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Original Article

Influence Analysis of Generative AI Usage Factors on Software Developers

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Abstract - *The growth of the Artificial Intelligence (AI) ecosystem has recently become increasingly crowded with the birth of generative AI technology, which has rapidly triggered changes in the way people communicate, create and do their daily work. Generative AI can help software development complete lines of code, write suggestions according to the correct writing structure, and even provide questions and answers according to the discussed context. However, according to McKinsey & Company in a survey in 2023, although the use of generative AI in the technology industry is relatively high compared to other industries, regular use for work needs is recorded at only 14% [1]. Despite many benefits and potential, generative AI has risks that are no less great, namely regarding security factors such as data bias, dependency and violations related to privacy data and leaks of company confidential information. So, how do software developers in Indonesia accept the presence of generative AI technology? This study involved respondents from various companies involved in the software development cycle and used the PLS-SEM model to investigate the Technology Acceptance Model (TAM). The results of SEM revealed that only a few variables had significant relationship direction, such as Intention to Use towards Actual System Usage, Perceived Ease of Use towards Perceived Usefulness, Perceived Security towards Intention to Use and Perceived Usefulness towards Intention to Use.*

Keywords - *Generative AI, GPT, Security, TAM, Software developer.*

1. Introduction

The growth of the Artificial Intelligence (AI) ecosystem has recently become increasingly crowded with the birth of generative AI technology, which has rapidly triggered changes in the way people communicate, create and do their daily work [2]. Several types of generative AI to generate text include GPT-4, ChatGPT, Luminous, Gemini, and Bing. AI generates images such as Stable Diffusion and DALL-E 2, videos such as Synthe-sia, audio such as MusicLM, and program codes such as GitHub Copilot and Gitlab Duo [2]. Of course, this is a breath of fresh air for many people because generative AI can be used for many needs and can support work in various industries. Based on the results of the annual global survey released by McKinsey & Company stating that the topic of generative AI has become a concern for corporate leaders, almost a quarter of C executive respondents said that they have personally used generative AI for work, more than a quarter stated that generative AI has entered the board of directors' agenda, and 40% of respondents stated that their companies will increase investment in AI because they see the development and progress of generative AI [1]. This shows that all of this is still in the early stages of generative AI management, and respondents hope that generative AI capabilities in the future can be a tool in their business transformation process. Still, a survey conducted by McKinsey & Company stated that based on their survey of respondents in various regions, industries and seniority levels regarding the use of generative AI, as shown in Figure 1, the use of generative AI in the technology, media and telecommunications industries is much higher when compared to other industries such as financial services, energy and even health.

However, only 14% of respondents use it routinely for work needs. In comparison, 19% use it routinely combined for work and non-work matters, 17% use it routinely for non-work matters, and 37% stated that they had tried it at least once, the remaining 9% were not interested, and 3% did not know about this technology [1]. This survey illustrates how people in various parts of the world accept generative AI technology. The survey illustrates that the acceptance and adoption of generative AI technology for work needs in the information technology industry on a global scale is still relatively low. One thing that can encourage the use of this technology to be higher is the policy to implement generative AI as one of the standards for completing work. One of the things the author suggests is to combine generative AI into the Software Development Life Cycle (SDLC).

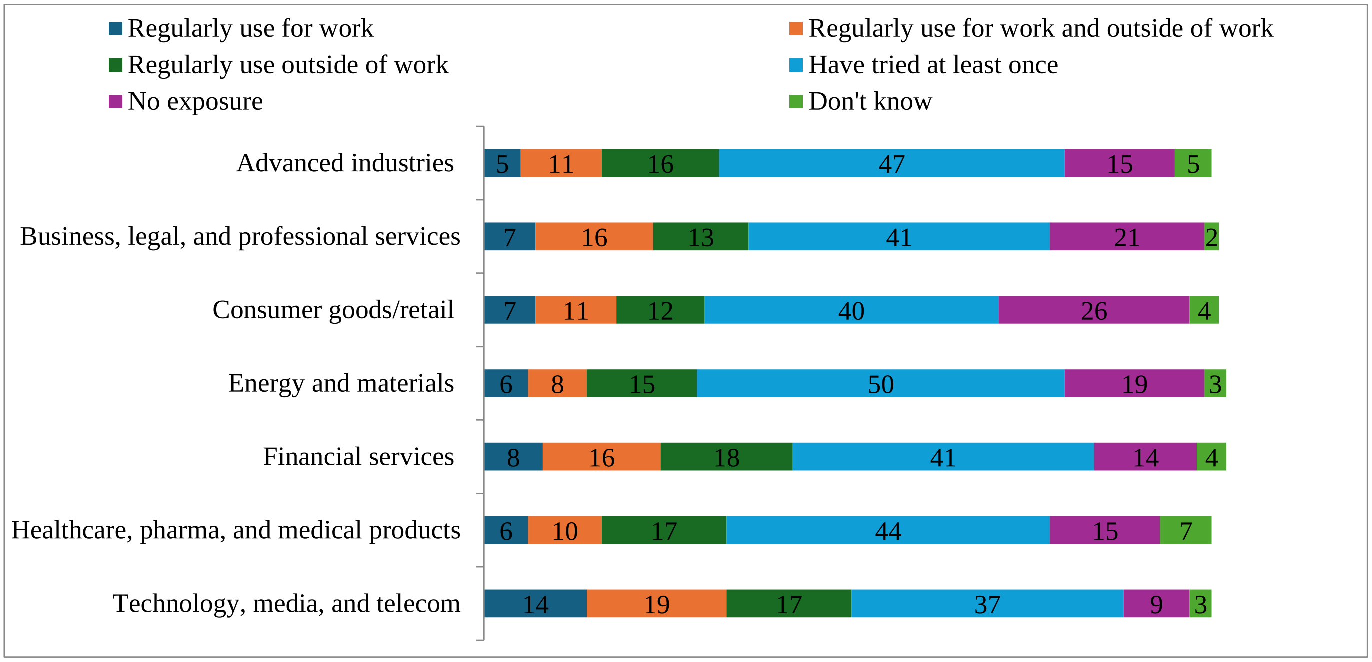

Fig. 1 Survey results on the use of generative AI across regions, industries and seniority levels [1]

In Indonesia, Populix surveyed what generative AI is often used, and the results showed that almost half or precisely 45% of workers have used generative AI. Of the 45% of respondents who use generative AI, 52% use ChatGPT, followed by Copy.ai, and as many as 29% [3]. Quoted the Minister of Communication and Information, Budi Arie Setiadi's speech at a seminar on the application of AI in industry and government, stating the great potential for utilizing artificial intelligence as a solution, even Indonesia itself is ranked 4th in the AI integration readiness index. It is estimated to contribute up to USD 366 billion by 2030 [4]. Based on the above, researchers see a very important role for software developers as one of the resource elements in digital transformation and AI integration, which ultimately led researchers to raise it as an object of research. Generative AI has enormous potential and benefits but has equally great risks [2].

