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The Level of Generative AI Use Among University Students and the Factors That Influence Its Use

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***Abstract*—Generative Artificial Intelligence (AI) applications that have recently emerged have now experienced very rapid development. The ability to think like humans is the advantage of these applications such as processing and producing text, images and even videos has opened up very broad opportunities in various fields. One of them is the use of generative AI in the world of education, currently students, especially students in the Jabodetabek area, have utilized the capabilities of generative AI applications to help complete assignments, then what factors cause these students to use generative AI applications and whether these students will plan to continue using generative AI. This study will answer these questions using the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Delone & McLean information system success model, and identify what factors influence the use of generative AI by analyzing variables such as performance expectancy, effort expectancy, social influence, and technology self-efficacy, system quality, information quality, digital literacy. The results of the study showed that the eight independent variables included in the research model influenced the intention to continue using it. Among the eight independent variables, the variables of performance expectations, system quality, and the efficacy of the technology itself are the biggest factors influencing the intention to continue use.**

***Keywords*—generative artificial intelligence, Unified Theory of Acceptance and Use of Technology (UTAUT), Delone & Mclean, higher education, Partial Least Squares-Structural Equation Modelling (PLS-SEM)**

I. Introduction

Technologies that emulate computer science, probability, statistics, and mathematical reasoning are known as artificial intelligence. World War II marked the beginning of technological advances in computing, allowing computers to perform increasingly complex tasks that were previously limited to human performance (Artificial Intelligence, 2024). AI progressed even faster after Alan Turing's groundbreaking study, "Computing Machinery and Intelligence," was published in 1950. In this book, Alan Turing—who is often called the "father of computer science"—asked the question, "Can machines think?" In response, he created the "Turing Test" to determine whether computers could demonstrate intelligence comparable to that of humans [1].

Generative Artificial Intelligence (Generative AI) is a type of artificial intelligence that can produce new content in the form of text, images, music, and videos [2] with examples of generative AI that are often used in Indonesia, namely Dall-E 2, Chat GPT-4, Copy.ai, Luminar [3]. Generative AI uses a neural network model to produce unique output, generative AI participates in producing unique and creative output, unlike traditional AI techniques that emphasize analysis and decision making. This technology provides innovation in many industries such as in the world of programming and creative arts [4]. With its more complex capabilities, generative AI has attracted a lot of attention in various disciplines and industries [5]. This is because generative AI helps individuals to complete work tasks and meet daily needs.

Technological advancements, widespread adoption, significant business benefits, and easier accessibility are driving the interest and influence of generative AI. According to Precedence Research, the global generative AI market is estimated to be worth USD 10.79 billion in 2022. The market is expected to grow at a compound annual growth rate (CAGR) of 27.02% from 2023 to 2032, or approximately USD 118.06 billion; this is shown in Fig. 1, which explains the development of generative AI.

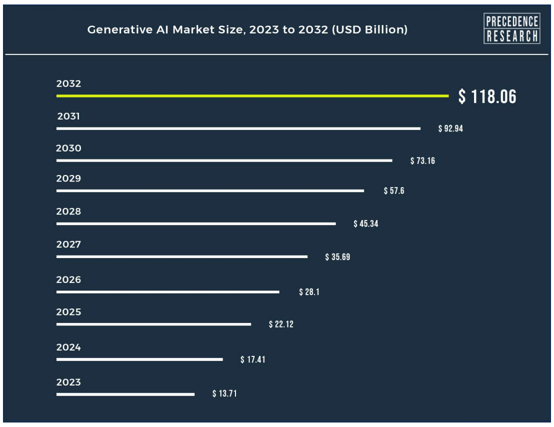

Fig. 1. Generative AI market size [6].

Given Precedence Research's estimate that the generative AI market will reach $118 billion by 2032, this study aims to understand how the adoption and utilization of this rapidly growing technology is reflected among college students, who are a potential and future user group of various generative AI applications.

AI has a lot of potential to improve college teaching. According to [7] smart tutoring systems can customize content, pace, and feedback for each student. A study investigating the use of AI in academic settings involved 1,000 undergraduate and graduate students. The results showed that 56% of students used AI tools to complete assignments or exams, another 40% stated that they had not used AI tools, and 4% chose not to answer [8].

The Fig. 2 shows that 56% of students have used AI to complete assignments or exams. Meanwhile, 41% of the students stated that they had not used AI, and 4% chose not

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to give an answer. At the same time, teachers give students specific tasks that involve using AI tools. More than 53% of the students said that they had been given coursework that required the use of AI as part of the assignment. According to Nam (2023), nearly 8 out of 10 students (79%) said that their teachers had explained the ethics and use of AI in class [8].

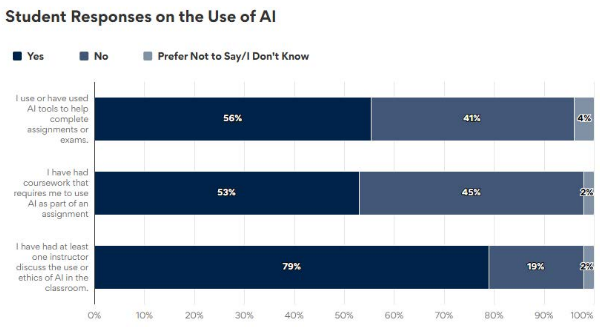

Fig. 2. Student responses on the use of AI [8].

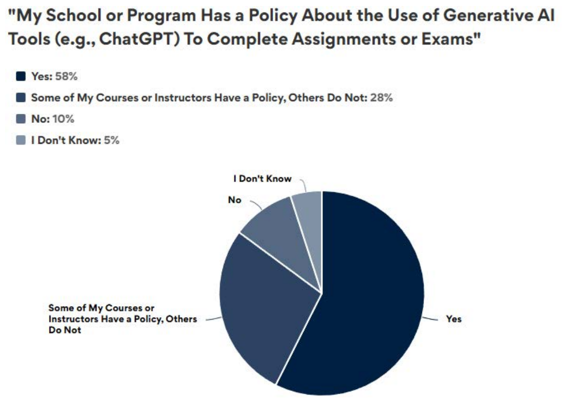

Fig. 3. How are colleges responding to the use of AI? [8].

