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Factor Analysis of AI Chatbot Continuance Use: An Extended Expectation Confirmation Model Perspective

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ABSTRACT

The adoption of technology in the workplace has grown rapidly alongside advancements in information and communication technology. One key innovation is the adoption of AI-based chatbots to support work activities. In the digital era, the success of the new technology relies heavily on user perception and response. This study aims to identify the factors influencing users' intention to continue using AI chatbots at work using the Extended Expectation Confirmation Model (E-ECM), with variables including confirmation, perceived usefulness, satisfaction, continuance intention and with additional variables being perceived ease of use and trust. A quantitative method was used by distributing questionnaires to 400 respondents. The respondents are workers who have used AI chatbots for their work. This research adopts a quantitative method and employs data analysis using the PLS-SEM technique. The findings reveal that perceived ease of use and trust significantly affect continuance intention, while confirmation, perceived usefulness, and trust significantly affect satisfaction. However, perceived usefulness and satisfaction did not significantly influence continuance intention. These insights can help stakeholders and users focus on key factors to optimize AI chatbot adoption in the workplace. The results of this study are expected to serve as a reference for developers and users to pay attention to what factors affect the intention of continuous use of AI chatbots so as to increase the effectiveness of using AI chatbots.

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1. INTRODUCTION

The use of technology in the world of work has experienced rapid development along with advances in information and communication technology. One of the latest breakthroughs in the digital world is the application of artificial intelligence-based chatbot technology which is increasingly popular in supporting various activities in the workplace (Komp-Leukkunen, 2024). This technology is designed to mimic human communication capabilities and interact in real-time with users, making it an efficient and effective tool in meeting the operational needs of modern organizations (Deng & Lin, 2023; Komp-Leukkunen, 2024). AI chatbots can boost workplace productivity and information access, but their continued use depends on worker acceptance and response. (Modgil et al., 2025).

In this digital era, the successful integration of new technologies in the world of work is greatly influenced by user perceptions and attitudes (Chowdhury et al., 2022). While AI chatbots offer convenience and flexibility, many early adopters are reluctant to continue using these chatbots after the initial interaction (Zou & Huang, 2023). Therefore, understanding the factors that influence the intention to continue using AI chatbots among workers is important to ensure that this technology can continue to be optimally utilized in the long run.

The Expectation Confirmation Model (ECM) is a commonly used approach to understanding users' sustainability intentions towards technology (Ambalov, 2018). This model identifies several key variables such as perceived usefulness, confirmation, and satisfaction that are used to measure the level of continued use (Bhattacherjee & Lin, 2015). The addition of these two variables allows researchers to identify more factors that could potentially influence the long-term success of technology implementations and thus provide more accurate insights for system development and improvement (Tam et al., 2020).

2. RESEARCH FRAMEWORK

2.1 Continuance Intention

Continuance intention refers to a condition where a person makes a decision to continue using a product or service for the future (Tan et al., 2023). Generally, continuance intention analysis is applied to technology-based products or technology services to support the contribution of these technology products and services (Jo & Bang, 2023). Continuance intention cannot be confused with acceptance, initial use, adoption or even behavioral intention because continuance intention is based on user experience after using the technology or product used (Nan et al., 2024; Wu & Li, 2023).

2.2 AI Chatbots

AI chatbot is a technology that can provide solutions, recommendations, ways / other ways in real time adjusted to the digital data owned and adjust the language used by its users (Zhu et al., 2022). AI-based chatbots, as they are popular today, rely on natural language processing (NLP) techniques to understand text or voice input from users, extract relevant intent and entities, and generate coherent and contextualized responses (Chou et al., 2024). The acceptance of AI chatbots varies by generation, with older workers generally more sceptical due to job security concerns, while younger workers view them as productivity-enhancing tools (Frey & Osborne, 2017; Twenge, 2014). However, over-reliance on AI chatbots may lead to concerns of decreased problem-solving abilities (Bughin et al., 2017). To make the most of AI chatbots, workers need to have new skills, such as digital literacy and the ability to adapt to technological change (Urbani et al., 2024).

2.3 Extended Expectation Confirmation Model (E-ECM)

ECM is a model that will describe how the actual experience of a person affected by an information system and confirm it based on their previous expectations (Bhattacherjee, 2001). The ECM model in this study will add the variables of perceived ease of use and trust so that it allows researchers to identify more factors that have the potential to influence the long-term success of technology implementation so that it can provide more accurate insights for system development and improvement.

PEOU, as an additional variable in the Extended ECM, adds relevant insight into the usability of new technologies like AI chatbots. Trust is included because users' belief in the system's security, reliability, and credibility can reinforce their intention to continue using it. The framework of the Extended Expectation Confirmation Model is illustrated in Figure 1.