One of the benefits that software developers can feel from generative AI includes being able to help developers complete lines of code [5], providing suggestions on how to write lines of code according to the correct writing structure and answering questions based on the context needed [6], even now generative AI can be linked as an extension to various popular programming language studios and integrated via API (Application Programming Interface). Although some believe that the development of generative AI in the future could threaten the position of software developers themselves, the most likely scenario at the moment is that generative AI is used as a tool that will help developers do their jobs in developing software [7], speed up the software development process [8] and can help improve the quality of developers' work with its innovative feedback features in solving a problem [9]. With its advantages and benefits, generative AI has the potential to be further exploited in the software development cycle. However, a major risk needs to be considered, namely regarding the security factor, where there is the potential for data bias, dependency and violations related to privacy data and leaks of confidential company information. One example of a case related to this that researchers found occurred in a company group, which ultimately decided to close access for group employees to use generative AI. The decision was taken after the company found some company information was spread and could be freely accessed as a result of the massive use of public-based generative AI in the operational environment by group employees, where the leak occurred when users sent questions or gave assignments accompanied by uploading company data to the generative AI platform to get the answers needed. Departing from this, this research will discuss the factors that influence the use of generative AI in software developers based on experiences that have been felt by several developers with different levels of expertise and experience from several different companies.

Based on these data, there are two points that researchers have proposed as research problems as follows:

1. Do security factors influence software developers' use of generative AI?
2. How do other factors in the TAM affect the actual use of generative AI?

In answering the questions in the problem formulation, the researcher carried out factor analysis by referring to Davis' theory [10] about the technology acceptance model or what is usually called TAM (Technology Acceptance Model), which is a model that many researchers have used to research how a population group accepts the use of information technology. [11]. Examining the results of the literature review that researchers conducted on previous studies that discussed generative AI and matters related to ChatGPT, it was revealed that previous studies have conducted experiments on the effects and benefits of generative AI in increasing the speed of task completion, as well as proposals that generative AI can be included in a new SDLC developed under the name Generative AI Assisted Software Development Lifecycle (GAASD), but there has never been any research on the acceptance of the technology itself among software developers, especially in Indonesia. In addition, the researcher added an external variable in the form of Perception of Security to the TAM model used in this research.

2. Literature Review
2.1. ChatGPT
ChatGPT has sparked a conversation about generative's emerging role and capabilities in the AI industry. There are many questions about how accurate the results produced by generative AI are [12]. However, in a short time, ChatGPT has produced impressive output, showing promising results in the future [13]. ChatGPT was developed by OpenAI, an artificial intelligence research company based in the United States. OpenAI launched the initial demo of ChatGPT on November 30, 2022 [12], and it quickly went viral on social media. Within five days of its launch, the chatbot attracted more than one million users [14]. The ChatGPT model was developed using deep learning techniques and complex Neural Network algorithms [7] to learn human language patterns, produce similar text, and interact naturally with users through conversation. ChatGPT has the flexibility to handle a variety of tasks in various fields and has great potential to be integrated with IoT. The collaboration of both can pave the way for more complex conversations, but the appearance and interaction layer becomes easier and simpler, such as devices that can communicate using natural language [13]. However, there are still challenges that ChatGPT must face in the future, such as bias in the data generated, ethical and security issues and model limitations [5].

2.2. Github Copilot
Github Copilot is a software development tool developed by Github and OpenAI. Since the beginning, GitHub Copilot was built and designed to increase efficiency and help developers write code faster. Copilot uses machine learning technology trained using millions of lines of code from various open sources on Github. Github Copilot is highly expected to help developers improve their productivity and efficiency in writing code. However, like other machine learning technologies, the copilot has weaknesses and limitations that developers must understand before using it fully. Github copilot allows users to type in some keywords or descriptions of the code they want to write in the software development process. Then, the copilot will generate relevant code in accordance with what is needed [15]. In recent years, copilot has become a popular tool among software developers. Many technology companies have adopted this tool to improve developer productivity and efficiency. Although the copilot is still in development, its use continues to expand and has become one of the main tools in developing modern code. Github Copilot works by submitting comments and code to the Github Copilot service, which uses the OpenAI Codex engine to extract the messages and find recommended solutions in the form of lines of code and entire functions [15]. The AI copilot robot is trained by utilizing billions of lines of publicly available code on its Github platform, thus providing benefits to its users by saving time and staying focused on writing logic.

2.3. Information Security Risk
Information security risks threaten information owned, processed, and exchanged between companies or individuals. The form of information is very diverse, and it can be personal data related to the protection of personal data, financial information, or related to health and other confidential information. Threats to information security can come from various sources, such as spam mail, the spread of computer viruses in a network, unrecognized links, hacking attempts and many other security incidents. Therefore, the information security risk is a shared responsibility and cannot be borne by only a few parties. Meanwhile, information security can be interpreted as an action or effort that needs to be taken to protect the information, including managing access rights and preventing modification or destruction by illegal users [16]. Some important aspects of information security are:

1. Privacy or confidentiality of information, where there are clear boundaries, information that is public or personal so that private data may only be accessed by certain people who have legitimate access rights.
2. Integrity means that the data is guaranteed to be protected and will not experience intentional or unintentional changes or additions.
3. Authorization means granting access rights to a person or user who is regulated in such a way and with certain limitations in the information system.
4. Access control to limit access to information.

2.4. Technology Aceeptance Model
The TAM model was developed from the Theory of Reasoned Action (TRA), which discusses the basic assumption that individuals will consciously control themselves and consider using information or technology available for various activities in their lives. TRA is popularized with the following principles: determining how to measure the attitude component of a relevant behavior, distinguishing between beliefs or attitudes, and identifying external driving factors. Therefore, the model induces reactions and perceptions of the use of information systems which ultimately determine the attitudes and behavior of its users [10].

