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Analysis of Factors Influencing the Adoption of Artificial Intelligence Assistants among Software Developers

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Abstract

Software development in the era of global competition requires strategic technology management to enhance a company's competitiveness and economic performance. The main challenges in this process include project complexity, changing requirements, and time constraints, which often lead to project failures globally. In Indonesia, only 27% of information system projects are completed on budget and on time, highlighting significant issues in software development. AI assistants have emerged as an innovation with great potential to address these problems. With features such as code completion, code interpretation, and bug detection, this solution has the potential to increase software developers' productivity in the future. Given this context, this research aims to identify the factors influencing the intention to adopt AI assistants, particularly among software developers. The study was conducted using PLS-SEM and applied factors from common technology acceptance theories such as TAM and UTAUT. Data collection instruments were distributed using self-selection sampling and snowball sampling (N=165). Major factors in UTAUT such as effort expectancy, performance expectancy, facilitating conditions, and social influence were found to be significant in influencing attitudes or adoption intentions. Additionally, AI-specific factors in the context of UTAUT extension, such as AI literacy, were found to have an indirect effect on attitudes and behavioral intentions, moderated by other factors. It is hoped that the findings of this research can help stakeholders evaluate their strategies if they wish to adopt AI assistants and provide academic impact through scientific publications that can complement existing literature, expanding the understanding of AI integration in the professional IT realm.

A. Introduction

In the context of global competition, technology plays a crucial role for companies. The development and strategic management of technology are essential for achieving and maintaining competitiveness, enhancing economic performance, and driving growth [1]. Technological advancements are greatly influenced by software development, which enables the creation of current and effective software products to meet the demands of rapid technological development [2]. The realm of software development faces significant challenges, necessitating anticipation and strategic planning due to the dynamic nature of digital products and the involvement of various stakeholders. The software development process includes different phases, such as design, documentation, programming, and testing, which demand a deep understanding of professional expertise and technology [3].

According to research conducted by [4], the issues identified in software development include a lack of domain knowledge, a lack of available technical knowledge, and unsustainable software engineering practices. On the other hand, issues such as software project complexity, changing requirements, and time constraints were highlighted by [5] as other frequent problems in software development. According to the Standish Group, the global success rates of IT projects can be identified as follows: 56% meet targets, delivering stakeholder satisfaction and previously defined requirements, 40% meet target completion times, and 44% do not exceed the budget.

On the other hand, integrating artificial intelligence (AI) into daily work is becoming increasingly common, offering various benefits and challenges. AI applications can support or replace human roles and are expected to become even more integrated into everyday life in the years to come [6]. In the workplace, AI applications can help employees reduce their workload or assist with repetitive tasks [7]. One form of AI application, the AI assistant, has significantly impacted the software development process, offering various benefits to developers [8]. AI assistants have the potential to enhance the productivity of software development companies by automating and optimizing software testing and development [9]. One AI assistant service provider, Github, has conducted a survey of software developers regarding the impact of its AI assistant, Github Copilot [10].

In this experiment, Github divided developers into two groups: one group using Github Copilot and the other not using it. The results showed that the group using Github Copilot had a higher success rate in completing tasks (78%, compared to 70% in the group without Copilot) [10]. The results can be seen in Figure1.

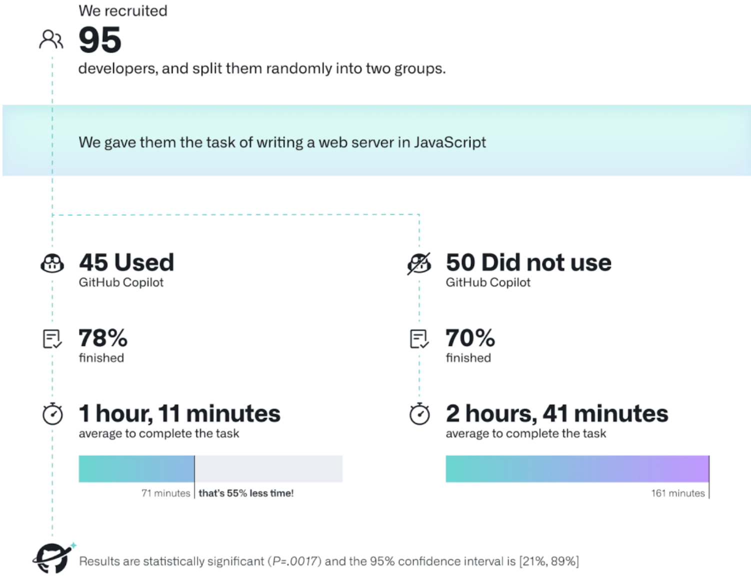

Figure 1. Github Experiment Result

Additionally, there was a significant difference in the time required to complete tasks, with developers using Github Copilot completing tasks significantly faster – 55% faster than developers not using Github Copilot [10]. This demonstrates the potential benefits offered by using AI assistant services. This study seeks to explore the factors influencing the adoption of AI assistants in software development environments. By identifying these factors, the research aims to provide insights that can enhance the successful integration of AI assistants, thereby improving productivity and efficiency within the software development industry.

B. Literature Review

a. Generative Artificial Intelligence

Generative Artificial Intelligence or generative AI refers to the application of artificial intelligence focused on creating new content such as text, images, audio, and video based on learned patterns from existing data [11]. A notable example of generative AI is ChatGPT, which achieved rapid growth by gaining one million users in just five days and reaching 100 million users two months [12]. Furthermore, there are distinctions between generative AI and related concepts like conversational AI. Generative AI differs from related concepts like conversational AI in its ability to not only respond but also generate content within those responses, enabling human-like interactions [13]. Unlike conversational AI, which usually relies on predefined responses, generative AI can produce novel replies [13]. However, not all generative AI systems involve conversational interaction, and some conversational AI can generate content [13]. Large Language Models (LLMs), which are a type of generative AI and the basis for ChatGPT, are designed to handle natural language processing tasks such as writing and generating text that resembles human conversation [14].

b. Large Language Model

Large Language Model (LLM) represents a significant advancement in artificial intelligence, particularly in natural language processing (NLP). LLMs are large neural networks with billions of parameters trained on extensive text corpora without supervision or labeled data [15]. Models such as those used in ChatGPT and BERT are first pre-trained on large, unlabeled text datasets and then fine-tuned for more specific tasks using smaller datasets [16]. Technically, LLMs require large-scale data from diverse sources like web pages, books, news articles, and code to generate coherent and contextually relevant text [17]. These models utilize self-attention mechanisms to capture dependencies between words in sentences, enabling parallelization and efficient processing of extensive dependencies [18]. Self-attention allows the model to assign varying weights to each word in the input sequence based on its relevance to the word being processed, thereby generating contextually relevant representations [18].

c. AI Assistant

AI assistants for programming have become valuable tools, leveraging artificial intelligence technology to support software developers in various programming tasks such as code generation, automatic code completion, code interpretation, code refinement, and bug detection [19]. These assistants utilize techniques like natural language processing using LLMs to enhance programming efficiency and accuracy [19]. Several AI assistant products for programming have been commercialized and are increasingly adopted by software developers, including Github Copilot, Amazon CodeWhisperer, and ChatGPT [20].