Studies on the use of AI in academia [8] in Fig. 3 show how educational institutions respond to the use of AI. More than 58 percent of students said that their school or program has a policy that allows the use of AI tools to complete assignments or exams, while one in ten students (10%) said that their school or program does not have a policy that allows the use of AI, and five percent did not know.

Based on the above studies, generative AI is an important topic in current research because generative AI is an application that has not long emerged but its growth and use are very fast, which raises the question of what factors influence students to use generative AI in an educational environment. According to Kasneci [9], a deep understanding of the advantages and limitations of generative AI technology is very important in this digital era. This is because generative AI has the potential to transform various aspects of education, such as teaching and learning methods, curriculum development, and assessment and administration.

This study opens the door to better understand "What is the level of use of generative AI among university students and the factors that influence the use of generative AI?" can bring positive contributions in various fields, from learning to future research.Students should understand how generative AI tools are used due to their increasing sophistication and accessibility. In addition, they should understand the reasons for using these tools in academia.

1) What factors influence a user's decision to use generative AI?
2) Will users continue to use generative AI and advise others to do so?

This study can offer theoretical insights about the extent to which students use GPT chat and the primary drivers of such usage. Teachers and software developers can use this research as a reference to learn more about how students use GPT chat in the classroom and what factors affect their usage.

II. Literature Review

Artificial intelligence is a technology that mimics computer science such as probability, statistics, and mathematical reasoning. Advances in computing technology that began during the Second World War allow computers to perform increasingly complex tasks that previously could only be performed by humans [10].

Haglund [11] aimed to identify and explore factors influencing students acceptance and use of ChatGPT in academic settings. The researchers use the unified theory of acceptance and use technology (UTAUT) theory. The results showed that student acceptance and use lies in Behavioral Intention, while Behavioral Initiation is influenced by both Effort Expectancy and Performance Expectancy.

The study of Faruk *et al*. [12] aimed to explore the factors influencing the adoption and acceptance of ChatGPT for educational purposes by taking a hybrid psycho-technical approach by considering the technology such as perceived usefulness, ease of use and facilitating conditions. Considering the contextual such as perceived human value and novelty and also considering the psychological such as agreeableness, extraversion, openness, conscientiousness, and neuroticism of the use of ChatGPT.

Data were collected from a sample of students using ChatGPT in two Asian countries. Then the data were analyzed using Partial Least Squares Structural Equation Modeling. The results showed that among the technical factors, only perceived usefulness successfully predicted the use of ChatGPT. Both contextual factors such as humanness and novelty of use significantly explained the use of ChatGPT. Finally, among the psychological factors openness, adverse affect, and neuroticism determined the usage scenario, however, the last two factors were found to be negatively associated with the use of ChatGPT.

Menon and Shilpa [13] aimed to identify the factors influencing users acceptance and use of ChatGPT using Unified Theory of Acceptance and Usage Technology Model (UTAUT). The study results demonstrated that the four factors UTAUT along with two extended constructs, i.e. perceived interactivity and privacy concerns, can explain users' inter action and engagement with ChatGPT. The study also found that age and experience can moderate the impact of various factors on the use of ChatGPT. The theoretical and practical implications of the study were also discussed.

Strzelecki [14] aimed to explore the factors driving students' acceptance of ChatGPT in higher education. The study employs the unified theory of acceptance and use of technology (UTAUT2) theoretical model, with an extension of Personal innovativeness, to verify the Behavioral intention and Use behavior of ChatGPT by students. The study uses data from a sample of 503 Polish state university students. The Partial Least Squares Structural Equation Modelling (PLS-SEM) method is utilized to test the model. Results indicate that Habit has the most significant impact (0.339) on

Behavioral intention, followed by Performance expectancy (0.260), and Hedonic motivation (0.187). Behavioral intention has the most significant effect (0.424) on Use behavior, followed by Habit (0.255) and Facilitating conditions (0.188). The model explains 72.8% of the Behavioral intention and 54.7% of the Use behavior variance.

Generative Artificial Intelligence (GAI) is a machine learning system that is fully or partially supervised by probability and statistics, and is capable of learning the patterns and distribution of digital content through deep learning [15]. Generative AI is not limited to text, video, images, graphics, audio, or anything else [16, 17]

Generative Adversarial Network (GAN) uses two neural networks. For example, one generates an image of a human face and is referred to as a generator. The second, known as the discriminator, assesses the authenticity of the content generator, determining whether the image is real or fake. The network repeats the cycle of generating and discriminating content until the generator produces content that the discriminator cannot distinguish between real and synthetic [18].

Generative Pre Trained Transformer (GPT) to communicate with interlocutors at a certain conversational level through text or voice, GPT is a combination of natural language processing and Artificial Intelligence (AI). The use of GPT can help answer and provide appropriate responses to questions [19, 20]

It is a type of AI that can generate outputs that depend on inputs, context, and previous experience. Here are some generative AI applications that are very popular in several fields:

A. Chat GPT

Chatbots use natural language processing and artificial intelligence to communicate with interlocutors at a specific conversational level via text or voice [19]. They can also help provide appropriate responses to questions [20].

B. Dall-E

Dall-E was developed by OpenAI and released for the first time in January 2021. It creates new images using deep learning models and the GPT-3 language model. The purpose of this initial idea was to show how to use neural networks with Dall-E to generate new high-quality images [21].

C. Copy.AI

Copy.AI is a platform that uses Artificial Intelligence (AI) to automatically create text and content, as well as social network updates, blog updates and ads [22].

D. Luminar AI

Luminar AI is a software program that uses Artificial Intelligence (AI) to make photo editing easier and better for photographers and enthusiasts who want to produce high-quality photos without much manual editing [23].

1) UTAUT

Unified Theory of Acceptance and Use of Technology (UTAUT) Venkatesh, 2003 created the Unified Theory of Acceptance and Use of Technology, which brings together various models that focus on user acceptance of technology and innovation [24]. This method can also be used to show the important elements that encourage people to use certain technologies under certain conditions [25].

2) Theory Delone & McLean

According to McLean's theory, there are six main dimensions of IS success: user satisfaction, information quality, system quality, usage, individual effects, and organizational effects [26]. According to general system information theory, if end users are satisfied with the system and make good use of it, quality and information quality can be positively correlated with system performance.

III. METHOD

This study will investigate the methods and approaches to be used in this research. Based on the research conducted by Nam [8] which showed that most undergraduate and graduate students use generative AI tools to complete assignments and exams, this study wants to investigate the level of use of generative AI tools among students and the factors that influence the use of such tools.