Table 1. Research hyphotesis table

No	Hyphotesis
H1	H_0: There is no significant influence between Perceived Ease of Use and Perceived Usefulness. H_1: There is a significant influence between Perceived Ease of Use and Perceived Usefulness.
H2	H_0: There is no significant influence between Perceived of Usefulness and Attitude Towards Using. H_1: There is a significant influence between Perceived of Usefulness and Attitude Towards Using.
H3	H_0: There is no significant influence between Perceived Ease of Use and Attitude Towards Using. H_1: There is a significant influence between Perceived Ease of Use and Attitude Towards Using.
H4	H_0: There is no significant influence between Perceived of Usefulness and Behavioral Intention to Use. H_1: There is a significant influence between Perceived of Usefulness and Behavioral Intention to Use.
H5	H_0: There is no significant influence between Perceived Security and Behavioral Intention to Use. H_1: There is a significant influence between Perceived Security and Behavioral Intention to Use.
H6	H_0: There is no significant influence between Attitude Towards Using and Behavioral Intention to Use. H_1: There is a significant influence between Attitude Towards Using and Behavioral Intention to Use.
H7	H_0: There is no significant influence between Behavioral Intention to Use and Actual System Usage. H_1: Behavioral Intention to Use and Actual System Usage have a significant influence.

From a TAM perspective, the main factors influencing a person's acceptance of technology are perceived usefulness and ease of use. These two variables explain behavioral aspects, so the TAM model states that user perceptions will determine their attitudes regarding the benefits of using information technology. The use of TAM has been adopted in many studies in the world, one of which is by A. Wibowo [11], who has developed the TAM variable into 5 variables, namely Perception of user ease (Perceived Ease of Use), perception of usefulness (Perceived Usefulness), Attitude Toward Using), Behavior to continue using (Behavioral Intention to Use) and the real condition of the user (Actual System Usage). In this research, the researcher added 1 external variable regarding perceptions of security.

3. Materials and Methods

3.1. Research Framework

The trend of using generative AI in the field of software development has increased in the last 2 years. As a tool, generative AI can benefit the software development cycle, help developers increase their knowledge, and become a source of information for finding solutions [7]. The main aim of this research is to determine the factors that influence the use of generative AI. Factor analysis refers to Davis' theory [10] regarding the technology acceptance model.

This research takes the TAM model framework modified according to research needs and follows the relationships between variables that will be tested in this research. This study uses Structural Equation Modeling (SEM) as a tool to help conduct analysis. This model allows researchers to test the relationship between variables to present a complete model. SEM conducts simultaneous testing to measure the relationship between indicators and their constructs with a structural equation model. The second part of this SEM method is Bootstrapping. Bootstrapping is a method used to estimate standard errors and p-values in SEM using resampling techniques that are useful when the sampling distribution of model parameters is unknown or difficult to calculate. Bootstrapping strictly describes conclusions about each population characteristic, thus providing information about a population and taking advantage of conditions where there are weaknesses in statistical theory regarding the distribution of a parameter [17].

3.2. Research Steps

The following image is a research design that the researcher determined in the research process related to writing this thesis. The research stages begin with conducting a literature review and identifying problems related to generative AI. Then, in the second stage, the researcher will enter the analysis stage, where the stages in this phase begin by determining the research variables based on a literature review regarding the use of variables in previous studies.

After the variables are determined, the researcher continues the stage by designing questionnaire questions and distributing questionnaires to respondents. The questionnaire results will be collected as data tabulation to facilitate processing. The data that has been processed is then evaluated using several tests, such as validity and reliability tests, normality, multicollinearity, heteroscedasticity and hypothesis tests. Then, the final stage is closed with a conclusion.

3.3. Hypothesis

The hypothesis used in this research refers to the hypothesis adopted from the TAM model [10] and the behavioral study model [11] as well as the research model that has been formulated in Figure 2, so it can be described in table 2.

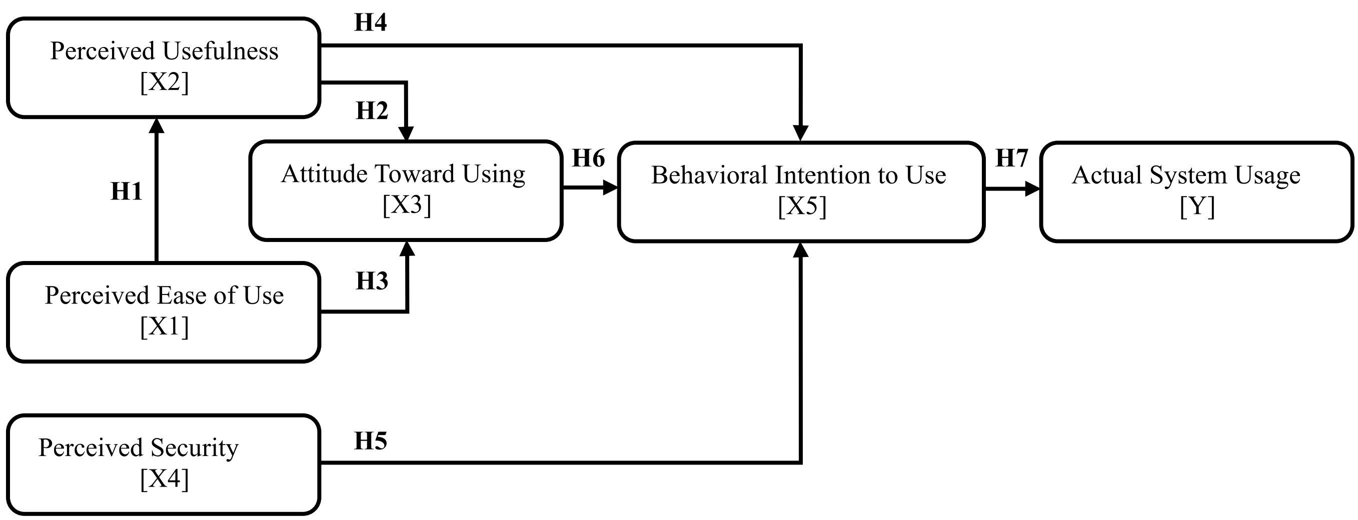

Fig. 2 Research model

Table 2. Research variable and indicator

No	Variable	Concept	Indicator	Questionnaire Statement	Item
1	Perceived Ease of Use	A situation where software developers believe that generative AI technology is well known and easier to use [10][18].	Very easy to learn	I feel generative AI is very easy to learn	X1.1
			Easy to use	I feel skilled in using generative AI	X1.2
			Clear and easy to understand	I feel that generative AI has a clear and easy-to-understand concept of interaction.	X1.3
2	Perceived Usefulness	Describe the system's performance to make users believe that using the system can increase productivity [19].	Make work easier	I feel generative AI makes my job easier	X2.1
			Improve user skills	I feel generative AI has improved my skills	X2.2
			Reduce knowledge gaps	I feel that generative AI helps reduce my knowledge gap with other team members.	X2.3
			Increase effectivity	I feel generative AI increases my work effectiveness	X2.4
			Increase productivity	I feel generative AI increases my work productivity	X2.5
			Increase time efficiency in solving problems	I feel generative AI increases time efficiency in solving problems	X2.6
3	Attitude Toward Using	Attitudes towards generative AI technology in the form of accepting or rejecting its use in their work [11].	Accept generative AI technology	I accept AI generative technology	X3.1
			Reject generative AI technology	I do not like using generative AI	X3.2
			Interesting experience using generative AI	I had a great experience using generative AI	X3.3
4	Perceived Security	Software developers' perceptions regarding the functionality and control of personal data information when using and interacting with generative AI [20].	The information provided is not misused	I trust that the information I provide will not be misused	X4.1
			There is a mechanism to deal with violations	I believe generative AI has mechanisms to deal with violations.	X4.2
			There is a belief that generative AI will not manipulate information	I believe generative AI will not manipulate information.	X4.3

