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THE DETERMINANTS OF SOFTWARE DEVELOPERS' INTENTION TO ADOPT CHAT GPT AS PROGRAMMING INFORMATION MEDIA

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ABSTRACT

In the digital era, technology is developing rapidly. One of them in the field of artificial intelligence is chatbots. A chatbot is a computer program designed to stimulate conversation or interactive communication with (human) users via text, voice, or visuals. One of the chatbots that is currently popular is ChatGPT. ChatGPT training models interact in a conversational manner with a dialogue format that allows ChatGPT to answer follow-up questions, admit mistakes, violate false premises, and reject inappropriate requests. Software Developers are one of the users who can take advantage of this ChatGPT technology tool. There are several problems that software developers often experience in the coding process, including code or algorithms that are too complicated, making the code difficult for other people to understand and problems in the code that are sometimes difficult to overcome. The purpose of this research is to analyze what factors influence software developers' intentions and adoption of using ChatGPT as an information media in programming. This research model is UTAUT. This study involved surveying 399 participants through the distribution of questionnaires. The data collected was then processed and analyzed utilizing the PLS-SEM method. The findings revealed that factors such as Performance Expectancy, Effort Expectancy, Trust, Perceived Risk, and Experience significantly influenced Behavioral Intention. Furthermore, Behavioral Intention was identified as having a significant impact on the Intention to Adopt. Meanwhile, Social Influence and Facilitating Conditions do not have a significant effect on Behavioral Intention.
Keywords: *Artificial Intelligence, Chatbot, ChatGPT, SMART PLS, UTAUT*

1. INTRODUCTION

In the digital era, technologies are developing rapidly. One of them is in the field of artificial intelligence, namely chatbots. A chatbot is a software application created to simulate interactive conversations or communication with users, typically employing text, sound, or visual interfaces. [1].

Conceptually, chatbots refer to various software applications that can conduct dialogue with humans and using language that humans can understand [1]. Chatbots can help people quickly disseminate up-to-date information, support healthy lifestyle habits, reduce psychological problems such as fear and isolation miner [2].

Chatbots leverage a range of technologies, including Artificial Intelligence (AI), Machine Learning, Deep Learning, and Natural Language Processing (NLP). Machine Learning is employed to enable the chatbot to study, analyze, and recognize diverse languages, while Natural Language Processing (NLP) allows it to comprehend and interpret human language, responding in accordance with the language used by the chatbot users.

Figure 1 shows the chatbot trend in Indonesia which has experienced a significant increase based on data derived from Google Trends.

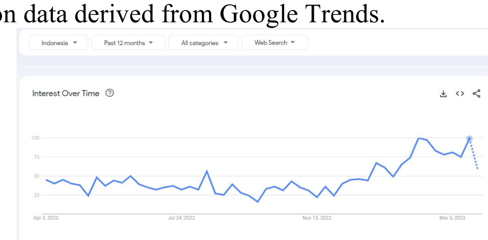

Fig 1. Chatbot Trends in Indonesia (Source: Google Trends [3])

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One widely used chatbot at present is ChatGPT. The training model of ChatGPT engages in conversations using a dialog format, enabling it to respond to follow-up questions, acknowledge errors, address false premises, and decline inappropriate requests [4].

To answer questions from users, this ChatGPT tool uses information from Wikipedia, Common Crawl, Reddit with 1.7 billion tags, Web Text with 45 million documents and 18.6 billion tags, Books Corpus with 74,000 documents and 800 million tokens, News with 680 million ID. consists of various sources such as CNN, BBC, and Reuters. In addition, GPT Chat pulls data from Books site with 570 million tokens and book data consisting of free books from Project Gutenberg [5].

Software developer as one of the users who can take advantage of this ChatGPT technology tools. Software developer is an expert involved in the process of creating, developing, and maintaining software. Their main task is to build software solutions that suit business needs and take advantage of the latest technology. In addition, software developers must have a deep understanding of programming and software design, as well as the ability to work in teams and solve problems [6].

Software developers frequently encounter various challenges during the coding process. These challenges include the creation of complex code or algorithms that can be challenging for others to comprehend. Additionally, developers often face difficulties in resolving issues within the code. When using search engine tools like Google, programmers may spend considerable time filtering through numerous search results and examining them one by one to find solutions based on specific keywords related to the problem they are trying to solve.

One of the things that ChatGPT tools can do is provide suggestions regarding the appropriate syntax and code structure so that it helps software developers in carrying out the coding process. In addition, the ChatGPT tools also provide explanations regarding certain programming languages with basic concepts. These tools also help provide the right algorithm and assist debugging so that problems experienced by software developers can be resolved.

Beginner or experienced software developers can ask ChatGPT to write code by simply typing the request in simple language and get workable code results, providing coding examples for programming information media [7].

Some speculation arises because of ChatGPT's ability to produce program syntax, such as ChatGPT can replace the role and reduce the number of software developers. There are also those who argue that ChatGPT can reduce the time and costs required for software developers to develop applications and systems and become more productive [8].

Figure 2 shows what is the role of ChatGPT in helping software developers.

