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Technology Paradox and User Intention: The Claude AI Application

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ABSTRACT: The purpose of this study is to develop a deeper understanding of the factors influencing user intention to adopt Claude, an AI-based chatbot designed to provide ethical, safe, and high-context interaction.The study involves 200 respondents in Indonesia who have used AI at least once, with data analyzed using AMOS 21. The results show that initial trust has a positive and significant effect on perceived usefulness and perceived ease of use, while social influence also significantly enhances both perceptions. Perceived usefulness and perceived ease of use significantly influence users' attitudes and directly affect their intention to use Claude. However, initial trust does not have a significant effect on attitude. Furthermore, attitude does not mediate the relationships between perceived usefulness or perceived ease of use and intention to use, indicating that behavioral intention is primarily shaped by direct cognitive evaluations rather than affective responses. Overall, perceived usefulness and perceived ease of use emerge as the main determinants of intention to use, with initial trust and social influence acting as important antecedents in shaping early user perceptions. This study extends TAM in the context of AI chatbot adoption and provides practical insights for improving AI acceptance among young users.

KEYWORDS: Initial Trust, Social Influence, Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, Intention to Use.

1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has introduced a paradox in modern technological adoption, where users simultaneously perceive substantial benefits and potential risks from AI-based applications. Mick and Fournier (1998) describe this phenomenon as the technology paradox, in which technology offers efficiency, automation, and convenience while at the same time evoking skepticism, uncertainty, and psychological discomfort among users. This paradox becomes increasingly relevant in the adoption of AI-powered chatbots, where interactions are highly autonomous, personalized, and dependent on users' trust in non-human agents.

Recent global surveys reinforce this concern, indicating that public apprehension toward AI remains significantly high. Edelman (2024) reports that 35% of respondents express rejection toward AI, while Pew Research Center (2025) finds that 51% of the U.S. population feels more worried than excited about the increasing presence of AI technologies. Similarly, Ipsos (2025) highlights that more than half of global respondents (53%) feel nervous about AI, raising critical questions about trust, perceived safety, and ethical considerations associated with AI-driven systems.

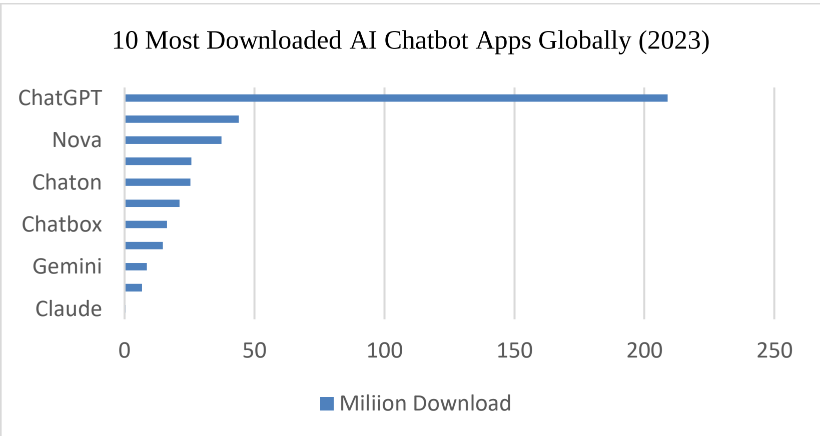

Figure 1. 10 Most Downloaded AI Chatbot Apps Globally (2023)
Sources: Databoks (2023)

Despite these concerns, the usage of AI applications particularly AI chatbots continues to increase globally. In 2023, more than 200 million people actively used AI applications, with ChatGPT topping global downloads at 209 million, followed by other chatbots such as Chat & Ask and Nova (Databoks, 2023). In contrast, Claude, an AI chatbot developed by Anthropic, recorded only around 0.5 million downloads. Although the adoption rate remains low compared with major competitors, Claude offers advanced capabilities and a distinctive ethical foundation through the Constitutional AI framework, which emphasizes transparency, safety, and responsible interaction.

Claude's unique features such as extended memory capacity of up to 200,000 tokens, enhanced semantic reasoning, and multilingual capabilities position it as a promising technology with strong future potential. However, the discrepancy between its technological sophistication and actual adoption highlights an important gap in public acceptance that requires further academic investigation.