C. Related Theories

a. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a fundamental theory for understanding user adoption of information systems. Introduced by Fred Davis in 1986, TAM proposes that perceived usefulness (PU) and perceived ease of use (PEOU) are key determinants of users' attitudes (A) towards a technology, which ultimately influence their behavioral intention (BI) to use that technology [21]. The simplicity and clarity of TAM have made it widely adopted for studying user acceptance of various technologies, including information systems, software applications, and websites [22]. However, TAM has limitations, such as being overly simplistic and not accounting for factors like trust, user experience, and social context [22].

In response to these limitations, several extensions of TAM have emerged, such as TAM2, TAM3, and TAMX. Additionally, theories that incorporate elements from TAM, such as Social Cognitive Theory (SCT) and Theory of Planned Behavior (TPB), have been developed. These research models attempt to address TAM's limitations by incorporating social factors, individual beliefs, and external conditions [23]. The integration of existing adoption theories has led to the development of the Unified Theory of Acceptance and Use of Technology (UTAUT).

b. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is an extension of several existing models related to technology adoption, such as TAM and TRA. The main concept of UTAUT integrates four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions [23]. Performance expectancy refers to the extent to which an individual believes that using a particular technology will help improve their job performance, while effort expectancy relates to the perceived ease of use associated with the technology [23]. Social influence includes subjective norms and the influence of significant others regarding technology adoption, whereas facilitating conditions involve the perceived support and resources available to effectively utilize the technology [23].

c. Perceived Intelligence

Previous research has examined how people evaluate the intelligence of intelligent systems such as robots based on factors like speech, voice, and appearance [24]. This aspect is referred to as Perceived Intelligence, which encompasses the competence, efficiency, and capacity of an intelligent system to provide appropriate responses [24], [25]. One of the early studies discussing perceived intelligence found that robots providing customized and interactive information to users showed increased adoption rates [26]. The intelligent framework in conversation-based systems has been around for about a decade [27]. [28] explain that AI algorithms embedded in chatbots can develop human-like intelligence. Chatbots or AI assistants are often well-known for their intelligent architecture designed to engage in meaningful conversations with users [29].

d. AI Literacy

AI literacy involves a comprehensive understanding of AI, including its applications in various fields, ethical considerations, and the ability to engage in discussions about AI [30]. Knowledge about an innovation influences individuals' attitudes and also affects their subsequent decision on whether to accept the innovation [31]. It is also stated that knowledge can change a person's beliefs, which in turn affects their attitudes and behaviors regarding the innovation [32]. In the context of educators, factors such as knowledge about AI along with general anxiety about AI have been identified as background factors influencing attitudes towards AI [33].

D. Proposed Model

This section discusses the process of constructing the theoretical framework based on the theories reviewed in the previous sub-chapters and the synthesis of previous research findings. The conceptual framework can be found in Figure 2. A total of 18 hypotheses have been formulated to explore the relationships and influences between variables on adoption intention or behavioral intention. The theory adopted for this study's theoretical framework comes from TAM and UTAUT. TAM and UTAUT has been widely used and validated in various technology adoption studies across different domains [34], [35], [36], [37]. Its robustness and reliability make it a suitable choice for investigating adoption

Beyond the main theories used, TAM and UTAUT, perceived intelligence is also included, considering the focus of the research is on artificial intelligence, which has a tangible and perceivable intelligence aspect for users, as seen in chatbots [38]. Additionally, in exploring the attitudes influencing adoption, it was identified that knowledge of AI is a factor that can affect the antecedents of attitudes towards AI. This hypothesis is derived from research on AI adoption in organizations, indicating that AI knowledge impacts attitudes towards AI [39]. However, that research also discussed that AI knowledge does not directly influence but through other variables or mediators. Therefore, a hypothesis was made regarding AI knowledge affecting other constructs that could potentially mediate AI knowledge. On the other hand, this study also aims to confirm that the impact of AI knowledge is not direct on intention or attitude towards AI. This means extending the initial UTAUT model by considering concepts closely related to artificial intelligence, namely AI literacy and perceived intelligence. Thus, the following research model was created.

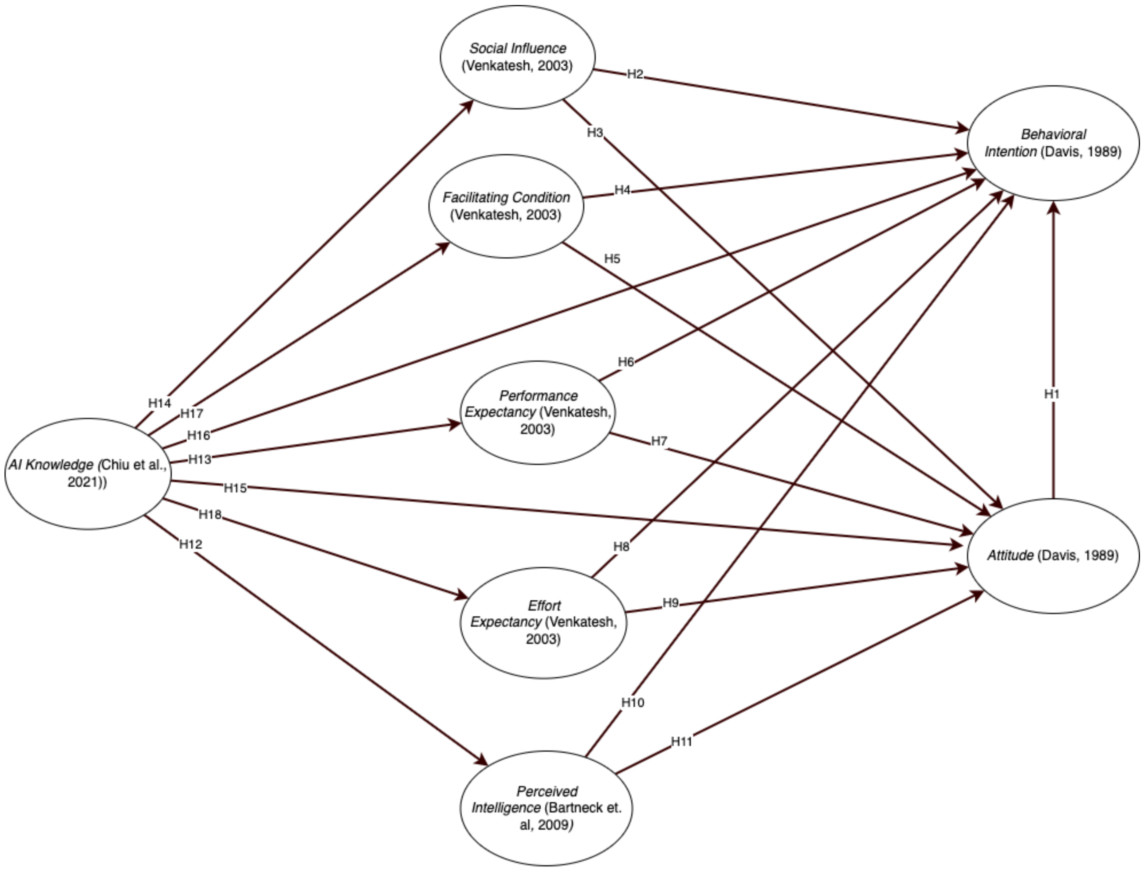

Figure 2. Proposed Model

Further discussion of the relationships between each factor will be provided in more detail in the next section.