			There is confidence in the security of the information provided	I believe in the security of the information provided	X4.4
5	Behavioral Intention to Use	The tendency of software developers to continue using generative AI technologies as if there is a motivation to continue using them [11].	The desire to always use generative AI	I have always felt like using generative AI for various purposes	X5.1
			The desire to get work done with generative AI	I have always felt like using generative AI to get my work done	X5.2
			Desire to motivate other users	I always motivate others also to use generative AI	X5.3
			Have no desire to use	I would not use generative AI for security reasons	X5.4
6	Actual System Usage	Measuring the frequency of use of generative AI technologies by software developers [11].	Always use	I always use generative AI to get my work done	Y1.1
			Use often	I often use generative AI to get my work done	Y1.2
			Only when you encounter problems	I use generative AI only when I encounter problems at work.	Y1.3

3.4. Variable

The variables used in this study require appropriate indicators, where these variables are measured using the following benchmarks:

3.5. Population and Sample

This research targets practitioners from several companies who work as developers or are involved in the software development cycle and have experience using generative AI in their software development routines. The targeted developers will be taken from several levels, from junior to senior developers, to get a variety of responses per each respondent's level of expertise and experience. The sample in this study will be determined by adopting the Slovin formula.

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

n = Number of samples
N = Population size
e = Percentage of allowance for inaccuracy

According to data from the *Badan Pengkajian dan Penerapan Teknologi* (BPPT), the number of programmers in Indonesia is 100,000 [21]. In the Slovin formula, there are the following provisions: the value of e = 0.1 (10%) for a large population and the value of e = 0.2 (20%) for a small population. So, the sample range that can be taken from the Slovin technique is generally between 10-20% of the research population. If applied to the slovin formula using a 13% leniency percentage, the calculation is as follows:

n = 100,000 / (1 + (100,000 x (13/100)^2))
n = 100,000 / 1,691
n = 59.13
n = 60 (Rounded)

Based on the calculation results, the research sample was adjusted to 60 software developers.

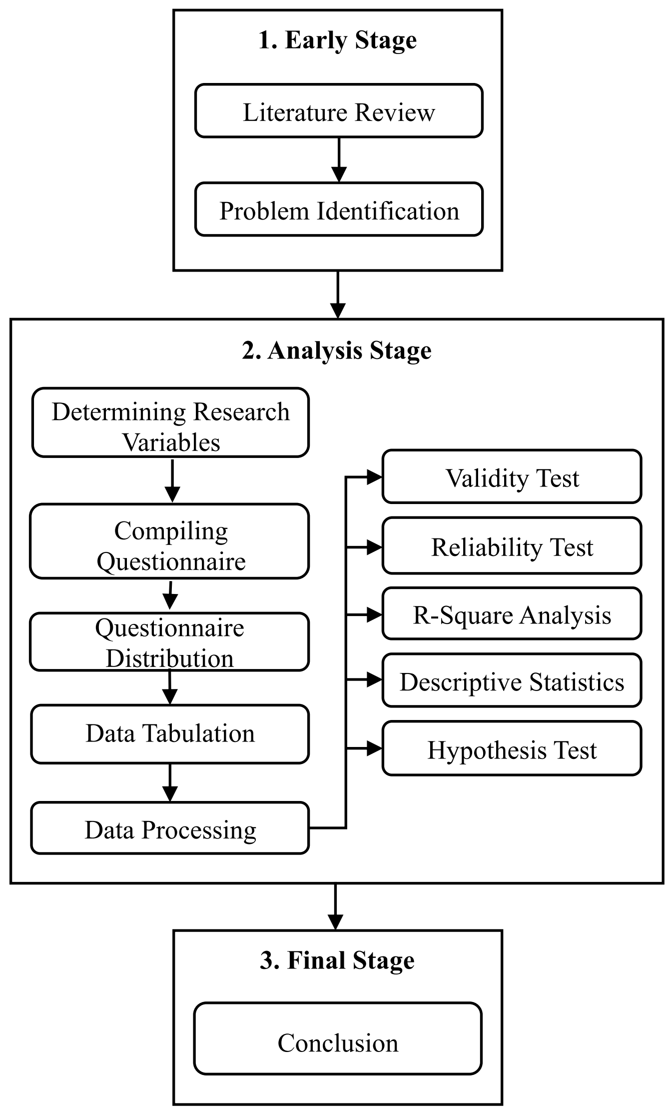

Fig. 3 Research Steps

3.6. Data Collection

Data collection in this research was collected through an online questionnaire instrument. A questionnaire was created using a data collection method, utilizing variable measurements using a Likert scale to measure how much the respondents agreed or disagreed with the questions that had been prepared. Psychometric response scales are primarily used in questionnaires to elicit participants' preferences or agreement with a statement or set of statements.

The Likert scale that will be used has five numbers with the following indicator levels:

- Strongly disagree: score 1
- Disagree: score 2
- Quite Agree: score 3
- Agree: score 4
- Strongly agree: score 5

3.7. Analysis

3.7.1. Validity Test

A validity test is used to measure whether a questionnaire can be said to be valid or otherwise. A questionnaire is valid if the compiled questions can reveal something that will be measured [22]. An instrument is said to be valid if the correlation coefficient of an instrument (r count) is greater than or equal to the regression table (r table). Conversely, the instrument is invalid if the r calculated is smaller than the table. Measurements carried out through measurement models are convergent validity and discriminant validity. A validity test using SmartPLS 4 was used to see the value of convergent and discriminant validity [23].