This condition suggests that advanced technological features alone do not guarantee user acceptance. Instead, acceptance is shaped by how users perceive usefulness, ease of use, initial trust, and social influence within their decision-making process. Rogers (1962), through the Diffusion of Innovations (DOI) theory, argues that individuals' perceptions of innovation attributes such as relative advantage and complexity significantly determine adoption. Nevertheless, diffusion theory alone is insufficient for explaining modern, interactive digital technologies. For this reason, the Technology Acceptance Model (TAM) developed by Davis (1989) provides a more robust explanation of user acceptance of computer-based systems. Davis (1989) asserts that perceived usefulness and perceived ease of use play central roles in shaping users' attitudes and intentions toward using a new technology. These constructs are particularly relevant in AI-based applications, where users must evaluate functional reliability as well as cognitive and emotional ease when interacting with autonomous systems.

To deepen the explanatory power of TAM, this study integrates two external variables: initial trust and social influence. Initial trust is essential when users engage with unfamiliar technologies for the first time. McKnight et al. (1998) emphasize that initial trust becomes vital in high uncertainty environments, where users lack experiential knowledge and therefore rely heavily on external cues such as reputation, ethical design, and system transparency. In the case of Claude, Anthropic's strong branding concerning AI safety and ethical responsiveness is expected to strengthen initial user trust, particularly among those who remain skeptical about AI reliability and data privacy. In addition, social influence is another critical factor that shapes user intention. According to Venkatesh et al. (2003), social influence reflects the extent to which individuals perceive that people important to them believe they should use a particular technology. For AI chatbots like Claude, recommendations from peers, experts, or online communities may serve as powerful signals that enhance perceived legitimacy, thus increasing adoption likelihood.

Although prior studies have explored TAM in various contexts, research gaps remain. Existing research often emphasizes perceived usefulness and perceived ease of use but provides limited attention to initial trust and social influenceespecially within the context of AI chatbots. Studies such as Abdalla (2024), Prasetya and Lestari (2024), and Yao et al. (2024) highlight that adoption of emerging technologies varies across sectors, yet integration of trust-related constructs and social influence in AI chatbot adoption is still limited. Furthermore, most prior studies focus on high-adoption technologies such as digital payments or mainstream AI platforms, while research on low-adoption yet high-potential AI systems such as Claude remains scarce. Therefore, analyzing Claude offers a unique opportunity to understand how external factors beyond usability influence user acceptance of ethical AI technologies.

Given these gaps, this study aims to investigate the determinants of user intention to adopt Claude by extending TAM through the inclusion of initial trust and social influence. Specifically, the study examines how these external variables shape perceived usefulness, perceived ease of use, attitude toward using, and intention to use Claude. The results of this study are expected to contribute both theoretically and practically. Theoretically, the research enriches TAM literature by integrating trust-based and socially driven determinants in explaining AI chatbot adoption. Practically, the findings provide strategic insights for AI developers and technology providers to design more trustworthy, user-friendly, and socially endorsed AI systems. Understanding how users form perceptions and intentions toward Claude can assist developers in enhancing product features, improving communication strategies, and reducing barriers to AI adoption ultimately supporting responsible and sustainable technological advancement.

2. LITERATURE REVIEW

2.1. Diffusion of Innovation (DOI)

Diffusion of Innovation (DOI) theory proposed by Rogers (1962) explains how an innovation is communicated through certain channels over time among members of a social system. Diffusion occurs because the novelty of an innovation creates uncertainty, prompting individuals to seek sufficient information to reduce that uncertainty. Rogers states that the adoption process takes place through five stages: knowledge, persuasion, decision, implementation, and confirmation, with each stage being influenced by social interaction and individuals' perceptions of the innovation. The DOI theory provides an important foundation for understanding how users respond to new technologies such as AI, including how initial perceptions are formed.

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) developed by Davis (1989) explains that technology acceptance is influenced by two main cognitive constructs, namely perceived usefulness (PU) and perceived ease of use (PEOU). TAM posits that external variables can influence the formation of PU and PEOU, which subsequently shape users' attitudes toward the technology and their intention to use it.

2.3. Initial Trust

Initial trust refers to the trust that emerges at the early stage of interaction, before users have direct experience with a technology. McKnight et al. (1998) explain that initial trust is formed based on cues such as reputation, interface appearance, third-party recommendations, and perceptions of system security. Initial trust is further emphasized by Koufaris and Hampton-Sosa (2004) as trust that develops following users' first interaction with digital technology. According to Choi and Ji (2015), indicators used to measure initial trust include dependability, reliability, and overall trust.

2.4. Social Inflence

Social influence refers to changes in perceptions, attitudes, or behaviors resulting from social interaction. Wang et al. (2013) demonstrate that in digital environments, social influence can also arise from online reviews, user recommendations, and opinions shared through social media, which in turn affect technology adoption. Venkatesh et al. (2003) emphasize that social influence is a key variable influencing users' perceptions of a technology's usefulness and ease of use. Its indicators include recommendations, peer usage, and influential individuals.