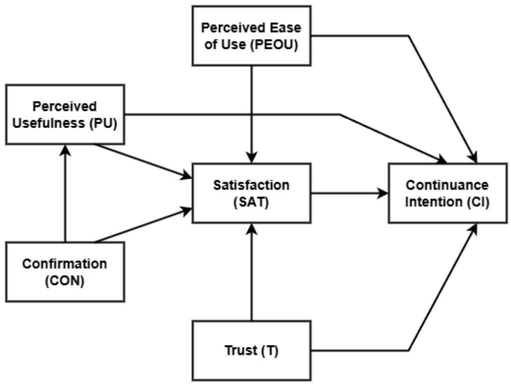

Figure 1. Extended expectation confirmation model framework

2.4 Hypotheses Development

Extended ECM has several variables that can describe how continuance intention and its influence on job use. The first variable is confirmation. This variable can be interpreted as a state where individuals have felt the benefits based on the experience gained from using a system (Hossain & Quaddus, 2012). Previous research suggests that confirmation has a positive influence on perceived usefulness, which in turn affects the intention to continue using a system (Ifada & Abidin, 2022; Oghuma et al., 2016). In addition to influencing perceived usefulness, this variable also has a positive impact on satisfaction in determining the intention to use learning applications continuously (Alshurideh et al., 2019). Based on this description, the following hypotheses are generated:

H1: Confirmation (CON) has a significant effect on perceived usefulness (PU).

H2: Confirmation (CON) has a significant effect on satisfaction (SAT).

The next variable is perceived usefulness. This variable can explain the extent to which a person believes that using a system or technology can be beneficial so as to improve their performance or productivity (Ma et al., 2024). Previous research has proven that when users feel there is usefulness while using a system or technology, these users are satisfied with the technology used (Amin et al., 2014; Baker-Eveleth & Stone, 2020). Research from Hamid et al. (2016) proves that users who feel the usefulness of the technology used, users tend to decide to continue using the technology in the future. Based on this description, the following hypotheses are generated:

H3: Perceived usefulness has a significant effect on satisfaction (SAT).

H4: Perceived usefulness has a significant effect on continuance intention (CI).

Satisfaction is the next variable. This variable can be measured based on their experience in using AI chatbots, both in terms of ease of use, perceived benefits, and how well the technology meets their work needs (Ashfaq et al., 2020). Research conducted by Nan et al. (2024) shows that satisfaction with the use of AI chatbots has a positive influence on generating interest in continued use in its users. Based on this description, the following hypotheses are generated:

H5: Satisfaction (SAT) has a significant effect on continuance intention (CI).

The next is perceived ease of use variable. This variable refers to the extent to which a person believes that using a system or technology will be free from effort or difficulty (Davis, 1989). Based on research conducted by Ashfaq et al. (2020), perceived ease of use can have a positive influence on user satisfaction in using certain systems. In addition, research from Hamid et al. (2016) proves that users who find it easy to use certain technologies tend to continue using them in the future. Based on this description, the following hypotheses are generated:

H6: Perceived of ease of use (PEOU) has a significant effect on satisfaction (SAT).

H7: Perceived of ease of use (PEOU) has a significant effect on continuance intention (CI).

The following variable is trust which explains user confidence that a particular system or technology is reliable, safe, and able to protect user interests during use (Gefen et al., 2003). Based on research conducted by Ginting et al. (2023), user trust in a system has a positive influence on user satisfaction. Various studies using the ECM model have also supported the finding that trust has a positive influence on sustainable use interest, especially in the use of service-based technology (Pham et al., 2024; Zhu et al., 2023). Based on this description, the following hypotheses are generated:

H8: Trust (T) has a significant effect on satisfaction (SAT).

H9: Trust (T) has a significant effect on continuance intention (CI).

3. Method

This research employs a quantitative approach to examine the influence of confirmation, perceived usefulness, satisfaction, perceived ease of use, and trust on workers' continuance intention to use AI chatbots at work. Data were collected through surveys distributed both online and offline in a hybrid manner. The responses were then analyzed using the Partial Least Square - Structural Equation Model (PLS-SEM).

3.1 Determination of Population and Simple

In this study, the population used is all workers in Indonesia. Based on the Official Statistics issued by Badan Pusat Statistik (BPS), the number of people working as of August 2024 was 144.64 million (Badan Pusat Statistik, 2024). The sampling technique used was purposive sampling. The criteria determined were workers who had used an AI chatbots for their work. The sample size was calculated using the Slovin method with an error rate of 5% and got the value of 399.98, which was rounded up to 400 respondents to facilitate the data processing process.

