

A STIN Model Adoption for Chatbot in Higher Education Online Learning

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Abstract: This study delves into the adoption of chatbot technology in higher education, with a focus on Indonesian online learning environments. Recognizing the potential of AI-driven tools to address academic support gaps, particularly in developing regions, the research explores how performance expectancy, effort expectancy, and facilitating conditions influence students' behavioral intentions and subsequent adoption of chatbots for academic use. The study employs Structural Equation Modeling (SEM) to analyze survey data from a diverse sample of university students, enabling a nuanced understanding of the complex relationships among these factors. The findings reveal that performance expectancy—the belief that chatbots will enhance academic performance and facilitating conditions, such as internet access and institutional support, play significant roles in motivating students to adopt chatbots. However, effort expectancy, or the perceived ease of use, does not directly drive adoption intentions. This suggests that students prioritize practical benefits over user-friendliness, an insight valuable for universities aiming to implement effective chatbot systems. Moreover, the results align with the Socio-Technical Interaction Network (STIN) model, which emphasizes the need for a cohesive social and technical framework to foster technological acceptance. The STIN model's perspective underscores that students' engagement with chatbots is not just a matter of usability but also of how well the technology is supported by the broader educational infrastructure. This study offers actionable insights for Indonesian universities and other institutions in similar contexts, proposing that enhancing campus resources, like reliable internet access and technical support, can drive chatbot adoption. By focusing on performance-based benefits and strengthening the socio-technical environment, universities can effectively integrate AI-based learning tools, addressing both technical and socio-cultural barriers. Such initiatives support students' learning experiences and foster an adaptive academic ecosystem where AI tools serve as essential assets in overcoming resource limitations. Thus, the study contributes a practical roadmap for advancing e-learning in resource-constrained settings through strategic support of AI technology adoption.

Keywords: Chatbot-Based online learning, e-Learning adoption, STIN model, Structural equation modeling

1. Introduction

AI-powered digital assistants may provide tailored assistance to students by addressing enquiries, streamlining administrative duties, and providing prompt feedback. Notwithstanding their increasing use across diverse industries, the integration of chatbots in educational settings remains comparatively insufficiently investigated, especially in underdeveloped nations such as Indonesia. The determinants affecting students' acceptance of chatbots in university environments need more research to enhance the integration of this technology in higher education. The integration of AI technology in education, such as chatbots, has shown favourable effects in enhancing learning outcomes. Multiple studies have emphasised the capacity of chatbots to provide tailored learning experiences and enhance administrative efficiency. (Kesarwani, Titiksha and Juneja, 2023). However, research on the specific variables influencing students' willingness to adopt chatbots remains limited, particularly in developing regions where factors such as inadequate infrastructure and lack of institutional support may pose significant challenges. While prior studies (Maulana and Arli, 2022; Muslem *et al.*, 2024) have

explored aspects of online learning in Indonesia, there remains a gap in understanding the specific drivers behind chatbot adoption in this context. This study addresses this gap by focusing on three key factors: performance expectancy, effort expectancy, and facilitating conditions within Indonesian campuses.

The main objective of this study is to investigate how these elements—performance expectancy (the belief that chatbots will enhance academic performance), effort expectancy (the perceived ease of utilising chatbots), and facilitating conditions (the presence of institutional resources and support)—influence students' intention to engage with chatbot-based learning. This study will evaluate the direct and indirect impacts on students' actual adoption of chatbots by examining these variables using Structural Equation Modelling (SEM). This study presents a new theoretical framework, the Socio-Technical Interaction Networks (STIN) model, aimed at elucidating the relationship between social and technical elements in the adoption of AI-based technologies. This emphasis on the STIN model provides valuable perspectives on how educational institutions can enhance the alignment of their technical infrastructure with the needs of students.

This research presents a comprehensive analysis of the factors influencing chatbot adoption within the context of a developing country. Existing literature has examined various determinants of technology acceptance; however, limited research has addressed the specific socio-technical challenges encountered by students in Indonesia. This study examines the challenges associated with chatbot adoption in higher education, offering a detailed understanding of the barriers and facilitators involved. The integration of the STIN model enhances the originality by providing a distinct viewpoint on the relationship between technical systems, such as chatbots, and social contexts, including university support and resources.

This research provides significant contributions to the domain of educational technology. It offers practical insights for colleges aiming to integrate chatbot-based learning into their educational frameworks by emphasising the essential role of performance advantages and institutional backing. Secondly, the results provide pragmatic suggestions for surmounting adoption obstacles in poorer nations, where infrastructure and assistance may be inadequate. The study enhances the theoretical comprehension of technology adoption in educational contexts by including the STIN model, which may function as a foundational framework for further investigations into AI-driven learning technologies across various educational settings.

2. Literature Review

In recent years, Higher Education in Indonesia has faced multiple challenges that hinder the overall development of an effective learning environment. These issues, such as the scarcity of qualified teachers, limited resources, and infrastructural shortcomings, coupled with increasing academic demands and intense competition, have created a scenario where students struggle to access adequate academic support and guidance. As the academic pressures mount, Artificial Intelligence (AI)-driven tools, have emerged as potential solutions to these challenges. This literature review explores the critical issues in Indonesian higher education, the role of AI tools.

This chapter will provide an in-depth explanation of the Technology Acceptance Model (TAM) and Socio-Technical Interaction Network (STIN) Model, covering its fundamental components, theoretical extensions, and its application in various domains, particularly in higher education and AI-driven learning tools.

This approach can be analysed through the Technology Acceptance Model (TAM), which explains how users accept and use technology (Davis, 1989; Venkatesh *et al.*, 2003). In the context of higher education in Indonesia, students and lecturers need to feel that AI tools are truly beneficial in improving the learning experience and reducing academic workload. If AI-based tools, such as intelligent tutoring systems and academic chatbots, are perceived as easy to use as well as providing tangible benefits in improving material comprehension and study efficiency, then it is more likely that these technologies will be widely accepted and adopted in academic settings, this study proposes a Research Design model as shown in Figure 1.