2.5. Perceived Usefulness

Venkatesh and Davis (2000) emphasize that perceived usefulness (PU) is influenced by system quality and organizational support, while Sun and Zhang (2006) find that PU increases when technology provides a user-friendly interface and rapid access to information. In robot-based services, Lu et al. (2019) highlight that PU is formed based on the efficiency, accuracy, and responsiveness of the technology.

2.6. Perceived Ease of Use

Perceived ease of use (PEOU) is defined as the perception that a technology is easy to understand and operate. Davis (1989) states that perceived ease of use influences users' attitudes and intention to use both directly and indirectly. Studies by Gefen et al. (2003)and Kim et al. (2009) demonstrate that initial trust can enhance PEOU by reducing concerns about system complexity, thereby making users feel more comfortable operating new technologies.

2.7. Attitude toward using

Attitude toward using reflects users' positive or negative evaluations of a technology. Attitude is shaped by perceived usefulness (PU) and perceived ease of use (PEOU), as explained by Davis (1989). McKnight et al. (2002) argue that initial trust can also foster a positive attitude by reducing uncertainty, while Gefen et al. (2003) find that initial trust leads to more favorable attitudes toward new technologies.

2.8. Intention to Use

Behavioral intention to use is determined by attitude, subjective norms, and perceived behavioral control (Ajzen, 1991). Venkatesh and Davis (2000) state that behavioral intention is the primary predictor of actual usage behavior. The indicators of intention to use in this study refer to willingness to use, future intention, and decision-making, as proposed by Choudhury and Shamszare (Choudhury & Shamszare, 2023).

2.9 Relationship of Inititial Trust and Perceived Usefulness

Initial trust refers to an individual's belief in a technology before having direct experience with it. This early trust is shaped by external cues such as system reputation, interface quality, and third-party endorsements (McKnight et al., 1998). In the context of technology adoption, initial trust influences users' early cognitive evaluations of technology benefits. Gefen et al. (2003) argue that early trust increases perceived usefulness because users believe the system is reliable even before interacting with it. Pavlou & Fygenson (2013) further confirm that stronger initial trust enhances users' beliefs that a technology will improve their efficiency and outcomes.

H1 = Initial Trust has a positive and significant effect on Perceived Usefulness.

2.10. Relationship of Inititial Trust and Perceived Ease of Use

Initial trust plays a critical role in reducing perceived risk and uncertainty during early interactions with technology (Koufaris & Hampton-Sosa, 2004). When initial trust is high, users tend to perceive a system as easier to understand and operate. Gefen et al. (2003) highlight that early trust reduces concerns related to complexity, resulting in higher perceived ease of use. Similarly, Kim et al. (2009) show that strong trust enhances user comfort in operating new technologies.

H2 = Initial Trust has a positive and significant effect on Perceived Ease of Use.

2.11. Relationship of Social Influence and Perceived Usefulness

Social influence refers to changes in individual attitudes or behaviors that result from interactions with their social environment, including friends, peers, and online communities (Kotler & Armstrong, 2016). In the context of technology adoption, positive social cues can lead users to perceive a technology as more useful. Wang et al. (2013) found that recommendations, online reviews, and social opinions strengthen users' beliefs about the usefulness of digital technologies. Venkatesh et al. (2003) also emphasize that social pressure and encouragement can amplify perceived usefulness.

H3 = Social Influence has a positive and significant effect on Perceived Usefulness.

2.12. Relationship of Social Influence and Perceived Ease of Use

Social influence not only shapes perceptions of usefulness but also users' perceptions of ease of use. When people see that others in their environment can use a particular technology effortlessly, they tend to view it as easier to operate (Rianto & Yoganingsih, 2020). Venkatesh et al. (2003) further argue that social influence can help users form expectations that a technology is simple and convenient, often through imitation and social learning.

H4 = Social Influence has a positive and significant effect on Perceived Ease of Use.

2.13. Relationship of Perceived Usefulness and Attitude Toward Using

Perceived usefulness (PU) describes the degree to which a person believes a technology can enhance performance. Davis (1989) identifies PU as a primary determinant of user attitude, explaining that individuals tend to form positive attitudes when they believe a technology provides substantial benefits. Sun & Zhang (2006) also state that higher perceived usefulness directly contributes to more favorable attitudes, as users feel the technology offers efficiency and added value.

H5 = Perceived Usefulness has a positive and significant effect on Attitude Toward Using.