3.2 Instrument

Data is obtained from surveys using questionnaires distributed online or in person. Online distribution will use commonly used social media, such as Whatsapp, Telegram, and others. In the offline distribution of questionnaires, the author will visit companies that are open to helping fill out questionnaires, such as worker training seminars, cafes and workspaces.

The questionnaire consisted of six constructs and 25 items. The six constructs are confirmation (four items), perceived usefulness (five items), perceived ease of use (five items), trust (four items), satisfaction (four items), and continuance intention (three items). The research questionnaire also had questions related to the demographics of the respondents. The construct question uses a Likert scale with five levels of assessment, which are 5 = strongly agree, 4 = agree, 3 = neutral, 2 = disagree, and 1 = strongly disagree (Hair et al., 2007). Details regarding the research instruments used in this study can be seen in Table 1.

Table 1. Research indicators

Variable	Indicator	Items measured	Source
Confirmation (CON)	CON1	My experience with the AI chatbot at work exceeded my expectations.	Bhattacherjee (2001); Ngo et al. (2024); Oghuma et al. (2016)
	CON2	The level of service provided by the AI chatbot is better than what I expected.	
	CON3	AI chatbots offer more benefits than I expected before.	
	CON4	Most of my expectations of the AI chatbot in assisting with work were met.	
	PU1	I find AI chatbots useful in my work.	Ashfaq et al. (2020); Davis

Variable	Indicator	Items measured	Source
Perceived Usefulness (PU)	PU2	Using an AI chatbot makes my job easier.	(1989); Oghuma et al. (2016)
	PU3	Using an AI chatbot increases my effectiveness at work.	
	PU4	Using an AI chatbot increases my productivity.	
	PU5	Using an AI chatbot improved my performance.	
Perceived Ease of Use (PEOU)	PEOU1	I find AI chatbots easy to use for work activities.	Ashfaq et al. (2020); Davis (1989); Rahayu (2023)
	PEOU2	It was easy for me to understand the response given by the AI chatbot.	
	PEOU3	It is easy for me to start a conversation or give a command the first time when using an AI chatbot.	
	PEOU4	It was easy for me to become proficient in using AI chatbots at work.	
	PEOU5	My interactions with the AI chatbot were clear and easy to understand.	
Trust (T)	T1	I believe the response given by the AI chatbot is trustworthy.	Choudhury and Shamszare (2023); Hyun Baek and Kim (2023)
	T2	I believe in the credibility of AI chatbots in providing answers.	
	T3	I believe AI chatbots are safe to be given sensitive information from me.	
	T4	I believe AI chatbots will be transparent in providing answers.	
Satisfaction (SAT)	SAT1	I was pleased with the AI chatbot's ability to help me with my work.	Nan et al. (2024); Ngo et al. (2024); Tam et al. (2020)
	SAT2	I feel like I've made the right decision to use an AI chatbot for work.	

Variable	Indicator	Items measured	Source
	SAT3	Based on my experience, I feel satisfied using AI chatbots at work.	
	SAT4	I think the use of AI chatbots in work is a good idea.	
Continuance Intention (CI)	CI1	I intend to continue using AI chatbots in my work.	Ashfaq et al. (2020); Pham et al. (2024)
	CI2	I will use the AI chatbot in my work as I normally do.	
	CI3	I would recommend others to use an AI chatbot for work.	

3.3 Evaluation of the Measurement Model

Evaluation of the measurement model in this study will be assisted by testing the outer model from PLS-SEM. In PLS-SEM, testing the outer model includes two main aspects, namely validity, which includes convergent validity and discriminant validity, and reliability, which is evaluated through composite reliability. Convergent validity can indicates that the latent construct explains the majority of the variance in its indicators if the AVE (Average Variance Extracted) is > 0.5 (Djoko & Sihono, 2021).

Table 2. AVE formula

Formula	Variable	Description
$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{\sum_{i=1}^{n} \lambda_i^2 + \sum_{i=1}^{n} var(\varepsilon_i)}$	λ_i (Lambda)	Loading of indicator variable i
	ε_i (Epsilon)	Measurement error of indicator variable i
	i	Indicator variable
	n	Amount of data
	$var(\varepsilon_i)$	Deviation of measurement ε_i

In the discriminant validity test, it can tell how correlated the indicators are with the variable itself if the cross loading value > 0.6 in their variable section (Darma, 2021).