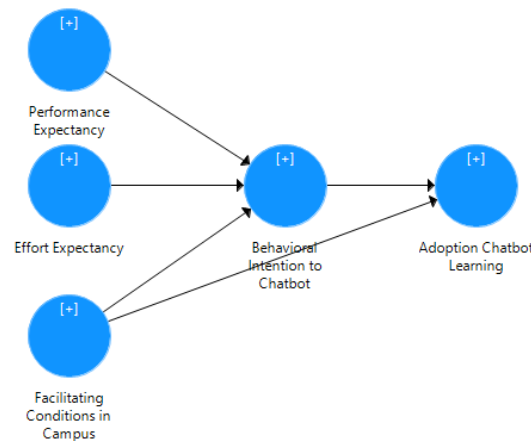


Figure 1: TAM for Research Design

2.1 Performance Expectancy in Higher Education

One of the most notable factors influencing technology adoption is performance expectancy, which refers to the belief that using a particular technology will enhance one's performance. In educational environments, especially those constrained by limited resources, tools that provide clear academic benefits are more likely to be embraced by students. For instance, (Chatterjee and Bhattacharjee, 2020) demonstrate that students are inclined to use technologies like chatbots when they perceive them as advantageous to their academic success. Similarly, (Chew and Cerbin, 2021; Pratita *et al.*, 2025) found that students who believed chatbots could simplify complex concepts and provide immediate academic assistance were more likely to express a strong intention to use the technology. Both studies underscore the importance of perceived academic benefits in driving adoption.

However, these studies also present some limitations. (Chatterjee and Bhattacharjee, 2020) focused on a generalized perception of chatbot utility without exploring variations across different subjects or disciplines, which could have revealed more nuanced insights into performance expectancy. Meanwhile, (Chew and Cerbin, 2021) primarily examined short-term engagement, leaving room to explore long-term impacts on academic performance and sustained adoption. The present study addresses these gaps by examining performance expectancy not only in terms of immediate academic success but also considering the long-term utility of chatbots across various educational domains.

In contrast, (José-María *et al.*, 2023) explored chatbot adoption specifically in the university setting, emphasizing its use for complex thinking. This approach is more aligned with subject-specific investigations, but it also lacks depth regarding how performance expectancy interacts with infrastructure and support systems in developing regions. (Artur, 2023, 2024) and (Sultan and M., 2024) further extend the UTAUT framework by examining how factors like social language and proactivity affect chatbot adoption, yet still within more developed contexts, leaving gaps in understanding how these factors operate in under-resourced environments.

The relationship between performance expectancy and behavioral intention is well-supported by the Technology Acceptance Model (TAM), which posits that perceived usefulness is a key predictor of technology adoption (Zaineldeen *et al.*, 2020; Suryanto *et al.*, 2022, 2023; Abuhassna *et al.*, 2023). In academic settings, if students believe that chatbots will help them complete tasks more efficiently, they are more likely to integrate these technologies into their study routines. Previous empirical studies, such as those by (Liao *et al.*, 2018) and (Alassafi, 2022), consistently show a positive correlation between performance expectancy and behavioral intention these studies often focus on technical features rather than pedagogical effectiveness.

Considering the Performance Expectancy factor is crucial for ensuring the successful adoption of educational technologies, as it directly influences students' motivation to integrate these tools into their academic activities and achieve long-term learning benefits.

2.2 Effort Expectancy and Technological Adoption

Effort expectancy, defined as the perceived ease of use of technology, has been consistently recognized as a key factor influencing students' technology adoption. (Villanueva and Aguilar-Alonso, 2021) affirm that students are more inclined to adopt AI-driven tools when they find them easy to use, which aligns with the core premise of

the Technology Acceptance Model (TAM), where ease of use is a significant predictor of user acceptance (Zaineldeen *et al.*, 2020; Fauzi *et al.*, 2021; Abuhassna *et al.*, 2023).

However, prior studies reveal certain limitations in understanding effort expectancy's impact. (Hair *et al.*, 2017; Hsiu-Ling, Gracia and H., 2020; Xinjie and Zhonggen, 2023) highlight that, while ease of use promotes behavioral intention, its influence is often overshadowed by performance expectancy, suggesting that users might value technology's functional benefits more than ease of use. This is particularly relevant in resource-constrained settings like Indonesian universities, where students prioritize practical outcomes over usability due to limited access to technology. On the other hand (Ondas, Pleva and Hladek, 2019) emphasize that in environments where students lack digital literacy, effort expectancy becomes a more critical factor. In such contexts, ease of use is paramount, as students with lower technical proficiency are more likely to embrace technology if it is intuitive and user-friendly.

The current study addresses these gaps by examining both the contextual significance of effort expectancy and its interaction with chatbot. Unlike previous research, this study considers the varying levels of students' technological exposure, providing a more nuanced understanding of how ease of use influences behavioral intention across different educational environments.

2.3 The Role of Facilitating Conditions in Campus Settings

(Meennapa, Napasorn and P., 2022) and (José, T. and J., 2020) argue that facilitating conditions, including infrastructure and institutional support, are critical for successful chatbot adoption. This is further validated by (Villanueva and Aguilar-Alonso, 2021), unfortunately, these studies only focus on technical support and ignore the impact of campus encouragement that contributes to students. Which include the availability of resources, infrastructure, and institutional support, are crucial in determining whether students will adopt technologies like chatbots. (Arun, Srinagesh and Ganga, 2019) argue that when students have access to stable internet connections, technical assistance, and encouragement from faculty, their likelihood of engaging with AI-driven tools increases significantly. Scott and Husain (2021) further validate this by emphasizing that institutional support plays a key role in fostering strong behavioural intentions to adopt new technologies among students.

However, previous studies have certain limitations in fully explaining how facilitating conditions affect both the intention to adopt and actual use of technology. For instance, while (Arun, Srinagesh and Ganga, 2019) highlights the importance of resources and support, they do not explore how these conditions interact with other factors, such as students' digital proficiency or motivation. (Ghorpade-Aher, 2019) adds that without adequate support structures, even the recognition of potential academic benefits may not translate into technology adoption. Yet, this study falls short in addressing the nuanced challenges faced in resource-limited environments, such as those in many Indonesian universities, where inadequate internet connectivity and a lack of faculty involvement may significantly hinder chatbot adoption.