2.14. Relationship of Perceived Ease of Use and Attitude Toward Using

According to Davis (1989), perceived ease of use influences attitude because users respond more positively to technologies that require minimal effort. Venkatesh & Davis (2000) explain that PEOU improves positive attitudes by reducing the cognitive burden associated with using technology. Thus, ease of use is an essential foundation for shaping favorable user attitudes.

H6 = Perceived Ease of Use has a positive and significant effect on Attitude Toward Using.

2.15. Relationship of Attitude Toward Using and Intention to Use

Behavioral intention is the strongest predictor of actual technology usage (Ajzen, 1991). A positive attitude toward a technology increases users' willingness to adopt it. Venkatesh; Viaswanath & Davis; Fred D. (2000) explain that attitude forms the affective basis for individuals' decisions to use a technology.

H7 = Attitude Toward Using has a positive and significant effect on Intention to Use.

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2.16. Relationship of Perceived Usefulness and Intention to Use

Perceived usefulness has consistently been identified as a strong predictor of intention to use technology. Davis (1989) states that when users perceive a technology as beneficial, their motivation to use it increases substantially. Several technology adoption studies confirm that PU directly influences behavioral intention.

H8 = Perceived Usefulness has a positive and significant effect on Intention to Use.

2.17. Relationship of Perceived Ease of Use and Intention to Use

Perceived ease of use affects intention both directly and through attitude (Davis, 1989). Kim et al. (2009) show that when users perceive a technology as easy to operate, they are more likely to develop strong intentions to continue using it.

H9 = Perceived Ease of Use has a positive and significant effect on Intention to Use.

2.18. Relationship of Initial Trut and Intention to Use

Initial trust reduces uncertainty and increases users' confidence in the safety and reliability of technology (McKnight et al., 2002). Higher initial trust leads to more positive affective evaluations toward using a system. Gefen et al. (2003) also demonstrate that trust significantly shapes positive user attitudes during the early stages of technology adoption.

H10 = Initial Trust has a positive and significant effect on Attitude Toward Using.

2.19. Relationship Perceived Usefulness to Intention to Use through Attitude Toward Using

According to TAM, attitude mediates the relationship between perceived usefulness and intention to use (Davis, 1989). When users perceive a technology as highly useful, they form positive attitudes that subsequently enhance their behavioral intention.

H11 = Attitude Toward Using mediates the effect of Perceived Usefulness on Intention to Use.

2.20. Relation of Beliefs to Loyalty through Customer Satisfaction

Davis (1989) also posits that perceived ease of use influences intention indirectly through user attitude. Users who find a technology easy to use tend to develop more favorable attitudes, which ultimately increase their intention to adopt the technology.

H12 = Attitude Toward Using mediates the effect of Perceived Ease of Use on Intention to Use.

2.21. Research Thinking Framework

This study demonstrates significant novelty compared to previous research in terms of research object, variable integration, and contextual relevance. Unlike Abdalla (2024), who examined the intention to use ChatGPT within the Technology Acceptance Model (TAM) framework without emphasizing the role of initial trust, this study highlights the importance of initial trust and social influence in the adoption of AI Claude, a chatbot with relatively low adoption levels. In addition, while Yao et al. (2024) investigated the acceptance of Urban Air Mobility technology by focusing on initial trust and perceived risk without incorporating social factors, this study integrates social influence to explain its effects on perceived usefulness and perceived ease of use. Furthermore, in contrast to Prasetya and Lestari (2024), who applied the core TAM constructs in the context of the GoPay digital payment application without external variables, this study extends TAM by incorporating initial trust and social influence within the context of artificial intelligence–based technology. Therefore, the novelty of this study lies in its specific focus on AI Claude, which remains underexplored in prior research, and in the expansion of TAM through the integration of external factors to provide a more comprehensive understanding of AI chatbot adoption. Figure 2 shows the frame of mind in this study.

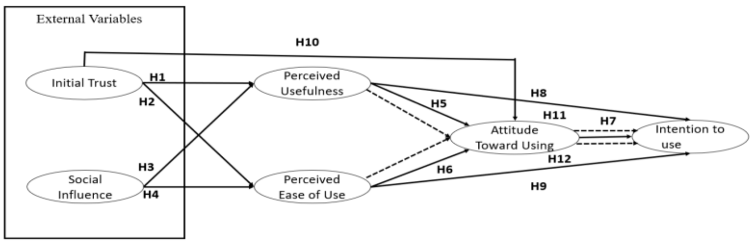

Figure 2. Research Concept Model

Sources: (Abdalla, 2024; Prasetya & Lestari, 2024; Yao et al., 2024)