3.7.2. Reliability Test

Reliability is how measurement can produce consistent responses in various situations over a long period of time so that the test emphasizes whether the respondents' answers are stable for each question asked. A measure is considered reliable if measurements are taken repeatedly against a concept and produce consistent values. In this study, instrument reliability testing is needed to obtain data consistently in accordance with the measured objectives. This reliability test is carried out to determine the level of consistency of measurement results if repeated measurements are carried out on the same symptoms and measuring instruments. To achieve this, the reliability test is carried out using Cronbach's alpha method, which is measured based on a scale of 0 to 1, where if the alpha coefficient value approaches 1, it can be said that the questions in the questionnaire are reliable. It can also be done by looking at the Composite Reliability value by measuring the actual value of the reliability of a construct. The Composite Reliability value must be greater than 0.7, which means it is acceptable.

3.7.3. R-Square Test

R Square is a value used to show how much a variable affects another variable, commonly called the coefficient of determination. R Square has a value between 0 and 1, with the criteria that the closer the value is to 1, the better.

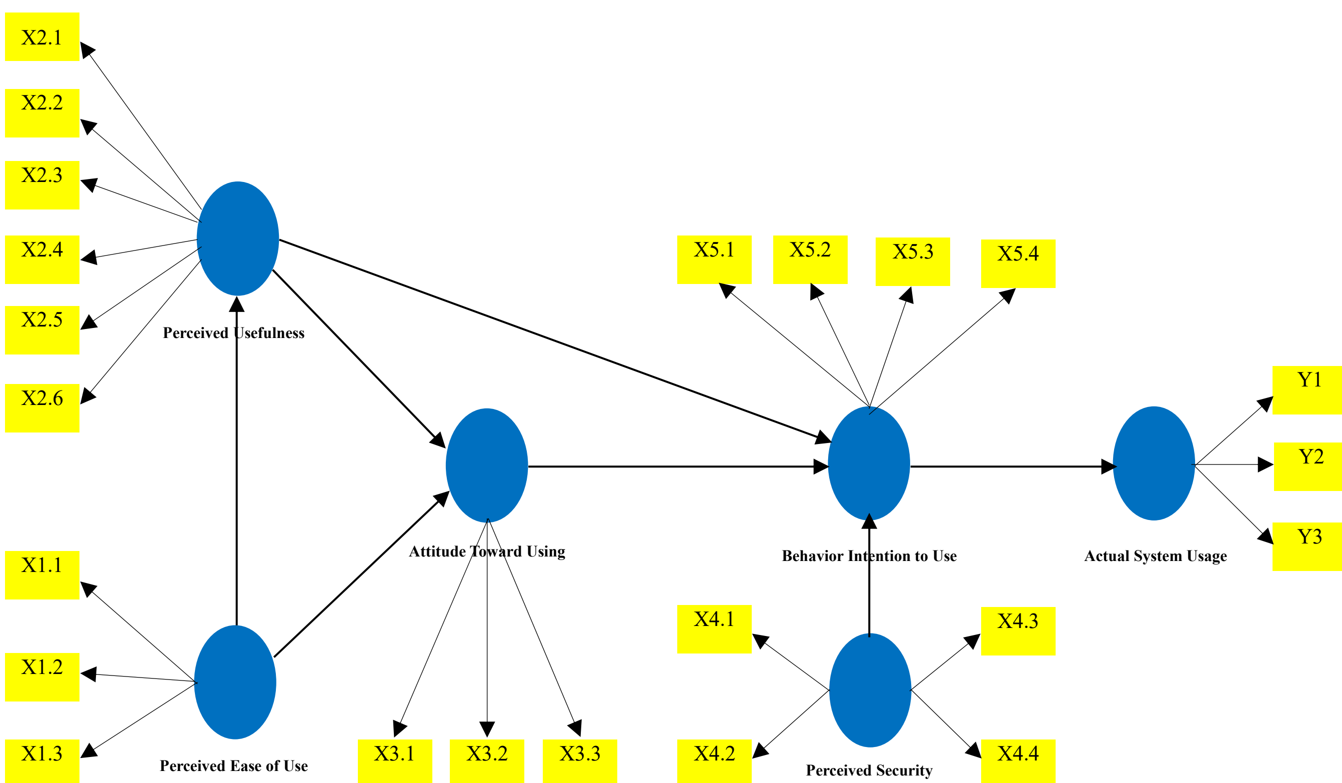

Fig. 4 Research model on SmartPLS

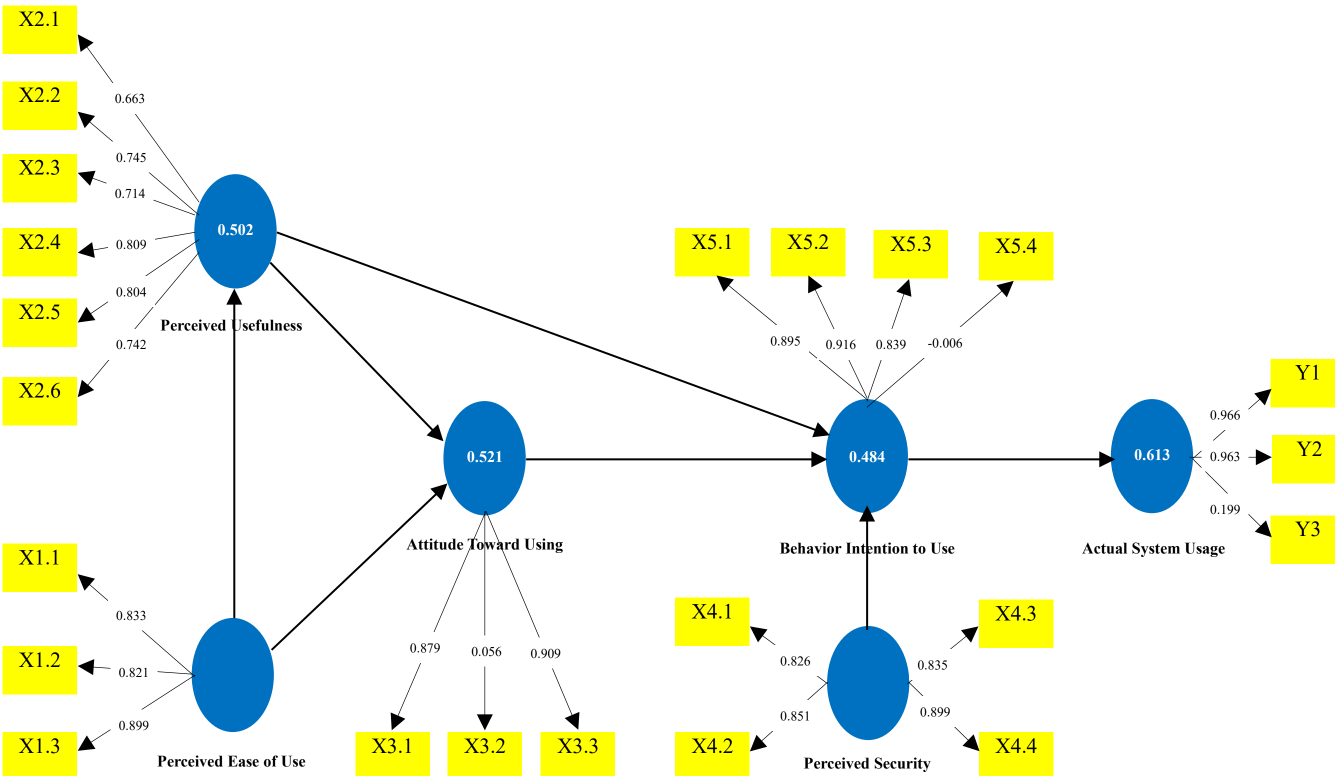

Fig. 5 SEM model algorithm step 1

Outer loadings - Matrix

	Actual System Usage	Attitude Toward Using	Behavioral Intention to Use	Perceived Ease of Use	Perceived Security	Perceived Usefulness
X1.2				0.832		
X1.3				0.903		
X2.1						0.655
X2.2						0.750
X2.3						0.760
X2.4						0.797
X2.5						0.794
X2.6						0.708
X3.1		0.867				
X3.2		-0.394				
X3.3		0.892				
X4.1					0.867	
X4.2					0.852	
X4.3					0.854	
X4.4					0.939	
X5.1			0.853			
X5.2			0.912			
X5.3			0.889			
X5.4			-0.289			
Y1.1	0.961					
Y1.2	0.949					
Y1.3	0.307					
X1.1				0.848		

Fig. 6 Outer loading matrix step 1

4. Result and Discussion

The data analysis contains the initial model used in this study adopted from the Technology Acceptance Model [11]. With the modification of the addition of the Perceived Security variable as an external variable from this research [20], the initial model for the research that has been carried out looks like Figure 4 with the indicators used for each variable.

4.1. Validity and Reliability Step 1

Each indicator's outer loading value can be considered valid if it is above 0.7, per generally applicable provisions. Therefore, the following is a description of the outer loading results of each indicator, seen in Figure 6 Outer Loading Matrix Step 1. In the figure, it can be seen that several indicators are colored red or have a value (<0.7), namely indicator X2.1 in the Perceived Usefulness variable, indicator X3.2 in the Attitude Toward Using variable, indicator X5.4 in the Behavior Intention to Use variable and indicator Y1.3 in the Actual System Usage variable. The next thing that must also be considered is the value of Construct Reliability and Validity, as depicted in the following table:

The table shows that the AVE value is above 0.5, which indicates that the variable can be said to be valid. However, if referring to Cronbach's alpha column, several variables have values below 0.7 or can be unreliable: Actual System Usage, Attitude Toward Using and Behavior Intention to Use. Valid but unreliable data has the potential to cause errors or uncertainty in the resulting analysis data, which means that the data has accurately measured the intended construct, but the results are inconsistent. So, to fix it, the question items with a loading factor value of less than 0.7 should be eliminated and the data re-processed.

4.2. Validity and Reliability Step 2

After eliminating invalid indicators in stage 1, the next step is reprocessing to obtain outer loading results above 0.7 to ensure that all indicators are valid, so the loading factor results after reprocessing are as follows:

The results of the reprocessing still show that there are indicators that still have values below 0.7, namely the X2.2 indicator in the Perceived Usefulness variable, so to re-confirm, it is necessary to look at the values in the Construct Reliability and Validity as shown in the following table:

Construct reliability and validity - Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Actual System Usage	0.636	0.924	0.805	0.633
Attitude Toward Using	0.405	0.737	0.709	0.534
Behavioral Intention to Use	0.693	0.851	0.809	0.586
Perceived Ease of Use	0.811	0.818	0.888	0.725
Perceived Security	0.875	0.883	0.915	0.728
Perceived Usefulness	0.842	0.850	0.884	0.559

Fig 7. Construct reliability and validity step 1

Outer loadings - Matrix

	Actual System Usage	Attitude Toward Using	Behavioral Intention to Use	Perceived Ease of Use	Perceived Security	Perceived Usefulness
X1.1				0.826		
X1.2				0.825		
X1.3				0.902		
X2.2						0.688
X2.3						0.722
X2.4						0.836
X2.5						0.868
X2.6						0.755
X3.1		0.887				
X3.3		0.909				
X4.1					0.827	
X4.2					0.852	
X4.3					0.834	
X4.4					0.898	
X5.1			0.901			
X5.2			0.918			
X5.3			0.836			
Y1.1	0.968					
Y1.2	0.967					

Fig. 8 Outer loading matrix step 2

Construct reliability and validity - Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Actual System Usage	0.932	0.932	0.967	0.936
Attitude Toward Using	0.760	0.766	0.893	0.806
Behavioral Intention to Use	0.862	0.865	0.916	0.784
Perceived Ease of Use	0.811	0.817	0.888	0.726
Perceived Security	0.875	0.883	0.915	0.728
Perceived Usefulness	0.834	0.848	0.883	0.604

Fig. 9 Construct reliability and validity step 2

The test results show that all variables' AVE values are above 0.5, and Cronbach's Alpha and Composite Reliability values are above 0.7, so the variables are valid and reliable. In addition, when viewed based on discriminant validity based on the Fornell-Larcker criteria, it also met the valid requirements because the AVE root value in the circled part is greater than the correlation value between latent variables below the circle.