A. Study Framework

This research aims to find out how often students use generative AI and what drives them to use the tool, as generative AI can be a very useful resource. In Fig. 4, the following is the framework for this research.

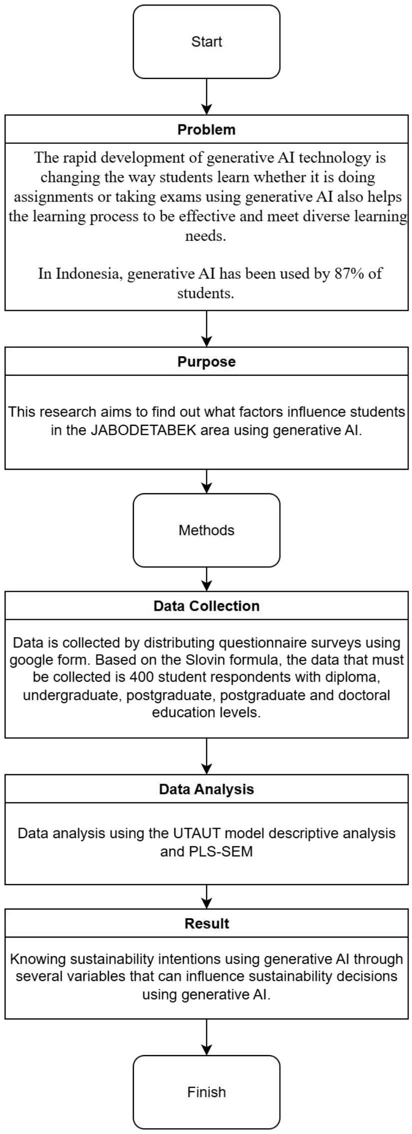

Fig. 4. Study framework.

B. Research Model

This study aims to determine the extent to which students accept and use generative AI in the classroom and its important aspects. The theory of technology acceptance model (UTAUT) is used to evaluate the adoption and utilization of technology. The main purpose of this study is to collect useful data to help the use of generative artificial intelligence in education in the future. Quantitative research will be used to evaluate the level of use of generative AI and the biggest factors affecting the acceptance and use of AI by students in higher education. To obtain systematic data, the survey method will be used. It is also suitable for research that requires in-depth data collection and analysis. Surveys are also a popular research method in the field of information systems [27]. This study aims to determine the future intention to use generative AI and Fig. 5 below is the model for this research.

Fig. 5. Research model.

For this study, several variables will be used, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Information Quality (IQ), System Quality (SQ), and Continuous Intention to Use (CIU), as described in the last UTAUT model and Delon & McLean's theory. The theoretical explanation for each of these variables is summarized in the following Table 1.

Table. 1. Variable research

Variables	Theoretical Explanation
Performance Expectations	According to Venkatesh, 2003 [24] expected results are defined as how using the system will make work easier for someone.
Effort Expectancy	According to Venkatesh, 2003 [24] expectancy of effort defines the way a system can be used easily. It is influenced by age, gender, and experience of the main moderator, especially at the beginning of technology use.
Social Influance	According to Venkatesh, 2003 [24] Social influence defines how important a person's opinion or social factors are when it comes to the use of a technology.
Facilitating Conditions	According to Venkatesh, 2003 [24] facilitating conditions indicate confidence that the technological foundation and system organization have been created to facilitate its use.
Information Quality	The quality of information perceived by users can be measured by information quality variables [28, 29]
System Quality	System quality variables consist of various indicators, including security, access speed (access speed), reliability (reliability), ease of use (ease of use), and flexibility (flexibility). These variables can be used to measure system quality [26].
Digital Literacy	How deep students' digital literacy is, especially their understanding of generative AI, will determine how they view and interact with this technology [30].
Technology Self-Efficacy	Technology self-efficacy is the belief that one can use technology to accomplish goals and succeed [31].
Continuance Intention to Use	The continuity of use variable is used to measure how consistently a person uses the system or technology they receive [29].

C. Research Hypothesis

Several variables, including performance expectancy, effort expectancy, social influence, facilitating conditions, decision to use, and continuous intention to use artificial intelligence, are included in the following hypotheses, as explained in Table 2:

Table. 2. Hypotheses table

Hypothesis	Hypothesis Effect
Hypothesis (H1)	PE has a significant effect on CIU
Hypothesis (H2)	EE has a significant effect on CIU
Hypothesis (H3)	SI has a significant effect on CIU
Hypothesis (H4)	FC has a significant effect on CIU
Hypothesis (H5)	IQ has a significant effect on CIU
Hypothesis (H6)	SQ has a significant effect on CIU
Hypothesis (H7)	DL has a significant effect on CIU
Hypothesis (H8)	TSE has a significant effect on CIU

D. Indicator Measurement

In order for variable measurements to be carried out correctly, appropriate indicators are required. Indicators are a description of the questionnaire statements that will be used in this study. All indicators for each variable are shown in the Table 3.

Table 3. Variable indicator

Variable	Number of source	Indicator	Source
Performance Expectancy	4	Effectiveness of using generative AI	[32]
		Trustworthiness using generative AI	
		Efficiency of using generative AI	
Effort Expectancy	4	Ease of using generative AI	[33]
		Using generative AI saves time	
		Ease of using generative AI for beginners	
		Using generative AI can shorten task time	
Social Influance	3	Influence of friends to use generative AI	[24]
		Influence from some conversations in the neighborhood	

		Influence on other people's experiences	
Facilitating Conditions	3	Help to deal with problems with the system	[34]
		There is new knowledge that I get	
		There is a way to use generative AI	
Digital Literacy	4	Knowing how content can be produced with generative AI	[30]
		Evaluation of generative AI's output quality and response accuracy	
		Being aware of and comprehending the creation of generative AI	
		It may be simpler to use generative AI if one has a basic understanding of AI technology.	
Technology Self-Efficacy	4	belief in utilizing AI to accomplish objectives	[35]
		Self-assurance in utilizing generative AI to do assignments	
		Using generative AI to solve problems	
		Interest in incorporating generative AI into educational exercises.	
Continuance Intention To Use	3	Plans to continue using generative AI in the future	[29]
		I believe the generative AI will continue to improve and provide accurate answers.	
		Plans to use generative AI are not only in the academic field	
		Plans to use generative AI for the next task	

E. Data Collection and Preparation Methods

Survey research is a method of data collection that uses and distributes questionnaires, which consist of a series of questions or statements arranged in a predetermined order. By conducting a questionnaire survey, it is expected to obtain relevant information to help solve research problems. The Likert scale size is used to represent respondents' answers in the form of quantitative data 1 strongly disagree, 2 disagree, 3 neutral, 4 agree, and 5 Strongly agree.