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3. METHODOLOGY

This study applied a quantitative descriptive research design, using numerical data collected through a structured questionnaire. Quantitative research refers to research that generates findings through statistical procedures and numerical measurement (Cooper & Schindler, 2014). The data were obtained using a cross-sectional approach, in which respondents participated at a single point in time. The research was conducted in Surakarta between April and May 2025, targeting individuals who had prior experience interacting with AI-based chatbot technologies. Primary data served as the main data source, collected directly from respondents. As defined by Sekaran & Bougie (2016), primary data are obtained through researcher-led observations, interviews, or questionnaires, which in this study were distributed online through Google Forms. The questionnaire consisted of closed-ended statements rated on a five-point Likert scale ranging from Strongly Disagree to Strongly Agree.

The population of this research comprised university students in Surakarta who had previously used chatbot technology and intended to switch to Claude AI. Population refers to a complete group of individuals sharing specific relevant characteristics (Cooper & Schindler, 2014). The sampling method employed was non-probability purposive sampling, in which participants were selected based on predetermined criteria. According to Sekaran & Bougie (2016), purposive sampling allows researchers to select respondents who meet specific requirements and can provide relevant information. The criteria included individuals aged 19–28, categorized as "digital natives" (Prensky, 2001); active university students living in Surakarta (Padmanabhan, 2023); those who had prior experience using AI chatbots, as familiarity influences user perceptions (Gefen et al., 2003); and those who voluntarily agreed to participate, consistent with Creswell's (2003) emphasis on informed consent.

The final sample consisted of 162 respondents. Determination of the sample size followed the recommendations by Hair et al. (2018), who suggest that SEM-based studies require five to ten respondents per indicator, and with 18 indicators, the minimum required sample is 162. This sample size meets methodological standards for SEM, supported by Ferdinand (2014) and Hair et al. (2014), who state that 100–200 respondents are sufficient for stable model estimation. Data analysis was conducted using Structural Equation Modeling (SEM). SEM is a second-generation multivariate technique capable of testing complex relationships among variables in both recursive and non-recursive models, providing a comprehensive understanding of the research framework (Ghozali, 2016). The analysis was performed using IBM SPSS AMOS 21 in accordance with recommended analytical procedures.

4. RESULTS AND DISCUSSION

Data collection was conducted by distributing an online questionnaire using Google Forms. The survey link was circulated through various social media platforms such as WhatsApp, Instagram, and Line to reach university students across several institutions in Surakarta, including Universitas Sebelas Maret (UNS), Universitas Muhammadiyah Surakarta (UMS), Universitas Slamet Riyadi (Unisri), Universitas Tunas Pembangunan (UTP), and Institut Seni Indonesia (ISI) Surakarta. The distribution period lasted from November 1 to November 22, 2025. A total of 200 responses were collected, and all 200 questionnaires were deemed valid and suitable for further analysis. The data obtained from these respondents were subsequently tabulated and processed for hypothesis testing related to users' intention to use the Claude AI chatbot. Validity testing was conducted to evaluate whether each item in the questionnaire accurately measured the construct it was intended to capture (Sekaran & Bougie, 2017). Convergent validity was assessed using Confirmatory Factor Analysis (CFA), with a loading factor threshold of > 0.50. Based on the results presented in Table 1, all indicators demonstrated loading values greater than 0.50, indicating that each item was valid and appropriate for measuring its respective construct.

Table 1. Validity Test Results

Variable	Item	Indicator	Estimate	Limits	Results
Initial Trust	1	IT1	0.858	0,5	Valid
	2	IT2	0.848	0,5	Valid
	3	IT3	0.801	0,5	Valid
Social Inflence	1	SI1	0.842	0,5	Valid
	2	SI2	0.846	0,5	Valid
	3	SI3	0.851	0,5	Valid
Perceived Usefulness	1	PU1	0.861	0,5	Valid
	2	PU2	0.843	0,5	Valid
	3	PU3	0.824	0,5	Valid

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	1	PeoU1	0.902	0,5	Valid
Perceived Ease of Use	2	PeoU2	0.794	0,5	Valid
	3	PeoU3	0.795	0,5	Valid
	1	ATU1	0.835	0,5	Valid
Attitude Toward Using	2	ATU2	0.802	0,5	Valid
	3	ATU3	0.867	0,5	Valid
	1	ITU1	0.856	0,5	Valid
Intention to Use	2	ITU2	0.853	0,5	Valid
	3	ITU3	0.841	0,5	Valid

Source: Processed primary data, 2025.