E. Hypothesis Formulation

a. Influence of Attitude on Behavioral Intention (H1)

In the TAM model, attitude serves as an intermediary between the influence of PU and PEOU on behavioral intention [21]. In TAM, it is revealed that a person's intention is determined by their attitude towards performing the behavior . Factors such as attitude and Behavioral Intention are variables developed by Fishbein and Ajzen through the Theory of Reasoned Action (TRA), which forms the basis of TAM. Attitude refers to an overall assessment or feeling, both positive and negative, towards using a particular technology [21]. Behavioral Intention describes an individual's readiness or willingness to engage in a behavior related to technology use, such as technology adoption [21]. This hypothesis has been used in several previous studies [40], [41], where the study by [41] showed significant results. The context of that research was the intention to use robots with AI technology to aid in education. Other studies in the context of AI adoption also showed similar results, such as research on the adoption of AI integration into travel services [42]. When users have a positive attitude towards AI, they feel safer relying on it, thus increasing their willingness to use the technology. Based on this, the following hypothesis is proposed:

H1: Attitude positively influences Behavioral Intention

b. Influence of Social Influence on Behavioral Intention (H2) and Attitude (H3)

By definition, Social Influence is the degree to which an individual perceives the importance of others believing they should use the technology [23]. Social influence in previous studies is often represented as the subjective norm construct in TRA and the social factors construct in MPCU [23]. According to research by Venkatesh & David in 2000, social influence becomes significant in mandatory use environments for new technologies. This study's target is software developers with various obligations related to AI use. Therefore, this hypothesis is applicable if compliance with company regulations and mechanisms like internalization and identification are considered [23]. Studies with general research backgrounds and no binding technology use regulations also frequently use this hypothesis, as in previous studies related to AI adoption [37], [43], [44].

In this research context, social factors are considered influential on both the attitude and behavioral intention of software developers, especially since some companies openly advocate AI use among employees, as seen at DANA [45]. Social factors are hypothesized to significantly influence behavioral intention directly and indirectly through attitude [40], [46]. This is supported by research on UTAUT updates [47], which found that social factors directly influence attitude. Based on the above explanation, the following hypotheses are proposed:

H2: Social Influence positively influences Behavioral Intention
H3: Social Influence positively influences Attitude

c. Influence of Facilitating Condition on Behavioral Intention (H4) and Attitude (H5)

Facilitating Condition is defined as the degree to which an individual believes that technical and organizational infrastructure supports system use [23]. Initial constructs forming the basis of this variable include perceived behavior control from TPB and compatibility from IDT [23]. These constructs explain how current technology and organizational conditions influence the intention to adopt new technology. The first hypothesis proposed by Venkatesh et al. states that facilitating condition is not significant for Behavioral Intention in general situations but is significant in specific situations like older users or those with low experience [23]. However, facilitating condition is still used in AI adoption research with diverse samples [40] and in other studies showing significant influence [37].

Another consideration for this hypothesis is research indicating that compatibility, a key aspect of facilitating condition, significantly influences the adoption of specific technology, such as AI [48]. For example, AI assistants like GitHub Copilot have constraints like limited IDE support, only supporting VS Code, Visual Studio, Neovim, and Jetbrain applications [49].

Beyond technical aspects, compatibility with typical user workflows is also considered [23]. This consideration highlights the differences in hypotheses regarding the influence of facilitating condition. In AI cybersecurity adoption research in the UAE, facilitating condition influences both directly and indirectly through attitude [40]. Conversely, AI adoption in HR found that facilitating condition only directly affects behavioral intention [37]. However, Dwivedi et al. found that facilitating condition influences attitude and behavioral intention directly. HR adoption research also shows that facilitating condition affects attitude, with HR leaders viewing AI applications as beneficial for productivity, efficiency, and quality, leading to positive attitudes towards AI adoption[50]. Thus, the following hypotheses are proposed:

H4: Facilitating Condition positively influences Behavioral Intention
H5: Facilitating Condition positively influences Attitude

d. Influence of Performance Expectancy on Behavioral Intention (H6) and Attitude (H7)

Performance Expectancy is defined as the degree to which an individual believes using a particular system or technology will improve their performance [23]. The impact of performance expectancy on behavioral intention has been investigated in various contexts like mobile service subscriptions and digital library systems. In mobile services, performance expectancy positively influences behavioral intention, subsequently affecting actual usage [51]. Similar findings apply to online learning satisfaction studies, emphasizing the crucial role of performance expectancy in adoption intention [52]. Additionally, research on educational media found that performance expectancy positively influences user attitudes, subsequently affecting behavioral intention [53].

In the AI adoption context, previous studies show similar results, such as AI adoption in construction companies [44], where performance expectancy indirectly influences attitude and directly affects behavioral intention. An AI assistant like GitHub Copilot can help software developers automate code generation using large models [49], providing AI-supported suggestions and automating repetitive coding tasks, enhancing performance as shown in the following statistics.

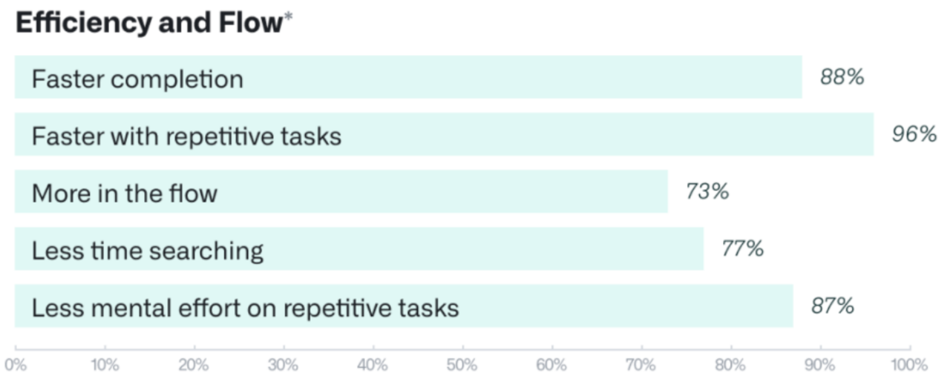

Figure 3. Github Survey Result

Given GitHub Copilot's potential, performance expectancy becomes crucial for understanding user views on AI assistants' usefulness and its influence on attitude and adoption intention. Based on the previous elaboration, the following hypotheses are proposed:

H6: Performance Expectancy positively influences Behavioral Intention
H7: Performance Expectancy positively influences Attitude

e. Influence of Effort Expectancy on Behavioral Intention (H8) and Attitude (H9)

Effort Expectancy is also considered a predictor of an individual's behavioral intention [23]. A study using PLS-SEM found that effort expectancy significantly predicts attitude in the context of Web 2.0 usage for learning [54]. This study highlights that effort and performance expectancy are critical factors in predicting user attitudes, ultimately influencing their intention to use the technology [54]. Similar findings are evident in AI adoption contexts, such as AI robot adoption in university student education [41]. In that study, effort expectancy significantly influenced students' positive attitudes towards AI [41]. Additionally, effort expectancy directly affects behavioral intention, as seen in AI adoption among accounting professionals [55] and mobile payment app adoption [56]. Previous studies on AI assistant usability like GitHub Copilot and ChatGPT [57] reveal about 30% of respondents experienced difficulty using AI assistants. Given this low difficulty level and previous research on the relationship between effort expectancy and attitude and behavioral intention, the following hypothesis is proposed:

H8: Effort Expectancy positively influences Behavioral Intention
H9: Effort Expectancy positively influences Attitude

f. Influence of Perceived Intelligence on Behavioral Intention (H10) and Attitude (H11)

Perceived Intelligence is explained as the intelligence displayed by a system to perform actions or achieve goals [58]. The intelligence displayed by AI assistants can be in various forms, such as the validity of responses or code generated based on user prompts or the accuracy of automatic suggestions for user-written code lines.

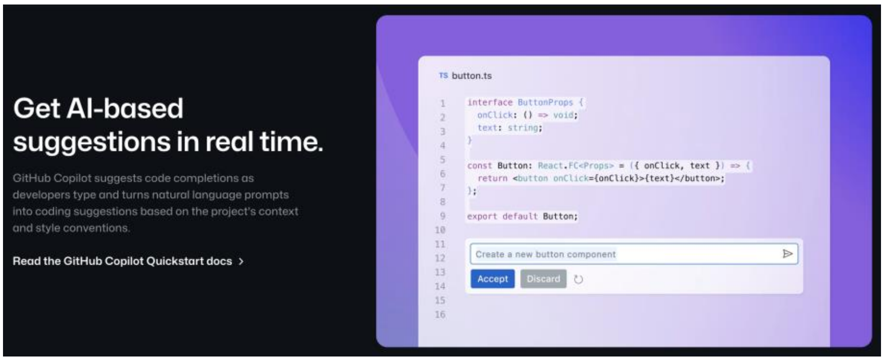

Figure 4. Automatic Code Generation

In AI chatbot adoption research, it is hypothesized that perceived intelligence directly influences adoption intention [59]. This study indicates that AI chatbots can provide real-time solutions for travel bookings, solving planning and scheduling issues, thereby potentially increasing usage intention [59]. Conversely, perceived intelligence can enhance adoption, with research on mobile banking by [60] discussing that perceived intelligence first predicts task technology fit, i.e., how well a specific technology aligns with tasks intended to support organizational activities. Attitude is also influenced by perceived intelligence, this positive attitude stems from the ability of AI to answer queries accurately and understand user needs through NLP, creating a seamless communication experience [59]. Thus, the following hypotheses are proposed:

H10: Perceived Intelligence positively influences Behavioral Intention
H11: Perceived Intelligence positively influences Attitude

g. Influence of AI Knowledge on Perceived Intelligence (H12)

The perception of the intelligence of an AI assistant can be significantly influenced by AI literacy, which consists of understanding and knowledge of how AI systems work [61] . Individuals with high AI literacy appreciate the complexity and effort required for AI to perform specific tasks, which can enhance their perception of its intelligence. For example, users with high AI literacy are more likely to understand why errors occur and may see them as part of the learning or operational process, rather than as a sign that the AI is not intelligent. This assumption is also supported by research that shows individuals with higher AI literacy tend to prefer automated decision-making systems compared to those with lower AI literacy [62], indicating that they appreciate the intelligence of AI. Based on this elaboration, the following hypothesis is proposed:

H12: AI Knowledge positively influences Perceived Intelligence

h. Influence of AI Knowledge on Performance Expectancy (H13)

In the context of technology adoption, the relationship between literacy and performance expectancy has been widely discussed in previous research. For example, in higher education, it has been discussed how digital literacy can influence attitudes and adoption intentions through performance expectancy derived from the use of digital technology [63]. In the financial domain, financial literacy has been identified as a moderator in the relationship between performance expectancy, effort expectancy, and usage intentions in the banking sector, illustrating how literacy in different domains can influence individual perceptions and behaviors [64]. Additionally, in the commercial application domain, it has been shown that digital literacy significantly affects effort expectancy for services like airline mobile applications [65]. Developers with strong AI knowledge are better able to assess the benefits and potential applications of AI assistants in their tasks. This awareness increases the perceived benefits of AI, as developers can clearly see how these tools can streamline their work, increase productivity, and solve complex problems. Based on this explanation, the following hypothesis is proposed:

H13: AI Knowledge positively influences Performance Expectancy

i. **Influence of AI Knowledge on Social Influence (H14)**

Good literacy in a particular subject can potentially drive a more positive perspective on the opinions of others regarding that subject. They are more likely to appreciate the influence of others regarding aspects of the AI domain, including AI assistants. This aligns with research related to minority opinion expression, where knowledge can influence the expression of minority opinions, showing that high confidence in knowledge can affect individuals' willingness to engage in social interactions [66]. In the financial literacy domain, individuals who are more financially literate are more open to the professional advice of financial experts [67]. Another example in the health domain is that research has shown that individuals with higher health literacy are more likely to have positive attitudes toward health literacy promotion [68]. Based on previous research, the following hypothesis is proposed:

H14: AI Knowledge positively influences Social Influence

j. **Influence of AI Knowledge on Attitude (H15)**

Previous research has shown that digital knowledge influences user attitudes, such as in the study by [69], which found that digital literacy affects staff engagement with information systems in healthcare settings, with poor computer skills and low experience influencing attitudes towards information and communication technology. Furthermore, in the domain of artificial intelligence adoption, it has been found that literacy and basic understanding influence participants' attitudes. In the AI domain, other research has found that knowledge of AI has the potential to positively influence attitudes, both cognitive and affective [39]. Similarly, research by [70]emphasizes the positive relationship between AI literacy and user attitudes, usage patterns, and expertise in AI technology, further strengthening the important role of literacy in shaping supportive attitudes towards AI. With comprehensive AI knowledge, software developers are likely to have a more positive attitude towards AI assistants. Understanding how AI works, its potential benefits, and its integration into development processes can lead to favorable perceptions of AI assistants. Therefore, the following hypothesis is proposed:

H15: AI Knowledge positively influences Attitude

k. Influence of AI Knowledge on Behavioral Intention (H16)

Studies have highlighted the impact of literacy or knowledge of a domain on behavioral intentions across various technologies and user groups. For example, research on educators using mobile learning emphasizes the importance of digital literacy, anxiety, and teaching self-efficacy in influencing their behavioral intentions [71]. Similarly, in the context of health education websites, literacy and information and communication technology skills were found to influence students' intentions to use the technology [72]. These findings underscore the importance of knowledge and literacy in shaping individuals' intentions towards technology adoption. Furthermore, in the financial domain, literacy has been identified as a significant factor influencing behavioral intentions towards various financial technologies, such as mobile banking and cryptocurrencies [73]. Users with higher digital literacy levels tend to show positive behavioral intentions towards adopting financial technologies [74]. In the AI domain, previous research has shown that individuals' AI literacy positively influences their self-efficacy in AI programming, satisfaction with AI courses, and intentions to engage in AI system development [75]. AI knowledge provides software developers with a deeper understanding of the capabilities and limitations of AI assistants, increasing their confidence in these tools. This increased confidence results in stronger behavioral intentions to adopt AI assistants. Based on this explanation, the following hypothesis is proposed:

H16: AI Knowledge positively influences Behavioral Intention

l. Influence of AI Knowledge on Facilitating Conditions (H17)

Understanding AI well means not only knowing the technical aspects of its use but also obtaining the appropriate devices and software to use it effectively. As AI becomes more prevalent in everyday life, such as in AI assistants or other applications, users with high AI literacy are aware of accommodating their needs, for example by equipping themselves with IDEs that support AI assistant integration. For example, in another domain, in the context of purchasing eco-friendly products, ecological literacy serves as a significant mediator affecting consumers' intentions to accommodate their awareness by purchasing sustainable products [76]. Additionally, another aspect of facilitating conditions is related to compatibility, assuming that the higher a person's literacy in a particular domain, the easier it is for them to adapt if there is innovation in that domain, such as in research related to health technology [77]. Based on this, the following hypothesis is proposed:

H17: AI Knowledge positively influences Facilitating Conditions

m. Influence of AI Knowledge on Effort Expectancy (H18)

Literacy or knowledge, whether digital, health, or financial literacy, can moderate the relationship between effort expectancy and behavioral intentions. For example, similar to performance expectancy, in the context of digital payment services, financial literacy influences effort expectancy in using FinTech services [64]. Similarly, during the COVID-19 pandemic, high levels of technology literacy among young individuals have been associated with low effort expectancy [78]. In the context of health literacy, improving literacy skills is essential for empowering individuals to make appropriate health decisions and navigate complex health information [79]. Understanding the complexity of AI allows developers to understand how AI assistants operate, making these tools appear more user-friendly. This enhanced understanding directly affects effort expectancy, as knowledgeable developers are better equipped to troubleshoot issues and maximize the functionality of AI assistants, reducing barriers to adoption. Based on this, the following hypothesis is proposed:

H18: AI Knowledge positively influences Effort Expectancy

F. Research Methodology

In conducting the research, a mono method quantitative study approach was used with the aim of identifying the factors influencing the adoption of AI assistants among software developers. Quantitative research emphasizes a deductive approach, which involves testing a theory with collected data .[80] Quantitative research examines the relationships between research variables through measurements conducted using specific statistical techniques [80]. Data in quantitative research is typically obtained through experimental or survey research strategies.

In this study, the research strategy employed will be a survey to collect data from a sample. Surveys are chosen for their economic advantages and consistent data [80]. In the process of creating survey questions, a questionnaire is developed containing questions about the factors to be investigated. The survey data is presented on a Likert scale for each question in the questionnaire. A Likert scale measures how much an individual agrees with a statement on a scale ranging from one to five (other options with ranges of 4, 6, and 7 also exist).

The sampling process for the survey is conducted using two sampling methods: self-selection sampling and snowball sampling. Self-selection is a sampling technique that involves voluntary participation of volunteers as research samples. In this technique, volunteers are obtained through announcements disseminated via various social media or by directly requesting the volunteers' willingness to participate. On the other hand, snowball sampling is used to expand the participant pool by asking initial participants to refer others who may have similar or relevant characteristics to the study.

To analyze the collected data, this study employs Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is a statistical technique that allows the examination of complex relationships between observed and latent variables [81]. It is particularly useful for exploratory research where the primary goal is to identify key driver constructs and predict target variables. PLS-SEM is chosen due to its ability to handle small to medium sample sizes and its robustness in dealing with non-normal data distributions. This method will help in assessing both the measurement model (validity and reliability of the constructs) and the structural model (the relationships between constructs). The application of PLS-SEM will provide a comprehensive understanding of the factors influencing the adoption of AI assistants among software developers.

G. Result and Discussion

a. Demography Summary

The data collection resulted in a total of 165 respondents with diverse backgrounds. The demographic distribution of the respondents is briefly discussed below. Here is the summary table of the survey demographics.

Table 1. Summary of Respondent Demographics

Category	Value	Frequency	Percentage
Gender	Male	143	87%
	Female	22	13%
Age	Under 25 years	98	59%
	25-35 years	63	38%
	36-45 years	4	3%
Education	Diploma	43	26%
	Bachelor	113	68%
	Master	9	6%
Position	Staff	136	83%
	Manager	7	4%
	Senior Staff	22	13%
Work Experience	Less than 3 years	87	53%
	3-6 years	73	44%
	More than 6 years	5	3%
Location	Greater Jakarta Area	152	92%
	Outside Greater Jakarta (Java Island)	13	8%
AI Assistant Usage	Yes	112	68%
	No	53	32%
Most Popular AI Assistant	Github Copilot	79	70%
	ChatGPT	15	13%
	Others	18	17%

The demographic data collection revealed that the majority of respondents (59%) are under the age of 25, indicating that most respondents are young developers, predominantly male (87%). This age group is assumed to be at the peak of their careers and interested in learning new technologies, as indicated by the high AI assistant usage rate of 73%. Most respondents (68%) have a bachelor's degree, indicating a high level of education among the respondents. Additionally, the majority of respondents (83%) work as staff, showing high AI assistant usage among junior and mid-level developers. Lastly, it was found that the most widely used AI assistant is Github Copilot among respondents who indicated they use an AI assistant.

b. Validity and Reliability Test

In testing the measurement model, two types of tests were conducted: validity and reliability of the outer model. The validity test is conducted to examine whether the research instrument measures the required metrics, while the reliability test is used to test the consistency of the respondents' answers to each indicator [82]. Convergent validity refers to the degree to which two indicators that should theoretically be related are indeed related [81]. Convergent validity is often evaluated by examining the correlation between various indicators of the same construct or variable. The first step in testing validity, specifically convergent validity, involves looking at outer loadings. Below are the results of the first iteration of outer loadings for the indicators of the research variables.