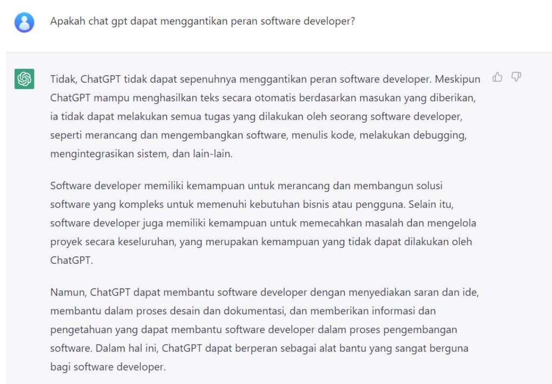

Fig 2. Search Results Regarding the Role of ChatGPT in Helping Software Developers [9]

As per information obtained from the tiobe-index website, the rankings for the most popular programming languages in October 2023 include Python, C, C++, Java, C#, Javascript, PHP, Visual Basic, SQL, and Assembly Language. Consequently, this study will concentrate on software developers utilizing these programming languages. Figure 3 shows the list of popular programming languages in November 2023.

Nov 2023	Nov 2022	Change	Programming Language	Ratings	Change
1	1		Python	14.16%	-3.02%
2	2		C	11.77%	-3.31%
3	4		C++	10.36%	-0.39%
4	3		Java	8.35%	-3.63%
5	5		C#	7.65%	+3.40%
6	7		JavaScript	3.21%	+0.47%
7	10		PHP	2.30%	+0.61%
8	6		Visual Basic	2.10%	-2.01%
9	9		SQL	1.88%	+0.07%
10	8		Assembly language	1.35%	-0.83%

Fig 3. Most Popular Programming Languages November 2023 [10]

To look more deeply at the factors that influence software developers' intentions to use ChatGPT as a programming information medium, research and measurements were carried out through this research.

The research questions from this study are as follows:

1. Does Performance Expectancy influence Behavioral Intention to adopt ChatGPT as a programming information medium for Software Developers?

2. Does Effort Expectancy influence Behavioral Intention to adopt ChatGPT as a programming information medium for Software Developers?
3. Does Social Influence influence Behavioral Intention to adopt ChatGPT as a programming information medium for Software Developers?
4. Do Facilitating Conditions influence Behavioral Intention to adopt ChatGPT as a programming information medium for Software Developers?
5. Does Trust influence Behavioral Intention to adopt ChatGPT as a programming information medium for Software Developers?
6. Does Perceived Risk influence Behavioral Intention to adopt ChatGPT as a programming information medium for Software Developers?
7. Does Experience influence Behavioral Intention to adopt ChatGPT as a programming information medium for Software Developers?

This research was conducted on Software Developers who know or are currently using ChatGPT tools in Indonesia.

It is hoped that the results of this research, in terms of practical benefits, can help Software Developers explore ChatGPT and recommend ChatGPT companies to develop features that help Software Developers optimally. Meanwhile, in terms of scientific benefits, the results of this research will add to research literature in the field of technology, especially regarding chatbots, especially regarding ChatGPT tools and the latest technology adoption theories.

2. LITERATURE REVIEW

2.1 Artificial Intelligence

Artificial Intelligence (AI) is an interdisciplinary domain that merges computer science with robust datasets to facilitate effective problem-solving. As AI progresses, its impact extends across diverse facets of our lives, notably in the medical sector. It is reshaping conventional approaches to medical imaging analysis, health data collection, and even medical education. While AI finds practical applications in distance learning and various inquiry systems, there is limited documentation regarding its use in trainee recruitment applications.

As AI progresses, its influence has permeated diverse aspects of our lives, particularly within the medical domain. It is transforming conventional approaches to medical image analysis, health data gathering, and even shaping the landscape of medical education. AI proves beneficial in practical applications like distance learning and various research systems, yet there is no documented mention of its utilization in the recruitment of trainees [11]

The development of artificial intelligence has come as a surprise to all of us. Efforts in implementing AI concepts over the past few years have made tremendous progress. Autonomous vehicles, big data analytics, and medical research are some examples of natural applications that have emerged from these advances in AI. For candidates interested in a career in artificial intelligence, it is safe to say that they have a much greater chance of success than expected [12].

2.2 Chatbot

Chatbots have the capability to replicate human conversation and find utility in various applications, including information retrieval and education [13]. AI and chatbots are consistently expanding the scope of tasks that machines can assume from humans, offering the potential to save both time and human resources.

AI chatbots are designed to engage with users in a manner resembling conversations with real humans. They possess the ability to comprehend context and vocabulary, demanding intricate logic implementation. These chatbots fall into three distinct categories: deep learning chatbots, end-to-end systems, and sequence-to-sequence models [14]

2.3 ChatGPT

ChatGPT trains a model to engage in conversation using a dialogue format, enabling it to respond to follow-up questions, acknowledge errors, question flawed assumptions, and decline inappropriate requests.

ChatGPT as a machine learning-based natural language model that utilizes deep learning and artificial intelligence technology. The model is designed to understand and generate human language automatically. By using machine learning algorithms, ChatGPT can learn human language patterns from large datasets and produce responses that are appropriate to the given input [15].

Specifically, ChatGPT is one implementation of the GPT (Generative Pretrained Transformer) architecture developed by OpenAI. This architecture is used to build natural language models that can be used for various tasks such as translation, writing, and answering questions. ChatGPT is trained using an extensive dataset of text sourced from diverse online platforms, enabling the model to replicate

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human language patterns and produce pertinent and coherent responses.

