsequently had a strong positive effect on students' Intention to Reuse chat AI-based LLMs in academic contexts.

PRACTICAL IMPLICATIONS

This study offers several practical implications for LLM chatbot developers, higher education institutions, and policymakers. For system developers, the strong influence of Information Quality on Satisfaction underscores the importance of positioning LLM chatbots not merely as information providers but as educational partners that deliver accurate, up-to-date, and contextually relevant content aligned with students' academic needs in Indonesia. The information presented should be easy to understand and capable of supporting problem-solving and critical thinking activities. This finding opens opportunities for collaboration between developers and academic experts to ensure the accuracy and integrity of educational content.

The significant impact of System Quality on Satisfaction also suggests that developers should prioritize maintaining and improving technical performance. This includes optimizing response speed for both text and image generation, as well as designing intuitive, user-friendly interfaces. Input areas, response displays, and conversation histories should remain simple and accessible, while system reliability must be ensured even under high-traffic conditions.

Regarding Service Quality, the results confirm that responsive and personalized services enhance user Satisfaction. Improvements such as faster response times and adaptive content delivery could further enhance perceived service quality. These features should be tailored to students' learning profiles, including their learning styles, comprehension levels, and language preferences.

The positive effect of Time Saving on Satisfaction indicates that LLM chatbots should be designed to streamline the learning process. Features that help students work more efficiently, such as generating outlines, comparing theories, providing ideas, or summarizing academic articles with proper citations, can increase satisfaction. Integration with academic databases and multi-source reference systems could further enable quick, accurate, and comprehensive responses.

Finally, these findings hold practical value for educational institutions and policymakers. The empirical evidence supports strategic decision-making for adopting LLM-based chat technologies in higher education. Information Quality, System Quality, Service Quality, and Time Saving played essential roles in enhancing Satisfaction, which in turn built Trust and long-term usage intentions. Therefore, these factors should guide policy formulation, system design, and service improvement. Strengthening these aspects is expected to promote effective, efficient, and sustainable use of LLM chatbots in improving learning quality and supporting future human capital development.

CONCLUSIONS

This study aimed to identify the key factors influencing the sustainable use of LLM-based chat AI tools in higher education by employing the Stimulus–Organism–Response (S-O-R) framework. SEM analysis revealed that the four stimuli, Information Quality, Service Quality, System Quality, and Time Saving, significantly impact Satisfaction, which in turn fosters Trust and positively influences students' Intention to Reuse these systems. Among these relationships, the path from Trust to Reuse Intention was the strongest, followed by the path from Satisfaction. These findings affirm that both technical and psychological factors, particularly Satisfaction and Trust, are essential foundations for ensuring the continued adoption of Chat AI LLMs in academic settings.

Theoretically, the study extends the S-O-R model through the integration of constructs from the Information Systems Success Model (ISSM) and demonstrates the mediating roles of user satisfaction and trust between system stimuli and continuous behavioral intention. Practically, the results offer practical guidance to higher education institutions on how to promote responsible and effective AI usage with emphasis on reliability, transparency, and user-centered design in AI-facilitated learning contexts.

Responding to such advances, Indonesia's 2024 Deputy Minister of Higher Education, Science, and Technology, Prof. Stella Christie, has urged the responsible utilization of artificial intelligence (AI) in education, with a balance between the embracing of technology and the cultivation of critical and analytical thinking (Firdaus, 2024). To the future, promoting responsible and sustained AI integration in higher education will require sustained policy support, interdisciplinary research, and stakeholder collaboration to ensure that technological innovation enhances, rather than replaces, the human elements of learning.

LIMITATIONS AND FUTURE RESEARCH

This study offers several avenues for future research. First, because the majority of respondents were undergraduate students, future studies should include a larger proportion of postgraduate (master's and doctoral) students to capture more diverse academic and professional perspectives. Second, the geographic coverage of this study was limited to three major cities in Indonesia: Surabaya, Makassar, and Semarang. Future research should expand to a broader range of cities across Indonesia to provide a more comprehensive representation. Cross-country or cross-continental studies using a longitudinal quantitative design are also recommended to observe trends over time and enhance data validity.

Third, future studies may focus on users enrolled in professional certification programs (e.g., industry training or credential-based education) to investigate whether the sustainable use of Chat AI LLMs can enhance learning effectiveness and task performance in certification contexts. Such research could contribute not only to theoretical model development but also to the practical relevance of LLM-based tools in professional education and lifelong learning.

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