Table 2. First Iteration Outer Loading Results

Indicator	Variable	Outer Loadings
A1	Attitude	0.921
A2	Attitude	0.879
A3	Attitude	0.822
AIK1	AI Knowledge	0.850
AIK2	AI Knowledge	0.957
AIK3	AI Knowledge	0.935
B1	Behavioral Intention	0.879
B2	Behavioral Intention	0.878
B3	Behavioral Intention	0.796
B4	Behavioral Intention	0.394
E3	Effort Expectancy	0.846
EE1	Effort Expectancy	0.835
EE2	Effort Expectancy	0.853
EE4	Effort Expectancy	0.849
FC1	Facilitating Condition	0.620
FC2	Facilitating Condition	0.727
FC3	Facilitating Condition	0.794
FC4	Facilitating Condition	0.811
PE1	Performance Expectancy	0.927
PE2	Performance Expectancy	0.699
PE3	Performance Expectancy	0.811
PE4	Performance Expectancy	0.929
PI1	Perceived Intelligence	0.826
PI2	Perceived Intelligence	0.796
PI3	Perceived Intelligence	0.883
PI4	Perceived Intelligence	0.564
SI1	Social Influence	0.363
SI2	Social Influence	0.850
SI3	Social Influence	0.505
SI4	Social Influence	0.411
SI5	Social Influence	0.618

Based on the first iteration of outer loading results, several indicators did not meet the threshold of 0.7 [81]. These indicators are B4, FC1, PI4, and three indicators of social influence. Indicators with poor loadings, excluding social influence, were removed to improve the AVE of the variable [81]. Additionally, for social influence, indicators far below the threshold, namely SI1, SI3, and SI4, were removed. The outer loading for SI5 improved with the removal of these indicators. The results of the second iteration of outer loadings are shown below.

Table 3. Second Iteration Outer Loading Results

Indicator	Variable	Outer Loadings
A1	Attitude	0.919
A2	Attitude	0.874
A3	Attitude	0.829
AIK1	AI Knowledge	0.849
AIK2	AI Knowledge	0.957
AIK3	AI Knowledge	0.936
B1	Behavioral Intention	0.929
B2	Behavioral Intention	0.915
B3	Behavioral Intention	0.758
B4	Behavioral Intention	0.844
E3	Effort Expectancy	0.835
EE1	Effort Expectancy	0.854
EE2	Effort Expectancy	0.849
EE4	Effort Expectancy	0.782
FC1	Facilitating Condition	0.792
FC2	Facilitating Condition	0.838
FC3	Facilitating Condition	0.931
FC4	Facilitating Condition	0.701
PE1	Performance Expectancy	0.803
PE2	Performance Expectancy	0.930
PE3	Performance Expectancy	0.869
PE4	Performance Expectancy	0.796
PI1	Perceived Intelligence	0.843
PI2	Perceived Intelligence	0.934
PI3	Perceived Intelligence	0.873
SI2	Social Influence	0.934
SI5	Social Influence	0.730

The next metric analyzed in the discriminant validity test is the Average Variance Extracted (AVE), with a threshold of 0.5 [81]. The AVE values obtained are shown below.

Table 4. AVE Values of Variables

Variable	Average Variance Extracted (AVE)
AI Knowledge	0.838
Attitude	0.765

Behavioral Intention	0.759
Effort Expectancy	0.715
Facilitating Condition	0.647
Perceived Intelligence	0.717
Performance Expectancy	0.717
Social Influence	0.702

It can be seen that all variables have AVE values above 0.5, indicating that the model has good convergent validity. Next, the analysis proceeds with discriminant validity testing, which assesses the extent to which concepts or measurements that are not supposed to be related are indeed not related [81]. The first measurement is using cross loading. The requirement for this metric is that for each construct, the lowest indicator value should have a higher loading value than the indicators on other constructs. The results show that no construct has indicators with lower loadings than the loadings of each construct itself, thus being valid. In addition to cross loading, the Fornell-Larcker criterion, which compares the square root of the AVE of each construct, is also used. The results are similar to the previous test, where the square root value of the AVE of each construct is greater than the largest correlation between the construct and other constructs.

With the validity tests fulfilled through convergent validity and discriminant validity, the analysis continues with reliability testing. The reliability test is used to examine the consistency of respondents' answers to the created indicators [81]. The first metric related to the reliability test is Cronbach's Alpha, which measures how closely related a set of indicators are as a group, providing an estimate of the consistency or homogeneity of the indicators. The results of Cronbach's Alpha measurement are shown below.

Table 5. Cronbach's Alpha Values of Variables

Variable	Cronbach's Alpha
AI Knowledge	0.902
Attitude	0.846
Behavioral Intention	0.838
Effort Expectancy	0.868
Facilitating Condition	0.729
Perceived Intelligence	0.804
Performance Expectancy	0.880
Social Influence	0.608

The table shows that Social Influence has a value lower than 0.7. According to some sources, values above 0.5 are still weak but can be considered. Furthermore, given that the construct Social Influence is valid in terms of validity, the threshold used is 0.5. This is supported by [83], stating that a valid construct can be considered reliable, but not vice versa. Another metric in the reliability test is Composite Reliability, which is similar to Cronbach's Alpha but more suitable for SEM as it accounts for measurement errors and provides a more accurate estimate of reliability in the context of latent variables [81]. The results for the observation of Composite Reliability or rho_c values are shown below.

Table 6. Composite Reliability Values of Variables

Variable	Composite Reliability (rho_c)
AI Knowledge	0.939
Attitude	0.907
Behavioral Intention	0.903
Effort Expectancy	0.909
Facilitating Condition	0.846
Perceived Intelligence	0.884
Performance Expectancy	0.909
Social Influence	0.823

It can be seen that for all variables, the rho_c values exceed the threshold of 0.7. It is also noted that in this metric, the Social Influence variable shows a good value, differing from Cronbach's Alpha. Lastly, the common method bias test is conducted. Common method bias is a common issue in research that can lead to distorted results by exaggerating associations or creating false correlations. This bias includes various forms such as recall bias and halo effect, which can significantly affect the validity of study findings [84]. Common method bias can be measured using the Variance Inflation Factor (VIF), where values exceeding 3.3 indicate extreme collinearity, i.e., when two or more predictor variables in a regression model are highly correlated, making it difficult to isolate the individual effects of each predictor on the dependent variable [85]. The results of VIF show that all variables have VIF values lower than 3.3, indicating freedom from common method bias.

c. Structural Model

Structural testing is conducted to determine the outcomes of research questions by analyzing the relationships among observed variables [81]. Hypothesis testing in this study uses a two-tailed approach with a significance level of 5% (p-value set at 5%). This means a hypothesis is accepted if the p-value obtained is less than 5%. The following table shows the results of hypotheses, where 11 hypotheses were accepted and 7 hypotheses were rejected.