2.4 UTAUT

UTAUT serves as a model elucidating user behavior in relation to information technology. The model is adapted with four central determinants affecting intention and usage—specifically, performance expectations, effort expectations, social influence, and facilitating conditions. Each of these determinants subsequently impacts behavioral intention and usage behavior.

The UTAUT model is further shaped by various moderator variables, including gender, age, experience, and the voluntariness of use. These moderating factors exert influence on independent variables concerning behavioral intention and usage behavior in the adoption of new technology. The framework of the UTAUT model, as depicted in the research conducted, incorporates these aspects [16].

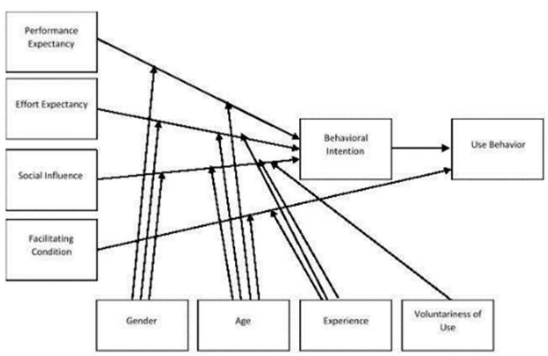

Fig 4. UTAUT Model

2.5 Previous Studies

This study applies research techniques grounded in past research models extensively applied as guidance in the research model: the UTAUT Model by Venkatesh et al., 2003 [16]. Apart from that, this research has special originality since it is supported by earlier research on chatbots and ChatGPT and the inclusion of three (three) new factors, namely Trust, Perceived Risk and Experience [17].

3. METHODOLOGY

3.1 Research Model

The research model used in this study is the result of the author's initial framework and assumptions that come from a combination of existing models and theories in the field of information systems and psychology, namely using the modified UTAUT model by adding four variables. The variables used are as follows: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition and with the addition of three variables namely Trust, Perceived Risk and Experience. The theoretical framework of the author in this study can be described as follows:

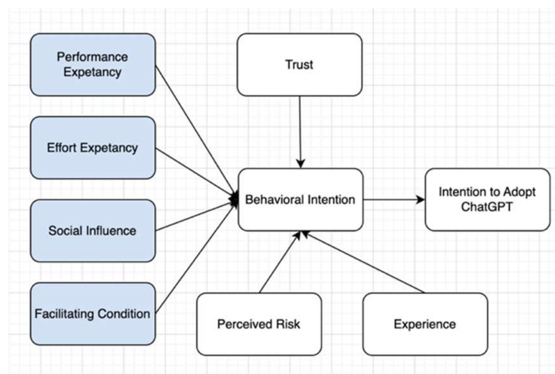

Fig 5. Research Model

There are nine variables in the research model meant for the study: notably: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Trust, Perceived Risk, Experience, *Behavioral Intention* dan *Intention to Adopt*. Below is a justification for every research variable:

1. Performance Expectancy
   This variable pertains to the degree to which users or software developers are inclined to embrace ChatGPT based on the tool's ability to furnish precise, pertinent, and valuable outcomes when responding to inquiries or offering solutions to programming challenges.
2. Effort Expectancy
   This variable refers to the extent to which Users or software developers are likely to show greater interest in utilizing ChatGPT if the tool is user-friendly, intuitive, and does not demand advanced technical skills.
3. Social Influence
   Social influence can be characterized as "the extent to which an individual perceives that influential individuals believe they should utilize a new system" [16]. In line with the theory of reasoned action (TRA), an individual's behavioral intentions are shaped by their positive or negative

sentiments that arise from the influence of other individuals familiar to the subject [18]. In the context of technology adoption, this concept is termed subjective norm, indicating the extent to which a user perceives that their peer group (friends, superiors) impacts their behavior in terms of use and adoption [19].
This variable shows that influence from other people can also influence a user's decision to adopt ChatGPT. If users see people around them using and recommending ChatGPT, they may be inclined to follow suit.

4. Facilitating Condition
Facilitating conditions can be defined as the extent to which an individual believes that the organizational and technical infrastructure is in place to support the utilization of the system. It encompasses external factors in the environment that contribute to making an action easy to execute [20] and exert an impact on an individual's inclination to carry out a task [21].
This variable shows that this factor includes the availability of access and ease of using ChatGPT. Users will be more likely to use ChatGPT if they can easily access it.
5. Trust
Baier (1986) defines trust as the conviction that others will, to the best of their ability, safeguard our interests and refrain from exploiting or causing harm to us. In the context of technology, trust can be delineated as the confidence that a specific technology possesses the essential attributes to operate as anticipated in each situation.[22].
This variable shows the level of user trust in ChatGPT is very important. This trust includes trust in the accuracy and reliability of the system, as well as trust in the confidentiality and security of data transmitted via ChatGPT.
6. Perceived Risk
This variable indicates that the risks from using ChatGPT, such as data being spread to the public, affect the intention to adopt ChatGPT as a medium for programming information.
7. Experience
This variable shows that users will be more likely to use ChatGPT if the user interface is well designed and easy to understand. The intuitive interface makes users feel comfortable and can interact with ChatGPT without any difficulty. This includes a clear layout, intuitive icons, and easy-to-understand navigation.
8. Behavioral Intention
Behavioral intention (BI) is characterized as "an individual's personal likelihood or probability that they will engage in a particular behavior" [18]. In this study, Behavioral Intention is impacted by factors such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Trust, Perceived Risk, and Experience.
9. Intention to Adopt
This study posits that the variable of Intention to Adopt ChatGPT is anticipated to be affected by Behavioral Intention. This is based on the premise that an individual's behavioral intention plays a crucial role in influencing their inclination to utilize ChatGPT. The perception of utility and anticipated benefits from using the tool is expected to contribute to its successful acceptance by the user.