F. Population and Sample

While the sample is merely a portion of the population, research involves the entire population [36] 940,255 students attend DKI Jakarta, per the 2022 Higher Education Database. The full population will not be examined in this study. In order to guarantee that the sample is accurately representative of the community, researchers only employ samples drawn from the population due to a lack of resources, staff, and time. The population is measured in this study using the Slovin formula. The display of the inaccuracy allowance is measured at a 5% sample error level. The following formula will be used:

$$n = \frac{N}{1 + N(e)^2}$$

With a population of 940,255 students and a standard error of 5%, the number of samples sought is as follows:

$$n = \frac{940{,}255}{1 + 940{,}255(0.05)^2} = 399{,}82991$$

So based on the calculations above, a sample of 400 students is needed. An online survey conducted via the Google Forms platform was used to collect this sample and using the proportional stratified random sampling technique.

G. Description Analysis

Descriptive analysis of variables will be carried out after the sample demographic analysis is complete. The purpose of this analysis is to determine the percentage of selected respondents' answers, which are represented in percentage form, as well as their average answers to each question or statement in the questionnaire. Additionally, the standard deviation will be calculated.

H. Outer Model Analysis

The outer model, also known as the measurement model, explains how the indicators and observed variables interact with each other [37].

I. Hypothesis Testing

Researchers use the following equation to analyze the data that has been collected.

CIU = β_0+β_1 PE+β_2 EE+β_3 SI+β_4 FC+β_5 IQ+β_6 SQ+β_7 DL+β_8 TSE+β_8 CIU+ϵ_2

These hypotheses, which are detailed in Table 4, are then used to test the equation.

Table. 4. Hypothesis

Hypothesis	Hypothesis Formulation
Hypotheses 1	H0 : $\beta 1 = 0$ There is no influence between Performance Expectancy and Continuance Intention to Use in using generative AI.
	HA : $\beta 1 \neq 0$ Performance Expectancy significantly influences Continuance Intention to Use in using generative AI.
Hypotheses 2	H0 : $\beta 2 = 0$ There is no influence between Effort Expectancy and Continuance Intention to Use in using generative AI.
	HA : $\beta 2 \neq 0$ Effort Expectancy significantly influences Continuance Intention to Use in using generative AI.
Hypotheses 3	H0 : $\beta 3 = 0$ There is no influence between Social Influence and Continuance Intention to Use in using generative AI.
	HA : $\beta 3 \neq 0$ Social Influence significantly influences Continuance Intention to Use in using generative AI.
Hypotheses 4	H0 : $\beta 4 = 0$ There is no influence between Facilitating Conditions and Continuance Intention to Use in using generative AI.
	HA : $\beta 4 \neq 0$ Facilitating Conditions significantly influence Continuance Intention to Use in using generative AI.
Hypotheses 5	H0 : $\beta 5 = 0$ There is no influence between Information Quality and Continuance Intention to Use in using generative AI.
	HA : $\beta 5 \neq 0$ Information Quality significantly affects Continuance Intention to Use in using generative AI.
Hypotheses 6	H0 : $\beta 6 = 0$ There is no influence between System Quality and Continuance Intention to Use in using generative AI.
	HA : $\beta 6 \neq 0$ System Quality significantly influences Continuance Intention to Use in using generative AI.
Hypotheses 7	H0: $\beta 7 = 0$ There is no influence between Digital Literacy and Continuance Intention to Use in using generative AI.
	HA: $\beta 7 \neq 0$ Digital Literacy significantly influences Continuance Intention to Use in using generative AI.

Hypotheses 8	H0: β7 = 0 There is no influence between Technology Self-Efficacy and Continuance Intention to Use in using generative AI.
	HA: β7 ≠ 0 Technology Self-Efficacy significantly influences Continuance Intention to Use in using generative AI.

IV. Results and Discussions

Partial Least Square (PLS) was used for hypothesis testing in the quantitative analysis of this study. The variables included in this study include performance expectancy, effort expectancy, social influence, conducive conditions, digital literacy, technological self-efficacy, decision to use, and intention to use generative AI continuously. The data collected in this study were 600 respondent data after data cleaning only 400 data were collected.

A. Respondent Demographics

1) Profile of respondents based on gender and based on level education

Fig. 6 illustrates that the proportion of females is higher than that of males. There were a total of 273 female responses (68%), compared to 127 male respondents (32%).

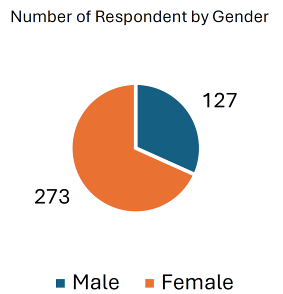

Fig. 6. Number of respondents by gender.

Fig. 7 shows the level of generative AI education in higher education as follows: 57 respondents (14%) are diploma level, 319 respondents (75%) the majority of generative AI users are at the undergraduate level, 48 respondents (11%) are at the master's level, and only 1 respondent (0%) is at the doctoral level. Based on this data, it can be concluded that the majority of generative AI users are at the undergraduate level.

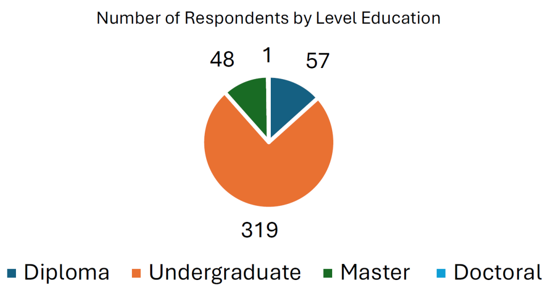

Fig. 7. Number of respondents by education level.

2) Frequently used generative ai applications

These four generative AI apps are frequently used in Indonesia. According to survey results, as displayed in Fig. 8, the Chat GPT app is frequently used by students, with 384 users overall. In contrast, Dall-E, Copy.AI, and Luminar.AI are used by only 34 respondents, 95 respondents, and 64 respondents, respectively. Our survey revealed that the majority of 67% of respondents are active users of the ChatGPT application, indicating a very high adoption rate of the application compared to other applications suggested in the research survey.