Discriminant validity - Fornell-Larcker criterion

	Actual System Usage	Attitude Toward Using	Behavioral Intention to Use	Perceived Ease of Use	Perceived Security	Perceived Usefulness
Actual System Usage	0.968					
Attitude Toward Using	0.536	0.898				
Behavioral Intention to Use	0.776	0.555	0.886			
Perceived Ease of Use	0.551	0.653	0.539	0.852		
Perceived Security	0.484	0.531	0.538	0.369	0.853	
Perceived Usefulness	0.673	0.662	0.552	0.700	0.364	0.777

Fig. 10 Discriminant validity Fornell-Larcker criteria

R-square - Overview

	R-square	R-square adjusted
Actual System Usage	0.602	0.594
Attitude Toward Using	0.509	0.490
Behavioral Intention to Use	0.448	0.415
Perceived Usefulness	0.490	0.480

Fig. 11 R-Square

Table 3. Perceived Security Respondent Distribution Table

No	Indicator	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
1	The information provided is not misused	5,5	12,9	29,6	44,4	7,4
2	There is a mechanism to deal with violations	0	25,9	25,9	38,8	9,2
3	There is a belief that generative AI will not manipulate information	3,7	25,9	42,5	20,3	7,4
4	There is confidence in the security of the information provided	3,7	16,6	46,2	25,9	7,4

4.3. R-Square Analysis

Based on the figure above, it can be concluded that:

1. The influence of Behavior Intention to Use on Actual System Usage is 0.602. This can be interpreted as the ability to influence the Behavior Intention to Use variable on the Actual System. The use variable is 60,2%, while other factors outside this research explain 39,8%.
2. The influence of Perceived Ease of Use and Perceived Usefulness on Attitude Toward Using is 0.509, which means that the ability to influence the Perceived Ease of Use and Perceived Usefulness variables on the Attitude Toward Using variable is 50.9%, while other factors outside of this research explain 49.1%.
3. The influence of Attitude Toward Using, Perceived Security and Perceived Usefulness on Behavior Intention to Use is 0.448, which means that the ability to influence the variables Attitude Toward Using, Perceived Security and Perceived Usefulness on the Behavior Intention to Use variable is 44.8%, while other factors outside of this research explain 55.2%.
4. The influence of Perceived Ease of Use on Perceived Usefulness is 0.490. This means that the ability to influence the variable Perceived Ease of Use on the variable Perceived Usefulness is 49%. In comparison, 51% can be said to be influenced by other factors outside this research.

4.4. Descriptive Statistic

Descriptive statistics are carried out to analyze data based on respondents' answers to the measurement indicators of a variable so that a conclusion can be obtained. The descriptive statistics that will be discussed are perceived security, which is an external variable in this study as follows:

Based on the data in Table 3, the question that received a positive response was question 1, with the answer "Agree" of 44.4%. No answer reached more than 50% for all questions related to security perception, and it can be said that the respondents' perceptions are quite careful about generative AI security.

4.5. Hypothesis Test

Hypothesis testing in this study was conducted by looking at the path coefficient, which shows the T statistic's parameter coefficient and significance value. The path coefficient value or inner model shows a significant level, and the hypothesis can be accepted if the P-value < 0.05 or the T statistic value > 1.96. The following is a table of hypothesis testing results.

Path coefficients - Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Attitude Toward Using -> Behavioral Intention to Use	0.167	0.168	0.189	0.881	0.379
Behavioral Intention to Use -> Actual System Usage	0.776	0.771	0.070	11.017	0.000
Perceived Ease of Use -> Attitude Toward Using	0.372	0.372	0.116	3.218	0.001
Perceived Ease of Use -> Perceived Usefulness	0.700	0.704	0.076	9.191	0.000
Perceived Security -> Behavioral Intention to Use	0.333	0.351	0.119	2.801	0.005
Perceived Usefulness -> Attitude Toward Using	0.402	0.400	0.137	2.938	0.003
Perceived Usefulness -> Behavioral Intention to Use	0.320	0.309	0.158	2.031	0.043

Fig. 12 Path coefficients

The results of the tests that have been carried out conclude that 6 of the 7 hypotheses can be accepted while the others are rejected.

1. H1: Perceived Ease of use is proven to have a significant effect on the Perceived Usefulness variable. This is stated by the T Statistic values (9.191 > 1.96) and P-Value (0.000 < 0.05). These results show that the more ease of using AI generative technology, the higher the benefits software developers receive.
2. H2: Perceived Usefulness is proven to significantly affect the Attitude Toward Using variable. This is stated by the T Statistic values (2.938 > 1.96) and P-Value (0.003 < 0.05). These results can be said that the greater the benefits of use felt by software developers, the higher the attitude towards using AI generative technology.
3. H3: Perceived Ease of Use is proven to significantly affect the Attitude Toward Using variable. This is stated by the T Statistic values (3.218 > 1.96) and P-Value (0.001 < 0.05). These results show that the higher the ease of using AI generative technology, the higher the attitude towards using AI generative technology.
4. H4: Perceived Usefulness is proven to affect the Behavior Intention to Use variable significantly. This is stated by the T Statistic values (0.881 < 1.96) and P-Value (0.043 < 0.05). These results can be said that the greater the benefits of using AI generative technology felt by software developers, the higher the behavior of continuing to use AI generative technology.
5. H5: Perceived Security is proven to affect the Behavior Intention to Use variable significantly. This is stated by the T Statistic values (2.801 > 1.96) and P-Value (0.005 < 0.05). These results show that the higher the perception of security by software developers, the higher the behavior of continuing to use AI generative technology.
6. H6: Attitude Toward Using is not proven to significantly influence the Behavior Intention to Use variables. This is

stated by the T Statistic values (2.801 > 1.96) and P-Value (0.379 > 0.05). These results can be said that the attitude towards the use of software developers does not affect the actual use of AI generative technology, so this hypothesis is rejected.
7. H7: Behavior Intention to Use is proven to affect the Actual System Usage variable significantly. This is stated by the T Statistic values (11.017 > 1.96) and P-Value (0.000 < 0.05). These results show that the higher the behavior of software developers to continue using AI generative technology, the higher the actual use of AI generative technology.

4.6. Discussion

Referring to previous research, there is literature that conducts trials and experiments to determine the significance of ChatGPT in increasing productivity, especially for those at the beginner level. In addition, research has produced a new SDLC model called the Generative AI Assisted Software Development Lifecycle (GAASD), intended to implement generative AI into the development cycle. In other sections, they reveal key challenges such as ethical issues, data bias, security and mitigation strategies. This research concludes the factors that significantly influence the use of generative AI technology, especially perceptions of security. It describes how software developers, especially in Indonesia, accept the technology.

5. Conclusion

Based on the results of the hypothesis test, it can be answered that the formulation of the problem proposed at the beginning of this research chapter is that perception of security is stated to have a significant influence on the interest in using generative AI and its actual use in the work of a software developer. Then, the formulation of the problem regarding awareness of security risks can be said that based on the distribution of answers to the security perception variable indicator, there are no positive answers that are too high or exceed 50%, the distribution of respondents is relatively even so that it can be said that the respondents' perception of generative AI security is quite careful about the risks that may occur. In addition, hypothesis testing states that Attitude towards use is not proven to have a significant influence on behavioural intention to use, but perceived security is proven to have an influence, so the higher the perception of security by software developers, the higher the intention to use.