3.2 Data Source

The model's structure encompasses both independent and dependent variables. As these variables are not directly observable, the author establishes various indicators for each variable, serving as benchmarks for questionnaires to be administered to participants.

The research covers Indonesian users of the GPT tool. 399 replies came from a purposive sample method using the Solvin formula with a 5% error tolerance. The Likert scale for the questionnaire went from 1 to 5 (1 = strongly disagree, 5 = strongly agree). Processing and evaluation of the gathered data will include structural model evaluation (inner model) and measurement assessment (outer model).

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Table 1: The design of the questionnaire incorporates variables and corresponding indicators.

Variable	Code	Indicators	Source
Performance Expetancy	PE1	I feel that ChatGPT improves my ability to understand concepts and complete programming tasks	[23]
	PE2	I feel that using ChatGPT can be an alternative in finding solutions to resolve bugs	[23]
	PE3	I feel that ChatGPT helps in improving the quality of the videos I have made previously to be better	[23]
Effort Expetancy	EE1	I feel that ChatGPT makes it faster to solve programming problems	[23]
	EE2	I find using ChatGPT to solve programming problems very easy	[23]
Social Influence	SI1	I use ChatGPT in coding because many other software developers use it	[23]
	SI2	I started using ChatGPT in coding because I saw advertisements and social media	[23]
Facilitating Condition	FC1	I find it easy to access ChatGPT via a laptop or smartphone device	[23]
	FC2	I feel that ChatGPT functions optimally in terms of helping me with coding	[23]
Trust	TR1	I choose and trust the code results produced by ChatGPT	[17]
	TR2	I feel that the code I entered and stored in the ChatGPT database was not misused	[17]
Perceived Risk	PR1	I feel safe using ChatGPT to help me work on company/personal projects	[17]
	PR2	I feel that ChatGPT is only a tool that helps in the coding process and cannot replace the position of software developer	[17]
Experience	EX1	I feel that my several years of programming experience does not hinder my intention to use ChatGPT as a tool in coding	[24]
	EX2	I feel that both beginners and experienced software developers will still use ChatGPT in coding	[24]
Behavioral Intention	BI1	I intend to use ChatGPT as a medium to help me with coding	[17]
	BI2	I will always use ChatGPT in the future for coding work	[17]
	BI3	I plan to adopt ChatGPT as a medium of assistance in coding work	[17]
Intention to adopt	AD1	I will adopt ChatGPT as a medium of assistance in coding work	[25]
	AD2	I will use ChatGPT in my daily life as a software developer	[25]

4. RESULT

4.1 Respondents

The data gathering process for this study involved the online distribution of questionnaires through the Google Forms platform. The distribution period spanned from November 19, 2023 to January 30, 2024. A total of 400 responses were collected, which were subsequently refined based on research requirements. Specifically, respondents who affirmed being a Software Developer, as indicated by a positive response to the question "Are you a Software Developer?" were considered, resulting in a final count of 399 respondents.

4.2 Modelling in SmartPLS

The research model, depicted in Figure 6, comprises the variables Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), Trust (TR), Perceived Risk (PR), Behavioural Intention (BI), and Intention to Adoption (AD). The anticipated relationships among these variables are illustrated by arrows, with each variable accompanied by its corresponding indicator.

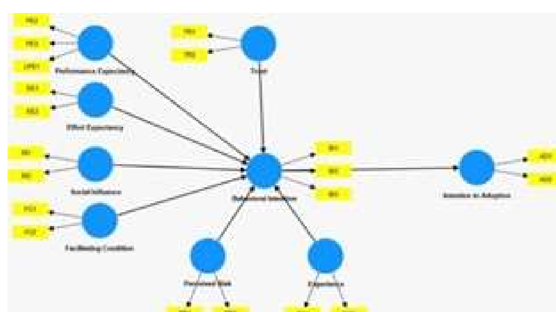

Fig 6. Modelling in SmartPLS

4.3 Measurement Model

SmartPLS was used for validity and reliability testing. While the reliability assessment took Cronbach Alpha (CA) and Composite Reliability (CR) values, the validity assessment looked at Loading Factors and AVE (Average Variance Extracted) values.

4.3.1 Validity Test

The validity test comprises two stages: convergent validity and discriminant validity. Convergent validity is assessed by examining outer loading and Average Variance Extraction (AVE) values. On the other hand, discriminant validity is evaluated by analysing cross-loadings and Fornell-Larcker Criterion values.

4.3.2 Convergent Validity

Indicators lacking the standards for convergent validity must be deleted or changed to guarantee compliance. For outer loading, the minimum requirement is set at 0.7 and above, while for AVE, the minimum threshold is 0.5 and above. The initial step in the validity test involved examining the values of outer loadings. In Table 2, it was identified that certain values fell below the minimum requirement of 0.7, indicating that these indicators would be eliminated.