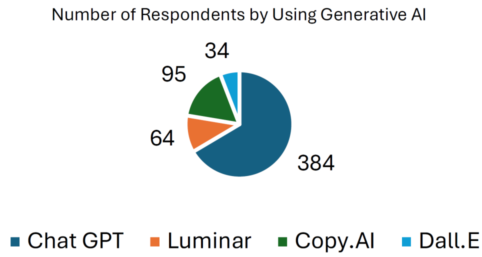

Fig. 8. Generative AI apps user.

B. Descriptive Analysis

Descriptive analysis is used to describe the respondents' assessment or perception of the questionnaire questions related to the research variables. This study uses averages and standard deviations.

- **Performance Expectancy (PE)**

This variable is used to measure the extent to which individuals perceive that using a system can improve their performance efficiently and effectively. The following are respondents' answers regarding this variable statement can be seen in Table 5.

Table 5. Analysis of performance expectancy data description

Variables	Mean	Standard Deviation
PE 1	4.19	0.848
PE 2	4.178	0.936
PE 3	4.218	0.857
PE4	4.213	0.826
Total	4.19975	0.86675

The performance expectancy variable's statements received from respondents had an average score of 4.17 to 4.21, with a total average score of 4.19 and a standard deviation of 0.86, as shown in Table 5 above. According to the aforementioned data, the majority of survey participants concur with the claims, indicating that users believe utilizing the generative artificial intelligence program can enhance performance in an efficient and effective manner.

- **Effort Expectancy (EE)**

This variable measures how much effort users put into using a system. The following are the respondents' answers regarding this variable statement can be seen in Table 6.

Table 6. Analysis of effort expectancy data description

Variables	Mean	Standard Deviation
EE1	4.317	0.788
EE2	4.25	0.798
EE3	4.23	0.835
EE4	4.213	0.786
Total	4.2525	0.80175

Based on Table 6 above, it can be seen that the respondents' answers to the statements submitted for the effort expectancy variable have an average of 4.21 to 4.31 with a total average value of 4.25 and a standard deviation of 0.80. Based on the data above, it shows that the majority of respondents agree with the statements in the survey, which means that respondents agree that generative ai can be easy to use.

- **Social Influance (SI)**

This variable measures the extent to which social influence can influence individuals to use generative AI. The following are respondents' answers regarding this variable statement can be seen in Table 7.

Table 7. Analysis of social influence data description

Variables	Mean	Standard Deviation
SI1	3.98	0.974
SI2	4.14	0.919
SI3	4.178	0.875
SI4	4.058	0.924
Total	4.089	0.923

Based on Table 7 above, it can be seen that the respondents' answers to the statements submitted for the social influance variable have an average of 3.98 to 4.17 with a total average value of 4.08 and a total standard deviation of 0.92. Based on the data above, it shows that the majority of respondents agree that social influence can influence the decision to use generative AI.

- **Facilitating Conditions**

This variable measures the extent to which people believe the system infrastru CIU re can facilitate the use of generative AI. The following are respondents' answers regarding this variable statement can be seen in Table 8.

Table 8. Analysis of facilitating conditions data description

Variables	Mean	Standard Deviation
FC1	4.215	0.767
FC2	4.16	0.821
FC3	4.173	0.763
Total	4.18566667	0.77833333

Based on Table 8 above, it can be seen that the respondents' answers to the statements submitted for the facilitating conditions variable have an average of 4.16 to 4.21 with a total average value of 4.18 and a total standard deviation of 0.77. Based on the data above, it shows that respondents agree with the statements given, which means that the generative ai system infrastructure can be used to facilitate user needs.

- **Information Quality**

This variable measures the extent to which people believe in the quality of information that generative ai can help users. The following are respondents' answers regarding this variable statement can be seen in Table 9 below.

Table 9. Analysis of information quality data description

Variables	Mean	Standard Deviation
IQ1	3.908	0.927
IQ2	4.005	0.957
IQ3	4.088	0.875
IQ4	4.08	0.868
Total	4.02025	0.90675

Based on Table 9 above, it can be seen that the respondents' answers to the statements submitted for the information quality variable have an average of 3.90 to 4.08 with a total average value of 4.02 and a total standard deviation of 0.90. Based on the data above, it shows that respondents agree with the statement given, which means that the information provided by generative ai is acceptable.

- **System Quality**

This variable measures the extent to which system quality can meet user needs. The following are the respondents' answers regarding this variable statement can be seen in Table 10.

Based on Table 10, it can be seen that the respondents' answers to the statements submitted for the system quality variable had an average of 3.52 to 4.49 with a total average value of 4.31 and a total standard deviation of 0.78. Based on the data above, it shows that respondents agree with the statements given, which means that respondents are willing to try the generative ai system.

Table 10. Analysis of system quality data description

Variables	Mean	Standard Deviation
SQ1	4.37	0.709
SQ2	3.683	1.132
SQ3	4.522	0.703
SQ4	4.495	0.725
SQ5	4.51	0.667
Total	4.316	0.7872

- **Digital Literacy**

This variable measures the extent to which an individual's ability to understand a system. The following are respondents' answers regarding this variable statement can be seen in Table 11.

Table 11. Analysis of digital literacy data description

Variables	Mean	Standard Deviation
DL1	4.08	0.908
DL2	4.162	0.843
DL3	3.87	1.011
DL4	4.28	0.746
Total	4.098	0.877

Based on Table 11, it can be seen that the respondents' answers to the statements submitted for the digital literacy variable have an average of 3.87 to 4.28 with a total average value of 4.09 and a total standard deviation of 0.87. Based on the data above, it shows that respondents agree with the statements given, which means that respondents understand literacy in using the system.

- **Technology Self-Efficacy**

This variable measures how much confidence to complete tasks using technology. The following are respondents answers regarding this variable statement can be seen in Table 12.

Table 12. Analysis of technology self-efficacy data description

Variables	Mean	Standard Deviation
TSE1	4.088	0.869
TSE2	4.077	0.952
TSE3	4.075	0.913
TSE4	4.145	0.827
Total	4.09625	0.89025

Based on Table 12 above, it can be seen that the respondents' answers to the statements submitted for the technology self-efficacy variable have an average of 4.07 to 4.08 with a total average value of 4.09 and a total standard deviation of 0.89. Based on the data above, it shows that respondents agree with the statements given, which means that respondents use generative ai to complete tasks.