Additionally, studies such as those by (Rumangkit, Surjandy and Billman, 2023) underscore that facilitating conditions do not only shape behavioral intention but also directly impact the actual adoption of chatbots. The absence of essential resources, such as reliable internet infrastructure, can obstruct students from fully integrating AI tools into their learning process, regardless of their intentions. These earlier studies primarily focus on the availability of infrastructure but often overlook the role of faculty training and preparedness, which are also critical in fostering the actual use of technology in academic settings.

The current study fills these gaps by not only investigating the availability of resources but also considering how institutional support, faculty involvement, and infrastructure interact to move students from behavioral intention to actual chatbot adoption. Unlike prior research, this study highlights the importance of a holistic approach to facilitating conditions, including continuous faculty development and adaptive technical support to accommodate varying levels among students.

2.4 Behavioral Intention to Chatbot Use in Indonesia

Behavioral intention is a critical predictor of whether students will adopt chatbots for learning, shaped by perceptions of usefulness, ease of use, and available support systems. (Rosmayanti, Noni and Patak, 2022; Artur, 2024; Weiqi *et al.*, 2024) emphasize that when students believe chatbots can improve task efficiency, their intention to use them strengthens. However, while effort expectancy contributes to this intention, its influence is often secondary to the perceived performance benefits. This is supported (Lutfi *et al.*, 2022) and (Candra *et al.*, 2024), who found that even if students believe chatbots will improve their academic performance, they may not adopt the technology without strong behavioral intention.

Despite its central role in adoption, behavioral intention's relationship with local contextual factors remains underexplored, particularly in developing countries like Indonesia. Previous studies, including those by (Marfuah *et al.*, 2022) and (Binowo *et al.*, 2024), have predominantly focused on developed regions, where high chatbot and widespread access to advanced technology are assumed. These studies often overlook the challenges faced by Indonesian universities, which may grapple with inadequate infrastructure, inconsistent internet access, and varying levels of digital proficiency. The adoption models, such as TAM and UTAUT, while effective in Western contexts, may not fully capture the complexities of behavioral intention in resource-constrained environments.

Additionally, while (Imdadullah and Yasser, 2023) and (Ayanwale and Ndlovu, 2024) explore educators' adoption of AI, providing insights into how behavioral intention is shaped by perceived ease of use and institutional support. However, like many studies, they do not account for variations in campus contributions, particularly in developing countries such as Indonesia, which provides an opportunity for deeper observation.

Therefore, the research suggests that factors like performance and effort expectancy interact dynamically with local conditions, they do not delve deeply into how these interactions are influenced by infrastructural and cultural differences, especially in non-Western settings. For example, students with limited exposure to advanced technologies in Indonesian universities might perceive chatbots as more complex or challenging to use, affecting their intention and overall adoption differently compared to their counterparts in more digitally advanced regions.

The current study addresses these shortcomings by focusing specifically on the Indonesian context, offering a more nuanced understanding of how behavioral intention is shaped by local factors such as chatbot, infrastructural constraints, and cultural attitudes toward AI technologies. Unlike previous studies, this research not only applies global models like TAM and UTAUT but also critically evaluates their relevance in a developing-country context, providing fresh insights into the unique factors driving chatbot adoption in Indonesian higher education.

2.5 STIN Model

However, AI technology adoption is not only influenced by individual factors as described in TAM, but also by social and technical interactions within an educational ecosystem. This is where the Socio-Technical Interaction Network (STIN) introduced (Walker and Creanor, 2009) becomes relevant. STIN emphasises that the success of technology implementation depends not only on the characteristics of the technology itself, but also on the social networks that use it, including institutional policies, infrastructure readiness, and the dynamics of relationships between students, lecturers, and administrators (Berleur, Nurminen and Impagliazzo, 2006; Meyer, 2006; Narayan and Macher, 2023). In higher education ecosystem, the implementation of AI should consider how this technology will interact with the existing education system, including how institutions manage policy changes, build supporting infrastructure, and ensure the active involvement of stakeholders.

By combining TAM and STIN, a holistic approach can be used to evaluate the effectiveness of AI implementation in Indonesian higher education. TAM helps understand technology acceptance from an individual perspective, while STIN provides insights into how AI technologies can be effectively integrated within the broader social and technical environment. If AI can be implemented with these two models in mind, then AI-based solutions have the potential to significantly improve the accessibility and quality of higher education.

3. Materials and Methods

3.1 Sample and Data Collection

This research employs a quantitative approach to explore factors influencing chatbot adoption among university students in Indonesia. Probability sampling is used to obtain samples of 299 respondents will be selected from various study programs to ensure representation of the diverse student population. Data collection will occur from January to June 2024 using both online and offline questionnaires.

The research method begins with the development of a structured questionnaire aimed at capturing data on performance expectancy, effort expectancy, facilitating conditions, behavioral intention, and actual chatbot adoption. The questionnaire will consist of validated measurement scales to ensure reliability and validity. Following this, a pilot test will be conducted with a small group of students to refine any ambiguous questions based on their feedback.

Data collection will then be implemented through online platforms, such as Google Forms, and in-person distribution at selected universities across Indonesia. This dual approach accommodates different access levels,

ensuring wider participation. Once data collection is complete, the data will be cleaned and prepared for analysis using Structural Equation Modeling (SEM). SEM is ideal for this research as it allows for the simultaneous assessment of complex relationships and testing of hypotheses, as highlighted in studies by (Hair *et al.*, 2017), (Chatterjee and Bhattacharjee, 2020), and (Villanueva and Aguilar-Alonso, 2021). This analysis will identify direct and indirect effects of performance expectancy, effort expectancy, and facilitating conditions on students' behavioral intention and chatbot adoption.

3.2 Structural Model

Provides a detailed explanation of key variables used in this study, ensuring clarity and consistency in measurement. Each variable is defined based on relevant literature and adapted to the research context to enhance validity and reliability, explained in more detail for definition operational in table 1 and questioner item's in table 2.