Table 2: First Outer Loading Value

	PE	EE	SI	FC	TR	PR	EX	BI	AD	Description
PE1	0.813									
PE2	0.818									
PE3	0.831									
EE1		0.912								
EE2		0.892								
SI1			0.956							
SI2			0.901							
FC1				0.827						
FC2				0.919						
TR1					0.922					
TR2					0.850					
PR1						0.962				
PR2						0.402				Indicator Removed
EX1							0.895			
EX2							0.863			
BI1								0.857		
BI2								0.857		
BI3								0.894		
AD1									0.912	
AD2									0.907	

After the PR2 indicator is removed, the outer loading value is checked again. Reference from Table 3, it is evident that all outer loading values now satisfy the stipulated requirements. Consequently, the assessment can proceed to the subsequent testing stage.

Table 3: Outer Loading Value After Indicator Removed

	PE	EE	SI	FC	TR	PR	EX	BI	AD
PE1	0.813								
PE2	0.818								

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PE3	0.831								
EE1		0.912							
EE2		0.892							
SI1			0.956						
SI2			0.901						
FC1				0.827					
FC2				0.919					
TR1					0.922				
TR2					0.850				
PR1						1.000			
EX1							0.895		
EX2							0.863		
BI1								0.857	
BI2								0.857	
BI3								0.894	
AD1									0.912
AD2									0.907

Following the value from outer loading shown in Table 3, the next step is to find the AVE value from the available variables. Each construct must meet a minimum AVE requirement of 0.5 for acceptance. As observed in Table 4, all variables exceed the threshold of 0.5, indicating the validity of the data. Subsequently, the analysis can progress to the testing of discriminant validity.

Tabel 4 The Values for Average Variance Extracted (AVE)

	AVE	**Status**
PE	0.673	Valid
EE	0.814	Valid
SI	0.863	Valid
FC	0.764	Valid
TR	0.786	Valid
EX	0.773	Valid
BI	0.756	Valid
AD	0.827	Valid

4.3.3.1 Discriminant Validity

Discriminant validity illustrates the extent to which a construct genuinely differs from other constructs [26]. The testing involves the examination of cross-loading values and the Fornell-Larcker Criterion. A cross-loading value is deemed acceptable if the indicator's outer loading for a particular construct is higher than the outer loading value for any other construct. This criteria also relates to the Fornell-Larcker criteria value, in which the correlation between the indicator and its related construct cannot be less than the correlation with other constructions. In case of non-compliance, a retest is conducted, starting from the convergent validity stage.

Table 5 indicates that all cross-loading values meet the specified requirements. The correlation values for all indicators with their respective constructs surpass the correlation values with other constructs. Consequently, further testing can proceed.

Table 5 The Values for Cross Loading

	PE	EE	SI	FC	TR	PR	EX	BI	AD
PE1	0.813	0.538	0.190	0.502	0.316	0.338	0.430	0.459	0.461
PE2	0.818	0.590	0.212	0.460	0.274	0.376	0.403	0.479	0.471
PE3	0.831	0.459	0.282	0.382	0.366	0.359	0.415	0.521	0.450
EE1	0.595	0.912	0.245	0.516	0.361	0.397	0.469	0.534	0.538
EE2	0.562	0.892	0.347	0.512	0.401	0.365	0.375	0.484	0.513
SI1	0.319	0.343	0.956	0.273	0.328	0,358	0.294	0.378	0.353
SI2	0.177	0.245	0.901	0.134	0.273	0.253	0.199	0.256	0.247
FC1	0.388	0.369	0.152	0.827	0.191	0.323	0.379	0.348	0.331
FC2	0.541	0.595	0.242	0.919	0.347	0.342	0.404	0.498	0.503
TR1	0.382	0.421	0.320	0.293	0.922	0.445	0.365	0.510	0.481
TR2	0.299	0.312	0.255	0.276	0.850	0.519	0.317	0.376	0.367
PR1	0.436	0.423	0.338	0.379	0.534	1.000	0.422	0.538	0.509
EX1	0.460	0.423	0.211	0.419	0.330	0.356	0.895	0.575	0.535
EX2	0.430	0.402	0.275	0.364	0.352	0.389	0.863	0.506	0.510
BI1	0.532	0.517	0.282	0.506	0.406	0.510	0.596	0.857	0.679
BI2	0.479	0.479	0.369	0.398	0.484	0.450	0.458	0.857	0.696
BI3	0.536	0.480	0.272	0.388	0.437	0.445	0.552	0.894	0,756
AD1	0.505	0.515	0.296	0.440	0.436	0.455	0.540	0.753	0.912
AD2	0.516	0.546	0.309	0.453	0.447	0.471	0.541	0.704	0.907

Table 6 shows that all values on the Forcknell-Larcker criterion have met the requirements. The correlation value of all indicators to their own construct is greater than the correlation value of indicators to other constructs. Therefore, further testing can be carried out.