- **Continuance Intention to Use**

This variable is used to measure individual decision plans to use the system in the future. The following are respondents' answers regarding this variable statement can be seen in Table 13.

Table 13. Analysis of continuance intention to use data description

Variables	Mean	Standard Deviation
CIU1	4.043	0.914
CIU2	4.09	0.841
CIU3	4.152	0.877
CIU4	4.2	0.849
Total	4.18566667	0

Based on Table 13 above, it can be seen that respondents' answers to the statements submitted for the continuance intention to use variable have an average of 4.04 to 4.20 with a total average value of 4.18 and a total standard deviation of 0. Based on the data above, it shows that respondents agree with the statements given, which means that respondents are willing to use generative ai in the future.

C. Outer Model Measurement Assessment

1) Validity, reliability and convergence testing

PLS-SEM validity was assessed using measures like outer loadings (≥ 0.7) [38], composite reliability (≥ 0.7) [39], Cronbach's alpha (≥ 0.7) [40], and Average Variance Extracted (AVE) (≥ 0.5) [39]. Convergent validity was established through AVE, and discriminant validity was assessed using the Fornell-Lacker criterion. These findings suggest that the PLS-SEM model effectively captures the relationships within the data.

According to Table 14, the PLS-SEM analysis results of this study show that one indicator cannot be used because it is below the minimum recommended value (0.6 or 0.7) in the SQ2 indicator (0.561), so the indicator should be removed. When the indicator is removed, the calculation will be performed. The purpose of recalculation is to obtain results that are different from the previous results.

Table 14. Outer model

Indicator Variables	Outer Loadings	Cronbach Alpha	Composite Reliability (rho_a)	AVE	Valid
CIU 1<−CIU	0.862	0.87	0.911	0.72	Valid
CIU 2<−CIU	0.88				Valid
CIU 3<−CIU	0.827				Valid
CIU 4<−CIU	0.823				Valid
DL1<−DL	0.857	0.827	0.885	0.659	Valid
DL2<−DL	0.816				Valid
DL3<−DL	0.781				Valid
DL4<−DL	0.792				Valid
EE1<−EE	0.757	0.781	0.858	0.602	Valid
EE2<−EE	0.766				Valid
EE3<−EE	0.802				Valid
EE4<−EE	0.778				Valid
FC1<−FC	0.861	0.796	0.88	0.711	Valid
FC2<−FC	0.844				Valid
FC3<−FC	0.823				Valid
IQ1<−IQ	0.891	0.879	0.917	0.735	Valid
IQ2<−IQ	0.857				Valid
IQ3<−IQ	0.796				Valid
IQ4<−IQ	0.883				Valid
PE1<−PE	0.884	0.839	0.892	0.675	Valid
PE2<−PE	0.786				Valid
PE3<−PE	0.835				Valid
PE4<−PE	0.777				Valid
SI1<−SI	0.811	0.863	0.907	0.708	Valid
SI2<−SI	0.849				Valid
SI3<−SI	0.851				Valid
SI4<−SI	0.855				Valid
SQ1<−SQ	0.864	0.801	0.867	0.572	Valid
SQ2<−SQ	0.498				Invalid
SQ3<−SQ	0.758				Valid
SQ4<−SQ	0.822				Valid
SQ5<−SQ	0.785				Valid
TSE1<−TSE	0.853	0.874	0.914	0.726	Valid
TSE2<−TSE	0.87				Valid
TSE3<−TSE	0.833				Valid
TSE4<−TSE	0.852				Valid

Table 15 shows, after removing the SQ2 indicator and recalculating, the value of the outer addition of the SQ indicator changes, but does not affect the value of other indicators; thus, it can be concluded that the SQ2 indicator does not affect the value of other indicators.

Table 15 shows the positive correlation between each indicator and its variable, which has a value above 0.5. The values in the previous table show that each variable shows a value of more than 0.6 or 0.7, which indicates that the survey data is already reliable [38]. Therefore, the data can be considered reliable.

Table 15. Outer model

Indicator Variables	Outer Loadings	Cronbach Alpha	Composite Reliability (rho_a)	Average Variance Extracted	Valid
CIU 1<−CIU	0.862	0.829	0.835	0.745	Valid
CIU 2<−CIU	0.88				Valid
CIU 3<−CIU	0.827				Valid
CIU 4<−CIU	0.823				Valid
DL1<−DL	0.857	0.828	0.838	0.751	Valid
DL2<−DL	0.816				Valid
DL3<−DL	0.781				Valid
DL4<−DL	0.792				Valid
EE1<−EE	0.757	0.781	0.796	0.601	Valid
EE2<−EE	0.766				Valid
EE3<−EE	0.802				Valid
EE4<−EE	0.778				Valid

FC1<–FC	0.861	0.796	0.797	0.711	Valid
FC2<–FC	0.844				Valid
FC3<–FC	0.823				Valid
IQ1<–IQ	0.891	0.879	0.882	0.735	Valid
IQ2<–IQ	0.857				Valid
IQ3<–IQ	0.796				Valid
IQ4<–IQ	0.884				Valid
PE1<–PE	0.884	0.839	0.805	0.57	Valid
PE2<–PE	0.786				Valid
PE3<–PE	0.835				Valid
PE4<–PE	0.777				Valid
SI1<–SI	0.811	0.863	0.844	0.675	Valid
SI2<–SI	0.849				Valid
SI3<–SI	0.851				Valid
SI4<–SI	0.855				Valid
SQ1<–SQ	0.864	0.801	0.864	0.708	Valid
SQ3<–SQ	0.804				Valid
SQ4<–SQ	0.86				Valid
SQ5<–SQ	0.82				Valid
TSE1<–TSE	0.853				Valid
TSE2<–TSE	0.87	0.874	0.877	0.726	Valid
TSE3<–TSE	0.833				Valid
TSE4<–TSE	0.852				Valid

1) Discrimnant validity

The discriminant validity test is used to determine whether the validity values of two variables are different. For each latent variable measured, each indicator must have a greater load. The cross-loading results are shown in the following table. Each indicator shows a high level of discriminant validity, as indicated by its value relationship with other variables.