Table 1: Definition Operational

Variable	Operational Definition	Reason for Inclusion	References
Performance Expectancy (PE)	The degree to which students believe that using chatbots will enhance their academic performance and efficiency in learning tasks.	This variable is crucial as studies have shown that students who perceive a positive impact on their performance are more likely to adopt new technologies	(Chatterjee and Bhattacharjee, 2020; Chew and Cerbin, 2021; Rosmayanti, Noni and Patak, 2022; Rumangkit, Surjandy and Billman, 2023; Artur, 2024)
Effort Expectancy (EE)	The perceived ease of use associated with engaging with chatbots in learning environments.	Understanding this variable helps identify if the user-friendliness of chatbots influences students' willingness to use them	(Chatterjee and Bhattacharjee, 2020; Villanueva and Aguilar-Alonso, 2021; Alamsyah <i>et al.</i> , 2022; Mohd Rahim <i>et al.</i> , 2022; Rosmayanti, Noni and Patak, 2022; Artur, 2024)
Facilitating Conditions in Campus (FC)	The availability of resources, support, and infrastructure necessary for effective chatbot usage within the campus environment.	This variable highlight how external factors like institutional support and technology accessibility can facilitate or hinder chatbot adoption	(Yadav, Herzog and Bolchini, 2020; Scott and Husain, 2021; Sarfraz, Khawaja and Ivascu, 2022; Zhou <i>et al.</i> , 2022; Rumangkit, Surjandy and Billman, 2023; Strzelecki, 2023)
Behavioral Intention to Chatbot (BIC)	The inclination or readiness of students to use chatbots for learning purposes based on their perceptions and experiences.	Behavioral intention is a strong predictor of actual usage behavior, linking perceived benefits and usability to the likelihood of adopting chatbots	(Cheng-Min, 2019; Shingte <i>et al.</i> , 2021; Ayanwale and Ndlovu, 2024; Candra <i>et al.</i> , 2024; Abdi <i>et al.</i> , 2025)
Adoption Chatbot Learning (ACL)	The actual utilization of chatbots by students in their learning processes and academic tasks.	This variable is the ultimate outcome of interest in this research, as it measures the effectiveness of efforts to enhance chatbot adoption and integration into learning.	(Arista and Abbas, 2022), (Lutfi <i>et al.</i> , 2022), (Rosmayanti, Noni and Patak, 2022), (Alamsyah <i>et al.</i> , 2022).

Table 2: Questioner Item's

No.	Var.	Question
1	ACL1	The implementation of Chatbot on campus is beneficial for the academic community.
2	ACL2	Integrating Chatbot into campus life will enhance the interactivity of the learning process.
3	ACL3	Utilizing Chatbot on campus will make learning more effective and efficient.
4	BIC1	I believe Chatbot is easy for beginners to learn.
5	BIC2	I am willing to use Chatbot to support my self-directed learning.
6	BIC3	I believe Chatbot can be used to assist with academic assignments.
7	BIC4	I would recommend exploring Chatbot as part of the independent learning initiative.
8	BIC5	I intend to use Chatbot as a new culture of independent learning.
9	EE1	I recognize that I need to put in significant effort to learn how to use Chatbot.
10	EE2	I can easily learn how to use Chatbot.
11	EE3	I can quickly find answers to my questions using Chatbot.

No.	Var.	Question
12	FC1	My campus has all the necessary resources to effectively utilize Chatbot.
13	FC2	I have access to all the necessary resources to use Chatbot.
14	PE1	Learning activities supported by Chatbot will enhance learning efficiency.
15	PE2	The responses generated by Chatbot are valuable for self-directed learning.
16	PE3	Intelligent educational content can be developed using Chatbot technology.

4. Results

This section presents empirical findings from the statistical analysis performed in the study, structured according to the measurement model, descriptive statistics, and the structural model evaluation. The results are systematically organized in a series of tables to enhance clarity and support interpretation.

4.1 Outer Model Analysis

To ensure the accuracy of the constructs used in this study, an outer model analysis was carried out. This analysis checks whether the indicators correctly measure the intended variables. First, convergent validity was tested using the Average Variance Extracted values shown in Table 3. Next, discriminant validity was assessed through cross-loading in table 4 and the Fornell-Larcker Criterion in table 5. Lastly, reliability was confirmed using Cronbach's Alpha and Composite Reliability, as presented in table 6.

Table 3: Convergent Validity Average Variance Extracted (AVE)

	Average Variance Extracted (AVE)
Adoption Chatbot Learning	0.832
Behavioral Intention to Chatbot	0.669
Effort Expectancy	0.696
Facilitating Conditions in Campus	0.750
Performance Expectancy	0.663

The analysis of convergent validity shows that the Average Variance Extracted (AVE) for all constructs is greater than 0.50, with the highest value being for Adoption Chatbot Learning (0.832). This indicates that the indicators of each construct explain more than 50% of the variance, meaning that each construct reliably measures the intended phenomenon. For instance, the adoption of chatbots for learning has a strong understanding among users, as evidenced by the high AVE value.

Table 4: Discriminant Validity Cross Loading

	Adoption Chatbot Learning	Behavioral Intention to Chatbot	Effort Expectancy	Facilitating Conditions in Campus	Performance Expectancy
ACL1	0.881				
ACL2	0.946				
ACL3	0.908				
BIC1		0.763			
BIC2		0.791			
BIC3		0.894			
BIC4		0.853			
BIC5		0.781			
EE1			0.766		
EE2			0.870		
EE3			0.862		

	Adoption Chatbot Learning	Behavioral Intention to Chatbot	Effort Expectancy	Facilitating Conditions in Campus	Performance Expectancy
FC1				0.870	
FC2				0.863	
PE1					0.813
PE2					0.831
PE3					0.798

The analysis of cross loadings provides strong evidence of discriminant validity. The high loadings of indicators on their respective constructs, compared to their loadings on other constructs, indicate that the measurement items are appropriately differentiated across constructs. This confirms that each latent variable in the model is distinct and well-represented by its indicators, thereby enhancing the reliability and interpretability of the structural equation model.

Table 5: Fornell-Larcker Criterion

	Adoption Chatbot Learning	Behavioral Intention to Chatbot	Effort Expectancy	Facilitating Conditions in Campus	Performance Expectancy
Adoption Chatbot Learning	0.912				
Behavioral Intention to Chatbot	0.795	0.818			
Effort Expectancy	0.523	0.571	0.834		
Facilitating Conditions in Campus	0.556	0.625	0.732	0.866	
Performance Expectancy	0.604	0.639	0.590	0.596	0.814

The Fornell-Larcker criterion reveals that the correlation between each construct and its indicators is higher than the correlation between the construct and other constructs. The highest correlation is for Adoption Chatbot Learning (0.912), followed by Behavioral Intention to Chatbot (0.818). This shows that students have a strong tendency to adopt chatbots if they have a strong behavioral intention to use them.