Table 6 The Values for Forcknell-Larcker Criterion

	BI	EE	EX	FC	AD	PR	PE	SI	TR
BI	0.870								
EE	0.565	0.902							
EX	0.617	0.470	0.879						
FC	0.495	0.570	0.447	0.874					

AD	0.817	0.583	0.594	0.490	0.910				
PR	0.538	0.423	0.422	0.379	0.509	1.000			
PE	0.594	0.642	0.507	0.543	0.561	0.436	0.820		
SI	0.352	0.325	0.274	0.233	0.333	0.338	0.281	0.929	
TR	0.508	0.421	0.387	0.321	0.485	0.534	0.390	0.328	0.887

4.3.3 Reliability Test

Two stages—that of convergent validity and discriminant validity phases—exist in the validity test. Evaluating the outer loading and average variance extraction (AVE) values forms the step of convergent validity. Looking at the cross loadings and Fornell-Larcker Criteria values helps one to determine the phase of discriminant validity.

The reliability test is carried out to ascertain the dependability or trustworthiness of the measuring tool applied. Two measurement tools—complementary reliability and Cronbach's alpha—are used on this exam. The instrument is judged trustworthy if both the Composite Reliability (CR) and Cronbach's Alpha scores are equal to or higher than 0.7.

Table 7 indicates that the values obtained from both tests satisfy the stipulated criteria. Consequently, it can be asserted that all variables are reliable.

Table 7 The Values for Cronbach's alpha dan composite reliability

	Cronbach's alpha	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	**Status**
BI	0.839	0.840	0.903	Reliable
EE	0.772	0.778	0.898	Reliable
EX	0.707	0.715	0.872	Reliable
FC	0.700	0.761	0.866	Reliable
AD	0.792	0.792	0.906	Reliable
PE	0.758	0.760	0.861	Reliable
SI	0.846	0.941	0.926	Reliable

4.4 Structural Model Evaluation

Combining features of factor analysis and regression, the structural equation model (SEM) is a multivariate analytic technique that incorporates both correlation and regression analysis.

The data is judged suitable for testing in the inner model if all indicators have effectively cleared the validity and reliability tests in the outer model. The internal model testing process will next cover the analysis of P-Value, coefficient of determination (R2), and effect magnitude (F2). Evaluating the linkages between variables in the model—including the links between indicators and their corresponding constructions as well as the links between various constructions—is the main aim of the inner model.

4.4.1 Coefficient of Determinant (R^2)

Determined by the R2 criterion, the analysis of the coefficient of determination helps one to find the degree of effect of other factors on the endogenous variable. Using these standards, 0.67 is judged good; 0.33 is rated intermediate; and 0.19 is considered weak.

Following the assessment of the coefficient of determination, the subsequent outcomes are as follows:

Table 8 R^2 Value

	R-square	Description
BI	0.575	Moderate
AD	0.668	Moderate

Table 8 presents the R2 values for the two endogenous variables under examination in this study. The two variables falling within the moderate category are elucidated as follows:

1. The Behavioural Intention (BI) variable is influenced by 57.5% due to the variables Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), Trust (TR), and Perceived Risk (PR). Furthermore, there is a 33.5% probability that other construct not specifically specified in the model shapes the BI construct.

2. The Intention to Adoption (AD) variable is influenced by 66.8% through the Behavioural Intention (BI) variable. Still, there is a 43.2% chance that another construct not specifically included in the model shapes the AD build.

4.4.2 Effect Size (F^2)

Apart from assessing the R2 value of every endogenous construct, the effect size (f2) value is also utilized to determine whether when exogenous factors are eliminated, they have a significant influence on endogenous variables [26]. By means of F2 values of 0.02, 0.15, and 0.35, one may ascertain if the latent variable predictor has little, medium, or high structural effect [27].

Table 9 shows on the endogenous variable the Effect Size (f2) values for every exogenous variable.

Table 9 Effect Size (F^2) Value

	f-square
BI -> AD	2.011
EE -> BI	0.016
EX -> BI	0.132
FC -> BI	0.008
PR -> BI	0.035
PE -> BI	0.041
SI -> BI	0.008
TR -> BI	0.032

According to the table, the association with the most substantial effect is the impact of Behavioural Intention (BI) on Intention to Adoption (AD) with a value of 2.011, indicating a high level of influence.

In contrast, the Effect Size (f^2) values for the relationships involving Experience (EX), Facilitating Condition (FC), Perceived Risk (PR), Performance Expectancy (PE), Trust (TR), and Behavioural Intention (BI) are categorized as moderate, falling within the range of 0.15 and below 0.35.

Furthermore, relationships with Effect Size (f^2) values below 0.02 are considered weak or negligible. Examples of such relationships include Effort Expectancy (EE) and Social Influence (SI) on Behavioural Intention (BI).

4.4.3 Q-Square (Q^2)

Apart from assessing the F2 value, one should give attention to the Q2 value. A Q2 score higher than 0 shows that the model has predictive value [26].

Table 10 shows that every Q2 value for the constructions included in the endogenous variables of the study model has predictive relevance.

Table 10 Nilai Q^2

	Q^2predict
BI	0.553
AD	0.511

4.4.4 Path Coefficient

In a structural model, the path coefficient shows the interaction among latent variables [26]. The bootstrapping technique helps one to evaluate the path relationship in the structural model by means of significance. Path Coefficient calculations consider values smaller than -0.1 as significant and inversely proportional, values greater than 0.1 as significant and directly proportional, and values within the range of -0.1 to 0.1 as insignificant [27].