Table 16. Cross loading

Variables	CTU	DL	EE	FC	IQ	PE	SI	SQ	TSE
CTU1	0.862	0.587	0.588	0.566	0.66	0.536	0.475	0.736	0.634
CTU2	0.88	0.594	0.585	0.519	0.679	0.534	0.557	0.669	0.582
CTU3	0.827	0.549	0.549	0.562	0.575	0.508	0.451	0.633	0.552
CTU4	0.823	0.553	0.577	0.481	0.623	0.465	0.567	0.641	0.559
DL1	0.63	0.526	0.577	0.551	0.549	0.492	0.525	0.642	0.63
DL2	0.539	0.479	0.575	0.541	0.519	0.435	0.447	0.592	0.539
DL3	0.517	0.511	0.505	0.592	0.522	0.545	0.342	0.593	0.517
DL4	0.534	0.469	0.495	0.395	0.566	0.411	0.586	0.529	0.534
EE1	0.462	0.757	0.515	0.433	0.471	0.492	0.474	0.449	0.462
EE2	0.452	0.766	0.542	0.483	0.523	0.533	0.41	0.527	0.452
EE3	0.581	0.802	0.55	0.448	0.597	0.444	0.458	0.546	0.581
EE4	0.572	0.778	0.582	0.584	0.611	0.503	0.448	0.612	0.572
FC1	0.572	0.635	0.861	0.536	0.588	0.543	0.548	0.58	0.572
FC2	0.55	0.547	0.844	0.564	0.525	0.509	0.394	0.563	0.55
FC3	0.59	0.602	0.823	0.481	0.522	0.48	0.507	0.563	0.59
IQ1	0.576	0.579	0.547	0.891	0.502	0.538	0.325	0.606	0.576
IQ2	0.505	0.486	0.481	0.857	0.463	0.494	0.287	0.547	0.505
IQ3	0.493	0.51	0.534	0.796	0.44	0.469	0.401	0.541	0.493
IQ4	0.569	0.579	0.576	0.884	0.496	0.465	0.447	0.603	0.569
PE1	0.681	0.641	0.56	0.492	0.884	0.55	0.547	0.654	0.681
PE2	0.616	0.543	0.477	0.472	0.786	0.455	0.329	0.589	0.616
PE3	0.61	0.591	0.521	0.387	0.835	0.495	0.564	0.579	0.61
PE4	0.546	0.576	0.576	0.477	0.777	0.46	0.535	0.567	0.546
SI1	0.502	0.513	0.467	0.464	0.531	0.811	0.44	0.529	0.502
SI2	0.526	0.561	0.55	0.513	0.488	0.849	0.4	0.568	0.526
SI3	0.478	0.519	0.48	0.472	0.505	0.851	0.36	0.509	0.478
SI4	0.518	0.528	0.539	0.478	0.491	0.855	0.382	0.547	0.518
SQ1	0.626	0.584	0.57	0.441	0.615	0.482	0.864	0.535	0.626
SQ3	0.447	0.42	0.409	0.3	0.439	0.329	0.804	0.388	0.447
SQ4	0.486	0.433	0.443	0.329	0.448	0.362	0.86	0.449	0.486
SQ5	0.421	0.464	0.478	0.329	0.472	0.373	0.82	0.429	0.421
TSE1	0.67	0.633	0.619	0.593	0.686	0.59	0.546	0.853	0.67
TSE2	0.703	0.567	0.54	0.613	0.626	0.552	0.383	0.87	0.703
TSE3	0.652	0.563	0.57	0.558	0.554	0.533	0.444	0.833	0.652
TSE4	0.669	0.598	0.574	0.521	0.616	0.51	0.49	0.852	0.669

Table 16 indicates that there is no need to resample or alter questions from related variables if each variable's cross loading value is dominant or higher than other variables. It is expected that the cross loading value will be more than 0.7.

2) Inner model

The inner model is evaluated in three stages to predict the causal relationship between variables. First, there is no multicollinearity between variables with the inner Variable Inflated Factor (VIF) measure when the Variance Inflated Factor (VIF) value is less than 5 [26]. The p value, or t statistic value, is tested in both hypothesis tests. If the p value is less than 0.05 or the calculated t-statistic, or t-table, is greater than 1.96, then the variables show a noteworthy correlation with each other. The predicted path coefficients and 95% confidence intervals also need to be changed. The influence of direct factors with criteria at the structural level is indicated by square f values of 0.02 low, 0.15 medium, and 0.35 high.According to [26].

a) Variance inflated factors

Determine whether there is multicollinearity between variables before evaluating the structural model hypothesis. A statistical measure of inner VIF with a value <5 indicates no multicollinearity between variables [26]. Table 17 shows the results of the low value of multicollinearity between variables.

Table 17. Variance inflated factors

Variable	VIF
DL > CIU	2.763
EE > CIU	2.978
FC > CIU	2.675
IQ > CIU	2.256
PE > CIU	2.888
SI > CIU	2.049
SQ > CIU	1.861
TSE > CIU	3.308

b) Hypothesis testing

Statistically testable statements about the relationship between two or more research variables are known as statistical hypotheses. Hypothesis testing is done to find out whether the observations or data obtained are in accordance with the hypothesis. The test results determine whether the hypothesis is accepted or rejected, which in turn will support or reject different hypotheses. If the *p* value is less than 0.05, the hypothesis is considered significant. Conversely, if the *p* value is more than 0.05, the hypothesis is considered insignificant [26]. The following Table 18 shows the table used to test the hypothesis.