Reliability testing was then performed to determine the internal consistency of the measurement instrument. According to Sekaran and Bougie (2017), reliability indicates the extent to which a measurement is free from error and produces consistent results across time and different conditions. A construct is considered reliable if its Construct Reliability (CR) value exceeds 0.70. As shown in Table 2, all constructs in this study had CR values above the recommended threshold, confirming that each variable is reliable and suitable for use as a measurement instrument.

Table 2. Reliability Test Results

Variable	Construct Reliability (CR)	Limit	Variance Extracted (VE)	Limit	Results
Initial Trust	0,874359	>0,7	0,698956	> 0,5	Reliable
Social Influence	0,883371	>0,7	0,716294	> 0,5	Reliable
Perceived Usefulness	0,880293	>0,7	0,710315	> 0,5	Reliable
Perceived Ease of Use	0,870398	>0,7	0,692022	> 0,5	Reliable
Attitude Toward Using	0,873517	>0,7	0,697373	> 0,5	Reliable
Intention To use	0,886518	>0,7	0,722542	> 0,5	Reliable

Source: Processed primary data, 2025.

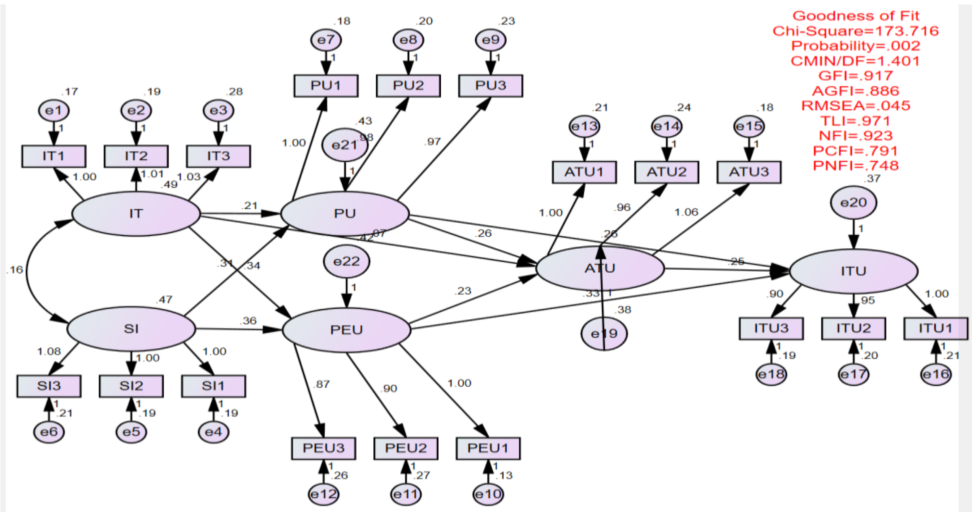

Figure 3. Output Model Diagram
Source: Processed primary data, 2025.

Goodness-of-fit evaluation was conducted to assess how well the proposed structural model aligned with the empirical data. The structural model, estimated using AMOS, included latent variables such as Initial Trust (IT), Social Influence (SI), Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude Toward Using (ATU), and Intention to Use (ITU), each measured through

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multiple indicators (e.g., IT1, PU2, PEU3). The directional arrows between constructs represented the hypothesized relationships examined within the extended Technology Acceptance Model (TAM).

Table 3. Goodness of Fit Index

Goodness of fit index	Cut-off value	Model Results	Results
Chi-Square	Expected to be small	173,716	Not Fit
Signifikansi Probability	≥ 0,05	0,002	Not Fit
CMIN/DF	< 2,00	1,401	Fit
Goodness of Fit Index (GFI)	≥ 0,90	0,917	Fit
Rood Mean Square Error of Approximation (RMSEA)	0,05 - 0,08	0,045	Marginal Fit
Adjusted Goodness of Fit Index (AGFI)	≥ 0,90	0,886	Marginal Fit
Tucker-Lewis Index (TLI)	≥ 0,90	0,971	Fit
NFI	≥ 0,90	0,923	Fit
PNFI	0.60 – 0,90	0,748	Fit
PCFI	≥ 0,90	0,791	Not Fit

Source: Processed primary data, 2025.