Table 11 Path Coefficient Values between variables

	Original sample (O)	***T statistics (|O/STDEV|)***	***P values***	**Result**
BI -> AD	0.817	40.195	0.000	Significant
EE -> BI	0.118	2.244	0.025	Significant
EX->BI	0.294	6.428	0.000	Significant
FC->BI	0.075	1.678	0.094	Not Significant
PR->BI	0.156	3.533	0.000	Significant
PE->BI	0.187	3.639	0.000	Significant
SI->BI	0.064	1.699	0.089	Not Significant
TR->BI	0.144	3.354	0.001	Significant

The acquired Path Coefficient values are shown in the table; one can develop them as follows:

1. The association between the Behavioural Intention (BI) variable and Intention to Adoption (AD) is notably significant. This conclusion is supported by a T-Statistics value exceeding 1.96 (40.195), a P-Value below 0.05 (0.000), and an Original Sample (O) value surpassing 0.1 (0.817), meeting the stipulated criteria.
2. The connection between the Effort Expectancy (EE) variable and Behavioural Intention (BI) exhibits a noteworthy impact. This determination is substantiated by a T-Statistics value exceeding 1.96 (2.244), a P-Value below 0.05 (0.025), and an Original Sample (O) value surpassing 0.1 (0.118), satisfying the established criteria.
3. The correlation between the Experience (EX) variable and Behavioural Intention (BI) demonstrates a noteworthy impact. This assertion is supported by a T-Statistics value exceeding 1.96 (6.428), a P-Value below 0.05 (0.000), and an Original Sample (O) value surpassing 0.1 (0.294), meeting the specified criteria.
4. The association between the Facilitating Condition (FC) variable and Behavioural Intention (BI) does not exhibit a significant impact. This determination is based on a T-Statistics value below 1.96 (1.678), a P-Value exceeding 0.05 (0.094), and an Original Sample (O) value less than 0.1 (0.075), indicating that it does not meet the specified criteria.
5. The correlation between the Perceived Risk (PR) variable and Behavioural Intention (BI) manifests a significant impact. This conclusion is supported by a T-Statistics value exceeding 1.96 (3.533), a P-Value below 0.05 (0.000), and an Original Sample (O) value surpassing 0.1 (0.156), meeting the specified requirements.
6. The association between the Performance Expectancy (PE) variable and Behavioural Intention (BI) demonstrates a significant impact. This determination is supported by a T-Statistics value exceeding 1.96 (3.639), a P-Value below 0.05 (0.000), and an Original Sample (O) value surpassing 0.1 (0.187), fulfilling the specified criteria.
7. The connection between the Social Influence (SI) and Behavioural Intention (BI) variables does not exhibit a significant impact. This conclusion is drawn from a T-Statistics value below 1.96 (1.699), a P-Value exceeding 0.05 (0.089), and an Original Sample (O) value less than 0.1 (0.064), indicating that it does not meet the specified criteria.
8. The association between the Trust (TR) variable and Behavioural Intention (BI) demonstrates a significant impact. This determination is supported by a T-Statistics value exceeding 1.96 (3.354), a P-Value below 0.05 (0.001), and an Original Sample (O) value surpassing 0.1 (0.144), meeting the specified requirements.

4.4.5 T-Statistics & P-Value

Apart In addition to assessing the R^2 value for all endogenous constructs, the effect size (f2) value is also employed to determine whether the removal of exogenous variables has a substantive impact on endogenous variables [26]. The f^2 values of 0.02, 0.15, and 0.35 can be interpreted to ascertain whether the latent variable predictor has a low, medium, or high influence at the structural level [27].

Table 4.20 below shows the values of T-statistics and P-Values.

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Table 12 Value of Path Coefficient between variables

	Original sample (O)	*Sample mean (M)*	*T statistics (|O/STDEV|)*	*P values*	**Result**
BI -> AD	0.817	0.817	40.195	0.000	Approved
EE -> BI	0.118	0.118	2.244	0.025	Approved
EX->BI	0.294	0.293	6.428	0.000	Approved
FC->BI	0.075	0.075	1.678	0.094	Rejected
PR->BI	0.156	0.153	3.533	0.000	Approved
PE->BI	0.187	0.192	3.639	0.000	Approved
SI->BI	0.064	0.063	1.699	0.089	Rejected

4.5 Hypothesis

H1: Performance Expectancy (PE) → Behavioural Intention (BI)

The Original Sample (O) value exceeds 0.1 (0.187), therefore indicating a positive direction between the Performance Expectancy (PE) coefficient and Behavioural Intention (BI). The P-value for this association is below the error rate of 0.05 (0.000), but the T-Statistics value for it is more than 1.96 (3.639). As so, this link shows a notable impact, therefore supporting the acceptability of H1. This shows that Performance Expectancy has a good influence and acts as a motivational element [28] for software developers to plan to utilize ChatGPT as a programming knowledge resource.

H2: Effort Expectancy (EE) → Behavioural Intention (BI)

Given the Original Sample (O) value of above 0.1 (0.118), the connection between EE coefficient and BI exhibits a positive tendency. This relationship's T-Statistics value exceeds 1.96 (2.244), but the P-Value is less than 0.05's error rate, 0.025. This link thus reveals a notable influence, hence H2 is accepted. This shows that effort expectation affects favorably and is a determinant of the behavioral intention of software engineers to utilize ChatGPT as a programming information media.