Table 7. Path Coefficient Result

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
AI Knowledge -> Attitude	0.007	0.007	0.093	0.070	0.944	Rejected
AI Knowledge -> Behavioral Intention	-0.057	-0.062	0.117	0.483	0.629	Rejected
AI Knowledge -> Effort Expectancy	0.415	0.421	0.076	5.487	0.000	Accepted
AI Knowledge -> Facilitating Condition	0.599	0.602	0.082	7.337	0.000	Accepted

AI Knowledge -> Perceived Intelligence	0.536	0.538	0.066	8.097	0.000	Accepted
AI Knowledge -> Performance Expectancy	0.447	0.455	0.062	7.264	0.000	Accepted
AI Knowledge -> Social Influence	0.514	0.516	0.084	6.091	0.000	Accepted
Attitude -> Behavioral Intention	0.857	0.838	0.153	5.610	0.000	Accepted
Effort Expectancy -> Attitude	0.317	0.321	0.061	5.153	0.000	Accepted
Effort Expectancy -> Behavioral Intention	-0.091	-0.069	0.118	0.769	0.442	Rejected
Facilitating Condition -> Attitude	0.313	0.311	0.101	3.098	0.002	Accepted
Facilitating Condition -> Behavioral Intention	-0.147	-0.138	0.147	1.000	0.317	Rejected
Perceived Intelligence -> Attitude	0.338	0.337	0.096	3.515	0.000	Accepted
Perceived Intelligence -> Behavioral Intention	-0.113	-0.128	0.125	0.907	0.364	Rejected
Performance Expectancy -> Attitude	-0.119	-0.121	0.083	1.428	0.153	Rejected
Performance Expectancy -> Behavioral Intention	0.253	0.254	0.107	2.354	0.019	Accepted
Social Influence -> Attitude	0.250	0.250	0.072	3.482	0.001	Accepted
Social Influence -> Behavioral Intention	-0.051	-0.032	0.131	0.386	0.699	Rejected

The first column, "O," indicates the average initial correlation coefficient for each relationship before resampling via bootstrapping. Column M represents the average correlation coefficient across all bootstrapped datasets. Standard deviation (STDEV) reflects how much these averages vary across all resampling results. The last two columns (T statistics and p values) help assess correlation significance. "T statistics" provides a score based on the initial correlation coefficient (O) and its standard deviation (STDEV). Higher scores indicate higher observed correlations. Finally, "p value" indicates the probability of obtaining extreme results like those in the original data. A lower p value suggests stronger evidence of significant correlation. Further discussion on hypothesis outcomes will be addressed in next section

d. Hypothesis Result Interpretation

Based on the obtained path coefficients, it is concluded that some hypotheses are rejected and others are accepted. Below is the research model along with information about the acceptance of hypotheses marked in green and the rejection of hypotheses marked in red.

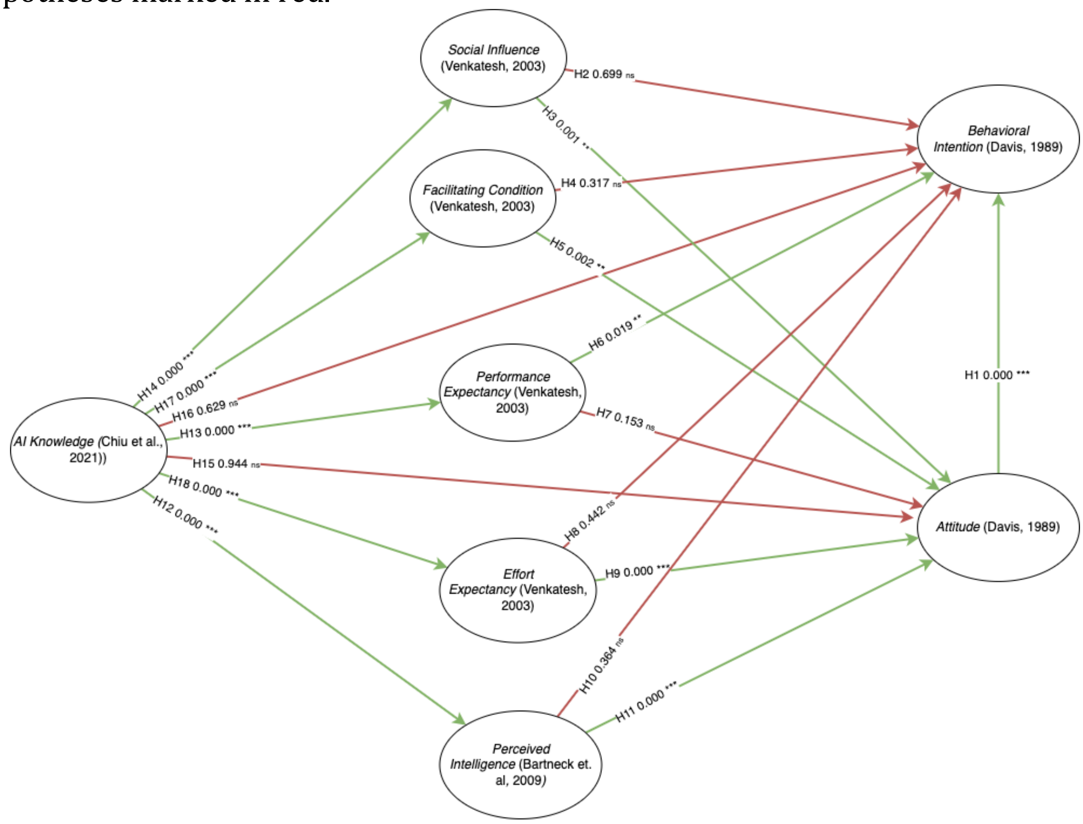

Figure 5. Results of Hypotheses in the Model

The results of hypothesis testing confirm several main theories in this study, namely TAM and UTAUT. It is evident that the most significant influence on behavioral intention comes from attitude, followed by performance expectancy. Attitude itself is most significantly influenced by perceived intelligence and effort expectancy, indicating that the perception that a system has a high level of intelligence greatly affects a person's attitude in the context of intelligent systems. On the other hand, AI knowledge is confirmed not to have a direct influence on the main factors driving adoption, but it significantly affects their antecedents.

The study confirms that attitude significantly influences behavioral intention (H1) in the context of AI assistants, aligning with the Technology Acceptance Model (TAM) proposed by Davis. This is consistent with several related studies on AI adoption, albeit in different applications such as cybersecurity systems and AI-based robots. Outside AI, this theory has been validated in studies on online travel applications and shopping applications [86], [87]. The findings indicate that as software developers' attitudes toward AI assistants improve, their behavioral intention to adopt these tools increases significantly. This relationship underscores the importance of fostering positive attitudes by highlighting the benefits and ease of use of AI assistants. Practically, adoption strategies should focus on enhancing developers' perceptions of AI assistants, potentially through training programs that demonstrate the practical benefits and utility of these tools [55], [88].