The model fit indices obtained from the analysis provide insight into the adequacy of the model. The Chi-square value was 173.716 with a probability of 0.002. Although the probability value was below 0.05—indicating a statistically significant Chi-square—this outcome is acceptable given the sensitivity of the Chi-square test to large sample sizes. Additional fit indices demonstrated satisfactory model fit, including CMIN/DF = 1.401 (< 2.0), GFI = 0.917 (> 0.90), AGFI = 0.886 (approaching 0.90), TLI = 0.971 (> 0.90), and NFI = 0.923 (> 0.90). The RMSEA value of 0.045 (< 0.08) further indicates a good level of fit, suggesting that the proposed model adequately represents the observed data. The results of the direct and indirect hypothesis testing can be seen in Table 4 and Table 5.

Table 4. Results of Direct Hypothesis

H	Hypothesis	Estimate	S.E.	C.R.	P	Results
H1	Initial Trust -> Perceived Usefulness	.212	.084	2.531	.011	**Significantly positive**
H2	Initial Trust -> Perceived Ease of Use	.338	.086	3.952	***	**significantly positive**
H3	Social Influence -> Perceived Usefulness	.309	.086	3.591	***	**significantly positive**
H4	Social Influence -> Perceived Ease of Use	.363	.087	4.166	***	**significantly positive**
H5	Perceived Usefulness -> Attitude Toward Using	.264	.077	3.406	***	**significantly positive**
H6	Perceived Ease of Use -> Attitude Toward Using	.232	.077	3.026	.002	**significantly positive**
H7	Attitude Toward Using -> Intention to Use	.246	.087	2.831	.005	**significantly positive**
H8	Perceived Usefulness -> Intention to Use	.263	.080	3.307	***	**significantly positive**
H9	Perceived Ease of Use -> Intention to Use	.334	.075	4.433	***	**significantly positive**
H10	Initial Trust -> Attitude Toward Using	.069	.086	.808	.419	positive but not statistically significant

Source: Processed primary data, 2025.

To examine the direct effect hypotheses, this study employed the regression weights produced by the structural model analysis. The criteria for hypothesis testing follow Ghozali (2016), which state that an exogenous variable is considered to have a significant effect on an endogenous variable if the critical ratio (CR) value is greater than 1.96 and the p-value is below the significance level of 0.05. The results indicate that Initial Trust has a positive and significant effect on Perceived Usefulness (CR = 2.531; p = 0.011). This suggests that higher levels of initial trust lead users to perceive greater usefulness of the technology. This finding aligns with Gefen et al. (2003), who emphasized the role of initial trust in shaping early user evaluations of technological benefits. Thus, H1 is supported.

Initial Trust is found to positively and significantly influence Perceived Ease of Use (CR = 3.952; p < 0.001). Users who initially trust the technology tend to believe that it is easy to operate. Prior research (Gefen et al., 2003; Kim et al., 2009) supports this relationship by showing that trust reduces concerns about complexity. Therefore, H2 is supported.

Social Influence has a positive and significant effect on Perceived Usefulness (CR = 3.591; p < 0.001). This means that recommendations, opinions, and social norms increase users' beliefs about the technology's usefulness. The result is consistent with TAM2 (Venkatesh & Davis, 2000), which identifies social influence as a key determinant of perceived usefulness in early adoption. Hence, H3 is supported.

The analysis shows that Social Influence positively and significantly affects Perceived Ease of Use (CR = 4.166; p < 0.001). Social support and peer encouragement make users perceive the technology as easier to use. This aligns with findings by Venkatesh & Bala (2008) and Schepers & Wetzels (2007), who highlight the role of social norms in shaping ease-of-use perceptions. Thus, H4 is supported.

Perceived Usefulness exerts a positive and significant influence on Attitude Toward Using (CR = 3.406; p < 0.001). Users who perceive strong benefits tend to form favorable attitudes toward the technology. This finding is consistent with Davis (1989) and Venkatesh & Davis (2000), who emphasize the central role of usefulness in shaping attitudes. Therefore, H5 is supported.

Perceived Ease of Use positively and significantly affects Attitude Toward Using (CR = 3.026; p = 0.002). When users find the technology easy to use, they tend to develop more positive attitudes toward it. This supports the TAM model proposed by Davis (1989), where ease of use influences attitudes by reducing psychological and technical barriers. Hence, H6 is supported.

Attitude Toward Using significantly predicts Intention to Use (CR = 2.831; p = 0.005). Users with positive attitudes are more inclined to adopt the technology. This finding is supported by TAM (Davis et al., 1989) and UTAUT (Venkatesh et al., 2003), which highlight attitude as a key determinant of behavioral intention. Thus, H7 is supported.

Perceived Usefulness has a positive and significant impact on Intention to Use (CR = 3.307; p < 0.001). Users who perceive the technology as useful are more willing to adopt it. This aligns with Davis (1989), who identified perceived usefulness as the strongest predictor of behavioral intention. Therefore, H8 is supported.