H3: Social Influence (SI) → Behavioural Intention (BI)

Given the Original Sample (O) value < 0.1 (0.064), the connection between SI coefficient and BI reveals a negative tendency. This relationship's T-Statistics value is below 1.96 (1.699), but the P-Value above the 0.05 error limit. H3 is thus excluded as this connection shows no appreciable influence. This shows that social impact does not positively affect and is not a factor that motivates software engineers' behavioral intention to utilize ChatGPT as a programming knowledge media [29].

H4: Facilitating Condition (FC) → Behavioural Intention (BI)

The Original Sample (O) value is below 0.1 (0.075), hence the connection between FC coefficient and BI exhibits a negative tendency. This relationship's T-Statistics value reveals below 1.96 (1.678), and the P-Value above the 0.05 (0.094) error limit. H4 is thus excluded as this connection shows no appreciable influence. This shows that encouraging conditions have no beneficial effect and are not a factor influencing software developers' behavioral intention to utilize ChatGPT as a programming knowledge media.

H5: Trust (TR) → Behavioural Intention (BI)

Given the Original Sample (O) value over 0.1 (0.114), the connection between TR coefficient and BI exhibits a positive tendency. This relationship's T-Statistics value exceeds 1.96 (3.354), but the P-Value is less than the 0.05 error rate, 0.001. H5 is thus acknowledged as this connection indicates a notable effect. This shows that trust is a positive impact and a component that motivates software engineers to utilize ChatGPT as a programming information media.

H6: Perceived Risk (PR) → Behavioural Intention (BI)

Given an Original Sample (O) value over 0.1 (0.156), the connection between PR coefficient and BI has a positive tendency. This relationship's T-Statistics value exceeds 1.96 (3.533), but the P-Value is less than the 0.05 error rate 0.000. H6 is thus acknowledged as this connection indicates a noteworthy effect. This shows that perceived risk is

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a positive effect and a component driving software developers' behavioral desire to utilize ChatGPT as a programming information media.

H7: Experience (EX) → Behavioural Intention (BI)

Given the Original Sample (O) value above 0.1 (0.294), the connection between EX-coefficient and BI points in the positive direction. This relationship's T-Statistics value exceeds 1.96 (6.428), and its P-Value falls short of the 0.05 error rate. This link thus reveals a notable influence, hence H7 is accepted. This shows that experience shapes favorably and is a determinant of the behavioral intention of software developers to utilize ChatGPT as a programming information media.

H8: Behavioural Intention (BI) → Intention to Adopt (AD)

Since the Original Sample (O) value of BI coefficient is over 0.1 (0.817), the connection between BI coefficient and AD exhibits a positive tendency. This relationship's T-Statistics value is above 1.96 (40.195) and the P-Value is below the 0.05 (0.000 error rate). H8 is thus acknowledged as this connection indicates a considerable influence. This shows that behavioral intention affects favorably and is a component that motivates software developers to adopt to utilize ChatGPT as a programming information medium.

4.6 Implications Result

The following reflects the outcomes of the implications derived from the above mentioned analysis and respondent responses:

1.ChatGPT can provide code recommendations that can be used, helping to provide better code quality. However, it must be detailed and include clear questions related to the problem you want to ask. And the results obtained are not 100% accurate and some are deprecated so it is necessary to add training data [30] from the ChatGPT database.

2. ChatGPT can increase speed in the coding process, but you still must enter the right key questions so that the results you get are as desired.

3. Beginning and professional software engineers may make more use of ChatGPT, therefore accelerating the process of mistake fixing and offering better code recommendations.

4. The software developer's intentions influence the intensity of using ChatGPT so that the more often the software developer accesses the system, the more useful the system is.

5. CONCLUSION

This study intends to investigate and evaluate the elements of intention to adopt ChatGPT as an information medium for software developers by means of questionnaires distributed to 399 respondents and data processing on the outcomes resulting from testing and structural model evaluation (inner and outer models). This analysis and testing help one to deduce the following as the elements influencing the intention of software developers to embrace ChatGPT as an information medium:1. The Performance Expectancy variable has a significant effect on Behavioural Intention in using ChatGPT as a programming information medium so that H1 is accepted.

2. The Effort Expectancy variable has a significant effect on Behavioural Intention in using ChatGPT as a programming information medium so that H2 is accepted.

3. The Trust variable has a significant effect on Behavioural Intention in using ChatGPT as a programming information medium so that H5 is accepted.

4. The Perceived Risk variable has a significant effect on Behavioural Intention in using ChatGPT as a programming information medium so that H6 is accepted.

5. The Experience variable has a significant effect on Behavioural Intention in using ChatGPT as a programming information medium so that H7 is accepted.

6. Intention to Adopt in employing ChatGPT as a programming information medium such that H8 is accepted is much affected by the Behavioural Intention variable.

Apart from that, the variable with the highest T-statistical value was identified, namely Behavioural Intention with a value of 40, 195 which may be stated that Behavioural Intention is the most significant component most influencing Intention to Adopt as evidenced by the acceptance of H8. Therefore, behavioral goals significantly affect the degree of software developers utilizing ChatGPT in the coding process as the system is more valuable the more often they are applied.

The conclusions of this study are important implications for practical research and science. The practical benefits, namely helping Software Developers explore ChatGPT and recommending ChatGPT companies to develop features that help Software Developers optimally. Meanwhile, in terms of scientific benefits, the results of this research will add to research literature in the field of technology, especially regarding chatbots, especially

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regarding ChatGPT tools and the latest technology adoption theories.

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