Table 6: Reliability

	Cronbach's Alpha	Composite Reliability
Adoption Chatbot Learning	0.899	0.937
Behavioral Intention to Chatbot	0.875	0.910
Effort Expectancy	0.781	0.872
Facilitating Conditions in Campus	0.667	0.857
Performance Expectancy	0.746	0.855

The Cronbach's Alpha and Composite Reliability values are all above 0.7 for all constructs, affirming the reliability of the instruments used in this study. Adoption Chatbot Learning has very high reliability (0.899 and 0.937), indicating that the questions measuring this variable consistently assess students' perceptions of using chatbots in learning.

4.2 Descriptive Analysis

Our study included a representative sample of 299 participants derived from data obtained via student surveys. The questions were administered both online and offline from January to June 2024. Shown in figure 2, the participants were actively involved in courses using AI technologies as course facilitators throughout the 2024-2025 academic year.

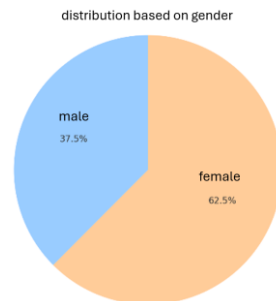


Figure 2: Distribution of Respondents by Gender

Here is the pie chart showing the assumed gender distribution based on names, with Male and Female the two categories. Show in figure 3, this is an estimate assuming the gender based on typical name patterns, where Female represents the larger proportion of the dataset.

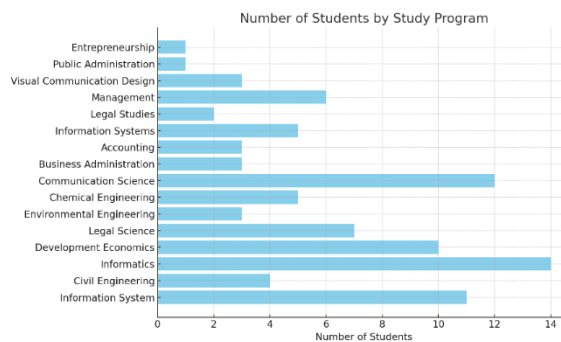


Figure 3: Distribution of Respondents by Study Program

The most represented programs are Information Systems, Informatics, and Communication Science, with other programs like Development Economics, Legal Science, and Management also having notable student counts.

Here is the pie chart showing how frequently students use Chatbot. It demonstrates the distribution among the categories very often, often, rarely, based on the data you provided. The largest proportion of respondents use Chatbot very often (59.9%), followed by those who use it often (37.5%), and a small number who rarely use it (3.0%).

Chatbot, an AI-based tool, has been widely used by students across various academic programs. Female students dominate the usage of Chatbot, accounting for around 62.5% of respondents. This suggests that female students, particularly in fields requiring substantial writing and research, are more likely to use it for tasks such as drafting, editing, and information retrieval. Male students, on the other hand, may still be a strong contingent, particularly in technical fields like Information Systems or Informatics.

The frequency of use for Chatbot is also high, with 61.1% of students using it very often, suggesting that the platform has become integral to their academic workflow. The remaining 38.5% use it for specific tasks, such as exam preparation or larger projects. As shown in figure 4, the small proportion of students who reported rarely using Chatbot might represent those who are unaware of its benefits, prefer traditional learning tools, or are in programs that do not demand frequent use of AI-driven applications.

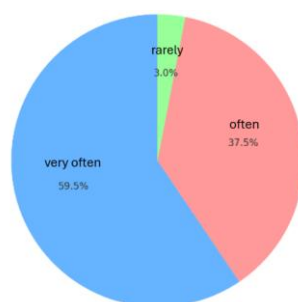


Figure 4: Distribution of Respondents by Intensity

Students from Information system, Informatics, and Communication Science show significant representation, where Chatbot is likely leveraged for its ability to assist with both technical and content-driven tasks. However, other fields like Civil Engineering and Entrepreneurship show lower adoption rates, suggesting that these students may find less utility in Chatbot for their specific academic needs or have alternative tools better suited for their disciplines. So, Chatbot's growing role as a vital academic tool is evident across various student demographics and academic programs. Future research could focus on understanding how different students use AI in their academic work and developing strategies to bridge the gap for less frequent users.

4.3 Inner Model Analysis

Inner model analysis is used to evaluate the relationships between the key variables in the study and test the research hypotheses. As shown in table 7, the path coefficients indicate the strength and direction of influence between constructs. To assess how much variation is explained by the model, the R-Square (R^2) values are presented in table 8. The effect size (f^2), shown in table 9, helps determine the contribution of each variable to the model. Lastly, table 10 presents the model fit indices, which show that the structural model fits the data adequately.

Table 7: Path Coefficient Significance

Variable Hypotesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
Behavioral Intention to Chatbot → Adoption Chatbot Learning	0.734	0.739	0.041	17.934	0.000
Effort Expectancy → Behavioral Intention to Chatbot	0.115	0.120	0.083	1.386	0.166
Facilitating Conditions in Campus → Adoption Chatbot Learning	0.097	0.091	0.064	1.504	0.133
Facilitating Conditions in Campus → Behavioral Intention to Chatbot	0.312	0.311	0.078	3.994	0.000
Performance Expectancy → Behavioral Intention to Chatbot	0.385	0.386	0.061	6.276	0.000

Behavioral Intention to Chatbot → Adoption of Chatbot Learning: The strongest path, with a coefficient of 0.734, a T-value of 17.934, and a p-value of 0.000, indicates a highly significant positive effect. This suggests that individuals' behavioral intention to use the chatbot strongly predicts the adoption of chatbot learning.

Effort Expectancy → Behavioral Intention to Chatbot: The coefficient is 0.115 with a T-value of 1.386 and a p-value of 0.166. This path is not significant, implying that the ease of use (effort expectancy) does not significantly impact the behavioral intention to use the chatbot. **Facilitating Conditions in Campus → Adoption of Chatbot Learning:** With a coefficient of 0.097, a T-value of 1.504, and a p-value of 0.133, this path is also not significant. Thus, facilitating conditions (e.g., resources or support at campus) do not significantly affect chatbot adoption directly.