5.1. Limitation Section

The author is aware that this study still has many limitations, including the number of respondents and their distribution, which cannot represent the overall picture of generative AI users in Indonesia. The sample collection process carried out has attempted to meet the established parameters, varying according to the experience of each software developer at different levels.

5.2. Future Research

Furthermore, researchers who wish to continue this research can consider the following points:
1. Adding external variables besides the Perceived Security variable outside the general Technology Acceptance Model (TAM) model, such as the Perceived Risk or Trust variables, can further explain the analysis of the acceptance of generative AI technology.
2. Adding variables that influence or cause software developers not to want to use generative AI so they can describe the rejection factors.
3. Expanding the scope of the sampling area and research subjects further to describe the conditions of generative AI acceptance in Indonesia.

5.3. Practical Recommendation

Some of the things that the author recommends in the application of generative AI in SDCL and its application in reducing security risks include:
1. Developers need to sort and assess the validity of the code writing suggestions given by generative AI before implementing them and ensure that they comply with security standards [24].
2. Generative AI integrated into the development studio will be very helpful for developers in getting suggestions per the programming language used. The risk can be considered smaller because it has passed the testing process and is recommended by the development studio developer.
3. Perform a vulnerability test before deploying the program to ensure the code security elements are met.
4. Security guidelines are still needed for each team involved in software development.

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References

[1] Michael Chui et al., The State of AI in 2023: Generative AI's Breakout Year, McKinsey and Company, 2023. [Google Scholar] [Publisher Link]

[2] Philipp Hacker, Andreas Engel, and Marco Mauer, "Regulating ChatGPT and other Large Generative AI Models" *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, New York, United States, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Cindy Mutia Annur, "Survey: ChatGPT is the Most Used AI Application in Indonesia," *Media Network Catadata*, 2023. [Google Scholar] [Publisher Link]

[4] Ahmad Churi, Indonesian AI Technology Market Potential, Fourth Largest, It Works, 2024. [Online]. Available: https://www.itworks.id/67444/potensi-pasar-teknologi-ai-indonesia-terbesar-keempat.html

[5] Partha Pratim Ray, "Chatgpt: A Comprehensive Review on Background, Applications, Key Challenges, Bias, Ethics, Limitations and Future Scope," *Internet of Things and Cyber-Physical Systems*, vol. 3, pp. 121-154, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Andreas Stavridis, and Axel Drugge, "*The Rise of Intelligent System Development a Qualitative Study of Developers View on AI in Software Development Processes*," Student Thesis, Department of Informatics, 2023. [Google Scholar] [Publisher Link]

[7] Adam Hörnemalm, "*ChatGPT as a Software Development Tool the Future of Development*," Master Thesis, Department of Applied Physics and Electronics, Umeå University, 2023. [Google Scholar] [Publisher Link]

[8] Ameya Shastri Pothukuchi, Lakshmi Vasuda Kota, and Vinay Mallikarjunaradhya, "Impact of Generative AI on the Software Development Life Cycle (SDLC)," *International Journal of Creative Research Thoughts*, vol. 11, no. 8, pp. b287-b291, 2023. [Google Scholar] [Publisher Link]

[9] Emerson Murphy-Hill et al., "What Predicts Software Developers' Productivity?" *IEEE Transactions on Software Engineering*, vol. 47, no. 3, pp. 582-594, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] Fred D. Davis, "User Acceptance of Information Systems: The Technology Acceptance Model (TAM)," *University of Michigan, School of Business Administration, Division of Research*, no. 529, pp. 1-33, 1987. [Google Scholar] [Publisher Link]

[11] Arief Wibowo, "Study of Information System User Behavior Using the Technology Acceptance Model (TAM) Approach," *Proceedings: National Conference on Information Systems*, Yogyakarta, vol. 9, 2008. [Google Scholar] [Publisher Link]

[12] Sukhpal Singh Gill et al., "Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots," *Internet of Things and Cyber-Physical Systems*, vol. 4, pp. 19-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Sukhpal Singh Gill, and Rupinder Kaur, "ChatGPT: Vision and Challenges," *Internet of Things and Cyber-Physical Systems*, vol. 3, pp. 262-271, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Bernard Marr, "A Short History of ChatGPT: How We Got to Where We Are Today," *Forbes*, 2023. [Google Scholar] [Publisher Link]

[15] Nhan Nguyen, and Sarah Nadi, "An Empirical Evaluation of GitHub Copilot's Code Suggestions," *Proceedings of the 19th International Conference on Mining Software Repositories*, New York, United States, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] Shinta Nurul, Shynta Anggrainy, and Siska Aprelyani, " Factors Affecting Information System Security: Information Security, Information Technology and Network (Literature Review Sim)," *Economic Journal of Information Systems Management*, vol. 3, no. 5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Joe Hair et al., "An Updated and Expanded Assessment of PLS-SEM in Information Systems Research," *Industrial Management & Data Systems*, vol. 117, no. 3, pp. 442-458, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[18] Rizky Nur Cholifah, "*Pengaruh Perceived Usefulness, Perceived Ease of Use Dan Trust Terhadap Intention to Use*," Bachelor's Thesis, Faculty of economics and business, UIN Jakarta, 2020. [Google Scholar] [Publisher Link]

[19] Stefan Wagner, and Melanie Ruhe, "A Systematic Review of Productivity Factors in Software Development," *Arxiv Preprint*, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[20] Afrizal Tahar et al., "Perceived Ease of Use, Perceived Usefulness, Perceived Security and Intention to Use E-Filing: The Role of Technology Readiness," *The Journal of Asian Finance, Economics and Business*, vol. 7, no. 9, pp. 537-547, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Muthia Primayunita, Indonesian Programmer Salary 2023: Promising Career Opportunities, Dicoding Blog, 2023. [Online]. Available: https://www.dicoding.com/blog/gaji-programmer-indonesia-2023-peluang-karier-menjanjikan/

[22] Imam Ghozali, *Structural Equation Modeling: Metode Alternatif Dengan Partial Least Square (PLS)*, *Diponegoro University Publishing Agency*, 2008. [Google Scholar] [Publisher Link]

[23] Willy Abdillah, and Jogiyanto Hartono, "Partial Least Square (PLS) Alternatif Structural Equation Modeling (SEM) Dalam Penelitian Bisnis," *Yogyakarta: Andi Publishers*, vol. 22, pp. 103-150, 2015. [Google Scholar]

[24] M. Mehdi Kholoosi, M. Ali Babar, and Roland Croft, "A Qualitative Study on Using ChatGPT for Software Security: Perception vs. Practicality," *arXiv preprint*, 2024. [CrossRef] [Google Scholar] [Publisher Link]