Perceived Ease of Use significantly and positively influences Intention to Use (CR = 4.433; p < 0.001). A simpler and more intuitive system increases users' intention to adopt the technology. This is in line with TAM and TAM3 (Venkatesh & Bala, 2008), which emphasize the importance of ease of use in early technology adoption. Hence, H9 is supported.

Initial Trust does not have a significant effect on Attitude Toward Using (CR = 0.808; p = 0.419). Although the coefficient is positive, the effect does not reach statistical significance, indicating that initial trust alone does not shape users' attitudes. Previous studies Koufaris & Hampton-Sosa (2004) suggest that trust may lose its direct influence when cognitive factors such as perceived usefulness and ease of use dominate attitude formation. Thus, H10 is not supported.

Table 5. Results of Indirect Hypothesis

H	Hypothesis	*Direct*	*Indirect*	Results
H11	There is a mediating effect of Perceived Usefulness on Intention to Use through Attitude Toward Using	.249	.062	Shows no mediating effect
H12	There is a mediating effect of Perceived Ease of Use on Intention to Use through Attitude Toward Using	.336	.057	Shows no mediating effect

Source: Processed primary data, 2025.

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To determine the presence of a mediating effect, the comparison between the standardized direct effect and the standardized indirect effect is used. According to Bahri and Zamzam (2015), if the standardized direct effect is greater than the standardized indirect effect, the mediating variable is considered unable to mediate the relationship between the two variables. Conversely, if the standardized direct effect is smaller than the standardized indirect effect, the mediating variable is considered capable of mediating the relationship indirectly.

The analysis shows that Attitude Toward Using does not mediate the relationship between Perceived Usefulness and Intention to Use. The indirect effect (0.062) is smaller than the direct effect (0.249), and the mediation pathway is statistically insignificant ($p > 0.05$). This indicates that users form their intention to use the technology primarily based on its perceived usefulness rather than through their attitude toward using it. While earlier studies (e.g., Davis, 1989; Venkatesh & Davis, 2000) highlight attitude as an important mediator, the present finding aligns with research suggesting that strong direct effects of perceived usefulness can overshadow the mediating role of attitude (Mathieson, 1991; Chau & Hu, 2002). Thus, H11 is not supported.

The results indicate that Attitude Toward Using does not mediate the relationship between Perceived Ease of Use and Intention to Use. The indirect effect (0.057) is weaker than the direct effect (0.336), with the mediation path failing to reach statistical significance ($p > 0.05$). This suggests that users directly develop intentions based on perceived ease of use, rather than through changes in their attitude. Although prior studies (Davis, 1989; Venkatesh & Bala, 2008) position attitude as a central mediator, this study supports evidence that the mediating role can diminish when the direct cognitive influence of ease of use is stronger (Mathieson, 1991; Hu et al., 2003). Therefore, H12 is not supported.

5. CONCLUSIONS AND SUGGESTIONS

Based on the analysis of data collected from 200 university students in Surakarta, this study demonstrates that the extended Technology Acceptance Model (TAM) provides a strong explanatory framework for understanding the factors influencing students' intention to use the Claude AI chatbot. The findings indicate that initial trust significantly enhances both perceived usefulness and perceived ease of use, while social influence also positively affects these two cognitive perceptions. Perceived usefulness and perceived ease of use significantly shape users' attitudes and directly influence their intention to use the technology. However, initial trust does not have a significant effect on attitude, and attitude does not mediate the relationships between perceived usefulness or perceived ease of use and intention, indicating that behavioral intention is formed primarily through direct cognitive evaluations rather than affective pathways. Overall, perceived usefulness and perceived ease of use emerge as the main determinants of intention, with initial trust and social influence serving as important antecedents in shaping early user perceptions. Theoretically, this study extends TAM in the context of AI chatbot adoption by emphasizing the critical roles of initial trust and social influence in the formation of early acceptance beliefs.

From a practical perspective, the findings suggest that AI developers should prioritize enhancing system transparency, data security, and overall user experience in order to build initial trust and foster positive perceptions of usefulness and ease of use from the early stages of adoption. Educational institutions can further support AI adoption by strengthening students' digital literacy and actively integrating AI-based tools into academic learning activities. For future research, it is recommended to incorporate emotional and psychological variables, expand the respondent population beyond university students, and employ actual usage or behavioral data to obtain more comprehensive and generalizable insights. Collectively, these efforts may contribute to a deeper understanding of the successful adoption of AI technologies such as Claude, which depends not only on system capabilities but also on trust, usability, and supportive social environments.

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