Facilitating Conditions in Campus → Behavioral Intention to Chatbot: The coefficient is 0.312 with a T-value of 3.994 and a p-value of 0.000, showing a significant positive effect. Facilitating conditions do influence users' intention to use the chatbot. **Performance Expectancy → Behavioral Intention to Chatbot:** The path is significant with a coefficient of 0.385, a T-value of 6.276, and a p-value of 0.000. This indicates that users' belief that the chatbot will improve their performance significantly impacts their intention to use it.

Table 8: R-Square (R^2)

	R Square	R Square Adjusted
Adoption Chatbot Learning	0.637	0.635
Behavioral Intention to Chatbot	0.507	0.502

R-Square values of more than 0.50 for both variables (Adoption Chatbot Learning and Behavioral Intention to Chatbot) indicate that the model has good predictive power. In a social context, R^2 values above 0.60 are often considered quite strong, as many external factors influence individual behaviour. Consequently, our findings demonstrate that the factors included in the model (including performance expectation, effort expectancy, and conducive campus settings) substantially affect students' decisions to adopt a chatbot and their intention to use it.

Table 9: Effect Size (f^2)

	Adoption Chatbot Learning	Behavioral Intention to Chatbot
Adoption Chatbot Learning		
Behavioral Intention to Chatbot	0.905	
Effort Expectancy		0.011
Facilitating Conditions in Campus	0.016	0.083
Performance Expectancy		0.179

From the Effect Size (f^2) results, the influence of Behavioral Intention to Chatbot on Adoption Chatbot Learning is very large (0.905), indicating that students' behavioral intention to use chatbots is the primary determinant in their adoption. On the other hand, the influence of Effort Expectancy (0.0011) and Facilitating Conditions (0.0083) on behavioral intention is relatively small. This shows that while environmental support and ease of use expectations are important, they are not as significant as behavioral intention.

Table 10: Model Fit Indices

	Saturated Model	Estimated Model
SRMR	0.078	0.079
Chi-Square	755.221	763.151
NFI	0.763	0.761

The model fit indices show that the SRMR (Standardized Root Mean Square Residual) for the saturated model is 0.078, which is below the 0.08 threshold, indicating that the model fits well. This is further supported by the NFI (Normed Fit Index) value of 0.763, which, although slightly below 0.90, is still acceptable in the context of this study.

5. Discussion

The findings from the data analysis displayed in Table 7 indicate a significant correlation between Performance Expectancy, Facilitating Conditions on Campus, and the Behavioural Intention to Utilise Chatbots within the learning environment. The impact of these variables was substantial, suggesting that students' views on the effectiveness of a chatbot (Performance Expectancy) and the available supporting infrastructure on campus (Facilitating Conditions) are essential in determining their intentions to utilise AI-based tools in their educational pursuits. Refer to table 10.

5.1 Impact of AI-Driven on Online Learning

Performance Expectancy refers to students' perception of how well chatbots can enhance their academic performance. In environments where teaching staff may be limited or overwhelmed, particularly in developing countries, chatbots offer a timely solution by providing accurate academic support. For example, in Indonesian universities, where there is often a high student-to-teacher ratio, chatbots can fill gaps by answering common questions, clarifying concepts, and helping with assignments. Students who believe that chatbots will help them achieve better academic outcomes are more likely to adopt these technologies. In such scenarios, chatbots help alleviate the burden on faculty, enabling them to focus on more complex tasks while the chatbot handles routine inquiries. This aligns with prior studies (Chatterjee and Bhattacharjee, 2020; Chew and Cerbin, 2021) that

underscore the significance of performance expectancy in adoption of driving technology, but adds that in resource-constrained environments, the utility of chatbots becomes even more pronounced. However, unlike these previous studies, this research highlights the contextual role of teaching staff limitations in enhancing the perceived value of chatbot systems. This unique finding suggests that chatbots serve as an essential supplement in educational settings with limited human resources.

The adoption of new technologies like chatbots also depends heavily on Facilitating Conditions, such as reliable internet access, sufficient IT infrastructure, and institutional support. Many universities in developing regions, including Indonesia, face challenges in delivering these conditions due to financial and logistical limitations. Without adequate infrastructure, the potential benefits of chatbots cannot be fully realized. This study found that when universities provide strong Wi-Fi coverage, well-maintained computer labs, and user-friendly learning management systems, students are more likely to adopt chatbot technologies. These findings are consistent with prior research (Scott and Husain, 2021; Villanueva and Aguilar-Alonso, 2021) which demonstrates that technical and infrastructural support significantly influences the adoption of e-learning tools. However, the current research diverges by showing that even when infrastructure is modest, institutional support—such as faculty encouragement and training programs—can mitigate some technological gaps, fostering a positive attitude toward chatbot usage. This underscores the idea that in developing contexts, institutional facilitation plays a more critical role than previously suggested in literature.

Behavioral Intention reflects a student's willingness to use chatbots in the future, influenced by both performance expectancy and facilitating conditions. In regions where teaching resources are limited, students may be more inclined to adopt chatbots as a means of overcoming these educational gaps. For instance, Indonesian students, who are generally adept at navigating digital tools, are likely to adopt chatbots when they perceive clear academic benefits, such as rapid responses to questions or personalized study assistance. If the necessary infrastructure supports easy access and use of these tools, students are more likely to integrate chatbots into their daily academic routines, leading to improved interaction within online learning environments. This corresponds with findings from (Chatterjee and Bhattacharjee, 2020) on the importance of behavioral intention in technology adoption yet differs in that it emphasizes the scarcity of human teaching resources as a critical factor driving behavioral intention in this context. The current research suggests that chatbots are perceived not just as supplementary tools, but as essential in filling educational gaps created by a lack of available teaching staff.

The Adoption of Chatbot Learning occurs when students fully incorporate chatbots into their academic processes. Even if the perceived ease of use (Effort Expectancy) is low, students are still likely to adopt chatbots if they see substantial academic benefits. For instance, even if students initially face challenges in navigating chatbot interfaces, they are more likely to continue using them if they believe the technology helps manage their workload more efficiently. This is particularly true in environments where direct access to teaching staff is limited. Like previous research (Rumangkit, Surjandy and Billman, 2023), this study highlights that ease of use is not the primary driver of chatbot adoption; rather, perceived performance benefits are. This study also reveals that in environments with inadequate teaching resources, the perceived necessity of chatbots increases adoption rates, even when the technology is not intuitive. This suggests that students in under-resourced environments are more adaptable and willing to overcome initial challenges when they perceive chatbots as essential academic tools.