Based on Table 18, the results of the hypothesis testing, as presented in Table 19, are as follows:

Table 18. Hypothesis testing

Hypothesis	Path Coefficient	p-value	95% Confident Interval Path Coefficient		F Square
			MIN	MAX	
Performance Expectancy> Continuance Intention to Use	0.251	0.008	0.068	0.431	0.078
Effort Expectancy> Continuance Intention to Use	0.006	0.924	−0.11	0.134	0
Social Influence> Continuance Intention to Use	0.652	0.652	−0.076	0.116	0.001
Facilitating Conditions > Continuance Intention to Use	0.134	0.134	−0.034	0.218	0.012
Information Quality> Continuance Intention to Use	0.081	0.160	−0.032	0.191	0.01
System Quality> Continuance Intention to Use	0.12	0.004	0.038	0.2	0.027
Digital Literacy > Continuance Intention to Use	0.05	0.402	−0.056	0.174	0.003
Technology Self Efficacy> Continuance Intention to Use	0.369	0	0.216	0.502	0.147

Table 19. Hypothesis

Hypothesis	Explanation
H1:	Continuance intention to use are greatly influenced by performance expectations. Performance expectations significantly influence the continuance intention to use, according to the hypothesis test results, which include a path coefficient of 0.251 and a p-value of 0.408 less than 0.05. Within the 95% confidence interval, the extent to which generative AI applications influence users' choices ranges from 0.068 to 0.431. However, as performance expectations have a significant impact, the generative AI application system should be improved (0.431).
H2:	Effort expectancy has an insignificant influence on continuance intention to use. The results of the hypothesis test are **rejected**, indicating that there is an insignificant influence between the effort expectation variable on the continuance intention to use, with a path coefficient (0.006) and p-value (0.924 greater than 0.05). Within the 95% confidence interval, the magnitude of user influence to decide to use generative AI applications ranges between −0.011 and 0.134.
H3:	Social influance has an insignificant influence on the continuance intention to use. The results of the hypothesis test are **rejected** and show that the social influence variable does not have a significant influence on continuance intention to use, with a path coefficient (0.652) and p-value (0.652 > 0.05). Within the 95% confidence interval, the magnitude of user influence on the decision to use generative AI applications ranges from −0.076 to 0.116. However, the social influence in improving the decision to use generative AI is low, with f-square = 0.001
H4:	Facilitating conditions have an insignificant influence on the continuance intention to use. The results of the hypothesis test are **rejected**, indicating that there is an insignificant influence between variables that support usage decisions on continuance intention to use, with a path coefficient of 0.134 and a p-value of 0.134 which is greater than 0.05. Within the 95% confidence interval, the influence of users on the decision to use generative AI applications ranges from −0.008 to 0.235. However, the variable that helps improve the continuance intention to use has a low influence, which is only 0.218 (f-square).
H5:	Information quality has an insignificant influence on the continuance intention to use. The hypothesis test results are **rejected** and show that information quality has a insignificant influence on continuance intention to use, with a path coefficient (0.081) and p-value (0.160 greater than 0.05). Within the 95% confidence interval, the influence of users to decide to use generative AI applications between −0.032 and 0.191.
H6:	System quality has an significant effect on the continuance use intention. The results of the hypothesis test were **accepted**, indicating an significant influence between the system quality variables on continuance use intention, with a path coefficient (0.12) and p-value (0.004 less than 0.05). Within the 95% confidence interval, the influence of users on the continuance use intention generative AI applications ranges from 0.038 to 0.2. However, the system quality variable does have a significant effect, i.e. (f-square = 0.027).
H7:	Digital literacy has an insignificant influence on the decision to use. The hypothesis test results are **rejected** and show that there is no significant influence between digital literacy variables on usage decisions, with a path coefficient (0.369) and p-value (0.402 greater than 0.05). Within the 95% confidence interval, the influence of users on the decision to use generative AI applications ranges from −0.056 to 0.174. However, the system quality variable has a smaller influence, which is only 0.003 (f-square).
H8	Technology self-efficacy has a significant influence on the decision to use. The results of the hypothesis test are **accepted** and show that self-success technology has a significant influence on usage decisions with a path coefficient (0.369) and p-value (0 less than 0.05). Within the 95% confidence interval, the magnitude of user influence to use generative AI applications lies between 0.216 and 0.502. However, the personal technology effectiveness variable has a significant effect, with f-square = 0.125.

a) R-Square

Regression analysis assesses how well a regression model fits the observed data using the R-squared (R2) statistical measure. The success of the independent variables-factors that influence the dependent variable-explains the variation in the dependent variable [24]. According to [26], the r square value is 0.19 which is low, 0.33 which is medium, and 0.67 which is high. The r squared Table 20 follows:

Table 20. Hypothesis testing

Variable	R *Square*
Continuance Intention to Use	0.719

Based on Table 20 above, it can also be seen that the R2 value of the continuance intention to use variable has a high value of 0.719. this shows that the variables that are significant to the continuance intention to use variable, namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Information Quality (IQ), System Quality (SQ), Digital Literacy (DL), Technology Self-Efficacy (TSE), Continuance Intention to Use (CIU).

b) Discussion

Students' decision to use generative AI is strongly influenced by performance expectations, system quality, and technology self-efficacy, according to this study, which used Smart PLS the variables of social influence, facilitating conditions, and effort expectancy had no significant effect on sustainable intention to use. The importance of performance expectations, system quality, and technology self-efficacy, in determining sustained use is highlighted by these findings, which are somewhat consistent with previous research. To promote students' continued acceptance of generative AI, these findings highlight the need for developers to concentrate on improving user experience and guaranteeing the production of high-quality information.

V. Conclusion

The results of the study indicate that the eight independent variables included in the research model affect the intention to continue. Among the eight independent variables, the variables of performance expectations, system quality, and technology efficiency itself are the largest factors influencing the intention to continue to use. In addition, this study found that the decision to use has a significant influence on the use of generative AI. The findings of this study are that 78% of respondents will continue to use generative AI applications while the remaining 22% of respondents may be hesitant or even will not continue to use generative AI.

This study has limitations, namely the geographical limitations of the research sample, which only includes students in Jabodetabek, can affect the representation of the views and experiences of students from other regions in Indonesia regarding the use of Generative AI. The limitations of time and research resources limit the ability to conduct studies that can track changes in the use of Generative AI and its impacts over a long period of time. This study may not have fully explored all potential variables that may influence the continued use of Generative AI. The rapidly evolving nature of Generative AI can be a limitation, as application features and capabilities can change rapidly, affecting student perceptions and usage over time.

Further research is suggested to expand the geographical scope and involve students from various regions in Indonesia to increase the generalizability of the findings. Future studies can use mixed research methods (qualitative and quantitative) to gain a deeper understanding of students' experiences and perceptions regarding the use of generative AI.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Authors contribution, Berton Atallah Brahmacari Parikesit: Conceptualization, Methodology, Data Collection, Data Analysis, Writing-Original Draft, Methodology, Validation. Tuga Mauritsius: Expert Guidance and Valuable Input throughout the article writing process, and he reviewed and refined the manuscript draft. All authors had approved the final version.

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