Social influence was found to significantly affect attitude (H3) but not behavioral intention (H2), contrary to the Unified Theory of Acceptance and Use of Technology (UTAUT) which posits a significant role of social influence on behavioral intention [23]. This finding aligns with updated UTAUT models showing the effect of social factors on attitude [47]. Accepted hypothesis H3 is consistent with previous studies on technology acceptance, such as those on e-money in Indonesia and cybersecurity systems in UAE [40], [89]. For practical application, organizations should leverage social influence to foster positive attitudes among developers, for example, by having senior management exemplify the use of AI assistants [90]. The rejection of hypothesis H2 suggests other variables may have a greater impact on behavioral intention than social influence, similar to findings in studies on online food delivery services and ERP adoption [36].

Facilitating conditions significantly influence attitude but not behavioral intention, deviating slightly from UTAUT, which posits a significant effect on behavioral intention [23]. This is supported by studies showing a relationship between facilitating conditions and attitude [47]. This suggests the importance of procedures, training, and policies in supporting positive attitudes towards AI [90]. Organizations should integrate AI assistants compatible with existing environments. The rejection of hypothesis H4 contrasts with findings in human resource studies but aligns with some showing no significant effect [37], [50]. These findings suggest facilitating conditions influence attitudes but not directly behavioral intention due to other more significant factors.

The analysis results indicate that performance expectancy significantly influences behavioral intention but not attitude. This aligns with the UTAUT theory[23], which hypothesizes that performance expectancy positively affects behavioral intention. The acceptance of hypothesis H6 supports previous findings by Na et al., suggesting that the perception of AI assistants enhancing software developers' performance motivates their intention to use them, as corroborated by other studies [55], [91]. Therefore, companies can highlight the tangible benefits of AI assistants to developers. The rejection of hypothesis H7, however, contrasts with previous research on AI-based robot adoption, where performance expectancy significantly influenced attitudes due to positive perceptions among teachers and students about the technology's benefits [41]. Organizations should highlight specific use cases and success stories demonstrating how AI assistants like GitHub Copilot or Amazon CodeWhisperer improve productivity and coding efficiency [92].

The study found that effort expectancy significantly influences attitudes but not behavioral intentions. The rejection of hypothesis H8 indicates a deviation from the UTAUT theory, which considers effort expectancy significant for intention. However, this result aligns with previous AI adoption studies, showing that effort expectancy does not significantly impact adoption intentions in AI applications within human resources [37] and AI integration in auditing processes [93]. The inherent complexity of AI might lead users to accept certain difficulties, making this factor less critical in decision-making. Ultimately, other factors seem to have a more direct impact on behavioral intentions. On the other hand, hypothesis H9 was accepted, showing that effort expectancy significantly affects attitudes. This finding corroborates previous research on the influence of effort expectancy on AI adoption attitudes [41], [44]. Additionally, studies have emphasized the mediating role of effort expectancy in shaping attitudes towards technology use [94], demonstrating a positive impact on attitudes, which subsequently affects behavioral intentions and actual usage. Consequently, companies can provide communities or open services to help developers become familiar with AI assistants, fostering positive attitudes towards these tools.

Furthermore, the study found that perceived intelligence significantly influences attitude but not behavioral intention, which contradicts some studies on AI chatbots and banking applications where both hypotheses were significant [38], [60]. The results suggest that higher perceived intelligence of AI systems builds a positive attitude towards using these systems [95], but this does not directly translate to an intention to adopt the technology. Organizations need to match their AI assistant offerings to developers' needs and ensure high performance, such as the GPT-3-based Codex model used in GitHub Copilot, which excels in various tasks [92], [96]. While perceived intelligence does not directly affect behavioral intention, it indirectly influences it by developing positive attitudes towards AI assistants.

AI knowledge significantly affects perceived intelligence, performance expectancy, effort expectancy, social influence, and facilitating conditions but not attitude or behavioral intention directly. This supports the proposition that AI literacy enhances the perception of AI intelligence [61], [62]. Higher AI knowledge allows users to better appreciate the potential performance and benefits of AI tools [63], [64]. Practically, organizations should enhance AI literacy among users to improve perceived intelligence and performance expectancy, driving effective adoption and utilization of AI technology. However, increasing AI knowledge alone may not suffice to foster positive attitudes or behavioral intentions. This suggests a need for a holistic approach that also addresses other significant factors such as social influence, facilitating conditions, and effort expectancy.

H. Conclusion

Through the conducted research, two research questions defined at the beginning of the study were answered. This research successfully found answers to those questions by identifying the factors that influence the adoption of AI assistants among software developers and providing recommendations for future development. A quantitative approach was used in this study, where data were collected through questionnaires. A total of 165 software developers completed the survey based on the Likert scale. The demographic summary shows that the majority were male (87%), under 25 years old (59%), held a bachelor's degree (68%), held a staff position (83%), had less than 3 years of work experience (53%), and resided in the Greater Jakarta area (92%). Besides demographic profiles, the descriptive information found is that many software developers already use AI assistants, amounting to 73%, with Github Copilot having the highest usage rate at

70%. Data processing was conducted using SmartPLS4 with SEM-PLS features utilizing bootstrapping capabilities.

In this research, several hypotheses were accepted while others were rejected, providing deep insights into the factors influencing the adoption of AI assistants among software developers. The accepted hypotheses include the relationship between attitude towards behavioral intention (H1), social influence on attitude (H3), facilitating conditions on attitude (H5), performance expectancy on behavioral intention (H6), effort expectancy on attitude (H9), perceived intelligence on attitude (H11), AI literacy on perceived intelligence (H12), AI literacy on performance expectancy (H13), AI literacy on social influence (H14), AI literacy on facilitating conditions (H17), and AI literacy on effort expectancy (H18). These findings indicate that factors such as a positive attitude towards AI, social influence, and performance expectancy play crucial roles in enhancing developers' intentions to adopt AI assistants. On the other hand, the rejected hypotheses include social influence on behavioral intention (H2), facilitating conditions on behavioral intention (H4), performance expectancy on attitude (H7), effort expectancy on behavioral intention (H8), perceived intelligence on behavioral intention (H10), AI literacy on attitude (H15), and AI literacy on behavioral intention (H16).

In variables with a specific context, such as in an intelligent system, it was found that perceived intelligence can influence developers' attitudes. This is due to the belief that the system's intelligence will affect the level of optimism about the system's potential, as well as the expectations for the final performance of the product produced. Lastly, AI knowledge and literacy were found to influence the antecedents of attitude and behavioral intention, but did not directly affect these two main factors. The reason is that AI knowledge and literacy can enrich individuals' understanding of this technology, alter their perceptions of its benefits and risks, and influence how they respond to or plan actions related to AI. Nevertheless, the main factors underlying attitude and behavioral intention, as previously mentioned, play a more significant role in individual decision-making.

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