In Higher Education institutions face limitations in teaching staff and struggle to provide students with adequate resources to explore their academic interests, the integration of AI tools such as chatbots becomes increasingly important. This research demonstrates that Performance Expectancy and Facilitating Conditions, combined with strong Behavioral Intentions, play crucial roles in the adoption of chatbot-based learning. By addressing the quality of teaching staff and enhancing institutional support through improved infrastructure and training, universities can better leverage chatbots to foster autonomous and engaged learners. While previous research has emphasized performance expectancy and technical infrastructure, this study adds that in contexts where teaching resources are scarce, chatbots take on a more critical role, not just as supplementary tools, but as essential components of educational experience.

5.2 A STIN Model Generation on Higher Education

In some ways, this study backs up what other research has found. However, it also shows some differences depending on certain environmental factors. In terms of what people expect from their success, the study agrees with (Pasmore *et al.*, 2019; Yao *et al.*, 2019), which underscore the importance of perceived performance benefits in technology adoption. The finding that performance expectancy significantly impacts students'

intention to use chatbots demonstrates that students are more inclined to adopt technology when the academic benefits are clearly perceived. This support is also consistent with (Pirzadeh, Lingard and Blismas, 2021) who indicate that users are more likely to adopt technology that offers immediate performance advantages, which in this context translates to improved learning efficiency.

The study further supports the views of (Beamer, 2019; Yin *et al.*, 2022) regarding the significance of facilitating conditions, including sufficient infrastructure and institutional support, in the implementation of socio-technical systems. In the educational context of developing countries such as Indonesia, institutional support, including internet access and technical assistance, is essential for promoting chatbot adoption. The findings suggest that successful technology adoption depends on both the quality of the technology and the supportive socio-technical environment.

However, this study diverges from the findings of (Jarrahi and Sawyer, 2019) regarding the significance of ease of use as a primary factor in technology adoption. Current findings indicate that ease of use (effort expectancy) does not directly affect students' intentions to adopt chatbots. Indonesian students prioritize concrete academic benefits over usability, likely due to infrastructural limitations that require them to focus on immediate, performance-related outcomes. Here, the unique local context influences user priorities in technology adoption. This study substantiates (Suthers, 2011; Manny *et al.*, 2022), who emphasize the necessity of social support in the adoption of STIN-based technology. This underscores that effective technology adoption requires a synergy between technical and social support, with institutions providing a conducive environment for users.

Employing a generalised model such as the Socio-Technical Interaction Networks (STIN) model is essential for addressing future challenges in technology adoption within Higher Education, as it effectively encompasses both social and technological dimensions. A structured framework is essential for effective technology integration, especially in chatbot-based online learning. The STIN model, as proposed by (Walker and Creanor, 2009) serves as an effective framework that offers a comprehensive perspective on the interaction between technology and social elements within educational institutions. The STIN model analyses the interactions among institutions, technology, students, and support systems, providing essential insights into their collective role in facilitating the effective adoption of AI-driven learning tools such as chatbots which is suggestion implementation in table 11.

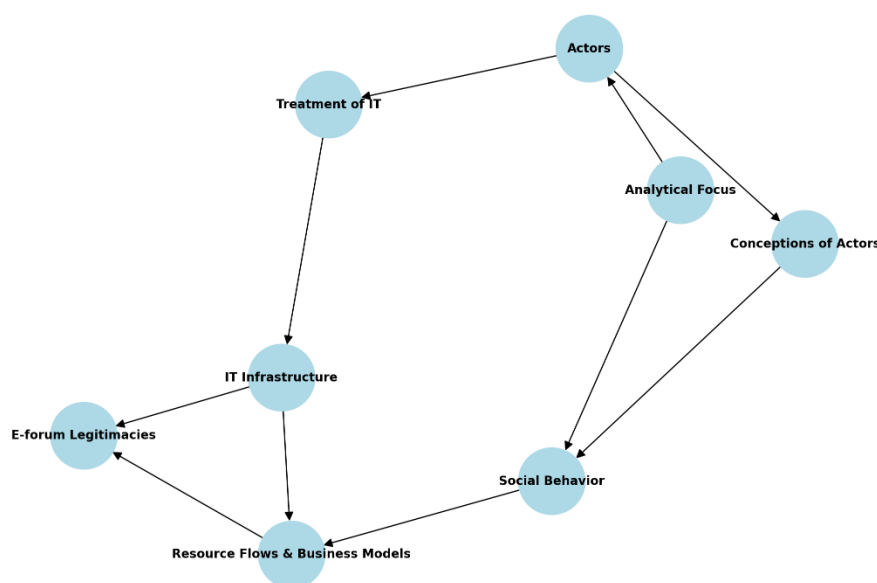
This approach guarantees that technology is implemented effectively, socially accepted, supported by necessary infrastructure, and aligned with institutional objectives, the correlation of which is illustrated in Figure 5. This facilitates the establishment of a novel culture of online learning in universities, wherein both social and technical elements work together to foster a seamless and efficient learning environment.

Table 11: Adoption Online Learning with STIN Model

Aspect	Chatbot Implementation Planning Suggestions
Analytical focus	A university might implement a chatbot to assist students in navigating course content, answering administrative questions, and participating in discussion forums. Students can interact with the chatbot to get instant feedback on quizzes, while instructors monitor participation in forums, tracking the impact of the technology on learning outcomes and student engagement within the institution's digital learning network.
Actors	In implementing chatbot-based learning, the university involves various actors such as IT support teams to maintain the system, faculty to integrate the chatbot into the curriculum, students as end-users, and external providers to supply the chatbot software. Administrative staff might also use the chatbot to answer queries regarding registration or deadlines.
Conceptions of actors	Students not only use the chatbot for educational purposes but also interact with it in extracurricular activities (e.g., club management). Staff might utilize the chatbot in their daily workflows for scheduling or troubleshooting, while technical support ensures the system is fully operational across multiple departments and functions.
Treatment of IT	The university's chatbot integrates with the institution's existing Learning Management System (LMS) and is customized based on faculty input to offer tailored academic responses. For example, the chatbot might be configured to automatically suggest additional reading materials based on student queries or behavior, enhancing personalized learning.
IT infrastructure	The chatbot's effectiveness could depend on the robustness of the university's IT infrastructure. A well-maintained, high-speed internet network is essential to ensure real-time interaction with the chatbot, while server capacity must be sufficient to handle peak usage during exams or assignment deadlines. Technical assistance is readily available to troubleshoot any issues students or faculty might encounter.

Aspect	Chatbot Implementation Planning Suggestions
Social behavior	Peer influence can be seen when students recommend using the chatbot for quick answers during study groups or when faculty encourage its use during class sessions. Outside the university, students might use other educational platforms or social media that link back to university chatbots, blending external and internal learning resources.
Resource flows and business models	Universities might allocate part of their budget to acquire and maintain the chatbot system, including purchasing licenses and investing in cloud infrastructure. Additionally, the institution ensures compliance with privacy regulations (such as GDPR) when handling student data, which the chatbot interacts with to provide personalized learning experiences.
E-forum legitimacies	The university secures funding and institutional support for chatbot implementation, with senior administrators promoting its use across departments. Faculty endorsements also lend credibility to the system, making students more likely to engage with technology as a legitimate and helpful academic tool.

Correlation Chart of STIN Model Components in Higher Education


Figure 5: STIN Model of Purpose Online Education

The analytical focus of chatbot-based online learning in higher education emphasises the roles of key actors, including students, faculty, and IT staff. The success of technology adoption is influenced by these actors, highlighting the significance of understanding how stakeholders interact with chatbots through their impact on social behaviour. The relationship between the Analytical Focus and Actors highlights the need for institutional policies that encourage active engagement from both students and faculty in the utilisation of AI-based tools.

For instance, teachers utilise chatbots to help students learn, and students may use them to help them with their academic work. Regarding actors, their various roles influence actors' conceptions, or how staff, instructors, and students see and use chatbot technology in the classroom. These ideas influence how IT is treated, particularly how chatbots are included into curricula. Faculty and students are more willing to interact with chatbots if they are seen as useful tools, which will increase the effort to tailor the technology to the demands of the user. Actors therefore have an impact on the technical and social elements of IT systems, such as system design and user expectations.

The evolution of actor conceptions greatly impacts social behaviour inside educational institutions. The perceptions and interactions of stakeholders using chatbot systems influence the overall learning network. Students who see chatbots as integral to their educational experience may enhance their involvement in online forums, resulting in elevated overall engagement within the university. The management of IT and its correlation with IT Infrastructure dictates the calibre of the infrastructure behind these technologies.

Elements like as internet connectivity, server capacity, and technical assistance are crucial in guaranteeing the efficient functioning of chatbot systems. A more integrated infrastructure enhances the efficiency and fluidity of the chatbot experience for both students and professors. The IT infrastructure also influences resource flows,

business models, and the legitimacy of e-forums. Investments in information technology, such server enhancements and software licensing, demonstrate a university's commitment to advancing chatbot systems. Robust infrastructure bolsters E-Forum Legitimacies, augmenting the credibility and broader acceptance of chatbots via sufficient technical assistance, academic endorsements, and regulatory compliance.

Lastly, as greater institutional investment in AI tools may result from higher chatbot interaction, social behaviour feeds back into resource flows and business models. A more technology-driven learning culture may be reinforced by universities allocating additional funds to improve chatbot functionality in response to favourable feedback. Universities should concentrate on how social and technological elements that influence chatbot adoption align to further the practical implications of these results.

Even though the study highlights the significance of user interaction and infrastructure, further research is necessary to determine how organisations may successfully expand chatbot-based learning across various educational environments. Universities should also look for ways to improve training programs for staff and students, encourage ongoing technology advancements, and include chatbots into more general academic regulations. Additionally, by comprehending input on chatbot performance and student happiness, colleges will be able to modify their systems to accommodate changing demands. For chatbot-based learning aids in higher education to be as successful and sustainable as possible over the long run, certain actions are essential.

6. Conclusions

In summary, this study illustrates that the effective implementation of chatbot-based learning in Indonesian higher education is significantly influenced by students perceived academic advantages (performance expectancy) and the availability of supportive institutional resources (facilitating conditions). The identified factors play a crucial role in influencing students' behavioural intentions regarding the utilisation of chatbots, whereas the ease of use (effort expectancy) does not have a direct impact on adoption intentions. This indicates that learners are mainly driven to incorporate chatbots into their educational experiences when they perceive that the technology will improve their academic outcomes and when the campus infrastructure sufficiently facilitates its implementation.

In accordance with the Socio-Technical Interaction Network (STIN) model, these findings highlight that successful technology adoption necessitates a strong social and technical ecosystem. A university setting that offers robust digital infrastructure and comprehensive institutional support is crucial for promoting the integration of AI-driven tools. In Indonesian universities, addressing resource limitations that may affect technology utilisation is crucial. By focussing on performance-driven advantages and strengthening support systems, the adoption of chatbot-based learning can be significantly improved.

Future research should priorities the development of context-aware, AI-driven chatbots that enhance academic support while preserving and promoting written cultural and historical heritage. Integrating AI with humanistic disciplines presents complexities that necessitate the development of chatbot frameworks capable of accurately processing and interpreting historical texts and culturally significant narratives. It is essential for researchers to investigate advanced Natural Language Processing (NLP) models that are trained on region-specific datasets to ensure that chatbots accurately represent local dialects, Indigenous knowledge, and historical manuscripts.

Furthermore, the advancement of chatbot models must include the concepts of becoming process learning, consisting of two aspects. The first aspect, flexibility in learning process and responds generating process, one of potential technology for this aspect semi-supervised learning AI. Second aspect concern to the reflective question and answering generation using combination of open and closed domains, this new domain can be considering a semi-open domain.

This study provides insights into advancements in e-learning, emphasizing the significance of strategic resource allocation and student-centered support for AI technologies. By addressing these socio-technical factors, educational institutions in comparable developing contexts can establish adaptive learning environments that utilize AI technologies to enhance student engagement and learning outcomes.

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