Table 3. Factor loading formula

Formula	Variable	Description
$\lambda_i = \frac{Cov(x_i \eta)}{\sigma_{x_i} \cdot \sigma_\eta}$	λ_i (Lambda)	Loading of indicator variable i
	x_i	The observed score of indicator i
	η	The latent variable score (construct) measured by the indicators
	$Cov(x_i \eta)$	Covariance between the indicator x_i and the latent construct η
	σ_{x_i}	Standard deviation of indicator x_i
	σ_η	Standard deviation of the latent construct η

In addition, the composite reliability test can tell how reliable the variable is if it has a composite reliability value and Cronbach's alpha > 0.7 (Sugiyono, 2013).

Table 4. Composite reliability formula

Formula	Variable	Description
$Composite\ reliability\ (\rho) = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + \sum_{i=1}^{n} var(\varepsilon_i)}$	λ_i (Lambda)	Loading of indicator variable i
	ε_i (Epsilon)	Measurement error of indicator variable i
	ρ (Rho)	Composite reliability
	i	Indicator variable
	n	Amount of data
	$var(\varepsilon_i)$	Deviation of measurement ε_i

3.4 Evaluation of the Structural Model

Structural model evaluation is conducted using the PLS-SEM inner model technique to analyze relationships between latent variables. This involves assessing path coefficients, R-square, effect size, and Q-square to determine the influence of independent latent variables on dependent ones. The r-square test can find how much the exogenous variables can explain the endogenous variables with the criteria, strong if it reaches 0.75, moderate if it is worth 0.50, and weak if it is at 0.25 (Hair et al., 2017).

Table 5. R-square formula

Formula	Variable	Description
$\eta = \gamma_1\xi_1 + \gamma_2\xi_2 + \gamma_3\xi_3 + \zeta$	η (Eta)	Endogenous latent variable
	γ (Gamma)	The coefficient of influence of exogenous variables on endogenous variables
	ξ (Ksi)	Exogenous latent variable
	ζ (Zeta)	Error model

The q-square test can find how well the model's predictive ability predicts the dependent variable with the criteria, large if it reaches 0.35, medium if it is 0.15, and small if it is 0.02.

Table 6. Q-square formula

Formula	Variable	Description
$Q^2 = 1 - (1 - {R_1}^2)(1 - {R_2}^2) \dots (1 - {R_n}^2)$	${R_1}^2, {R_2}^2, \dots, {R_n}^2$	Endogenous latent variable
	Q^2	The coefficient of influence of exogenous variables on endogenous variables

The effect size test can find how much influence exogenous variables have on endogenous variables with criteria, large if it reaches 0.35, medium if it is 0.15, and small if it is 0.02 (Hair Jr et al., 2021).

Table 7. Effect size formula

Formula	Variable	Description
$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$	f^2	Effect size
	$R^2_{included}$	R-square obtained if the independent variables are included in the model
	$R^2_{excluded}$	R-square obtained if the independent variable is excluded from the model

The path coefficient test can measure the significance (p-value) and relevance (t-value) of the relationship between variables with a significance of 5% (p-value < 0.05 and t-value > 1.96).

Table 8. T-value formula

Formula	Variable	Description
$t - value = \frac{\beta}{SE(\beta)}$	β	Path coefficient/original sample estimate
	$SE(\beta)$	Standard error of the path coefficient

The last test is the model fit test which can measure the ability of the research model to represent the relationship between variables and existing data with the criteria, chi-square ≥ 0.05, SRMR ≤ 0.10, NFI ≥ 0.90 indicates that the model used is good-fit, and if it does not meet the poor-fit criteria (Hair et al., 2017).

Table 9. Chi-square formula

Formula	Variable	Description
$x^2 = (N-1) \cdot F_{min}$	x^2	Chi-square value
	N	Number of samples
	F_{min}	Minimum fit function value

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4. Result and Discussion

A total of 449 questionnaire responses were collected, with 400 randomly selected for further analysis based on the predetermined sample size. Data screening using Microsoft Excel found no missing data, unengaged responses, or outliers, as shown in Table 10.

Table 10. Data screening result

Description	Data
Total data	400
Missing data	0
Unengaged response	0
Outlier data	0
Total	400

4.1 Evaluation of the Measurement Model (Outer Model)

4.1.1 Convergent Validity

This evaluation is carried out by paying attention to the outer loading and Average Variance Extracted (AVE) values. Variables are declared to have good convergent validity and each item represents the latent variable of the item if it has an AVE value of more than 0.5 and an outer loading value of more than 0.6 (Hair et al., 2017). Referring to Table 11, the outer loading exceeds 0.6 and the AVE value is above 0.5, indicating that the data is valid and eligible for subsequent testing.

Table 11. Convergent validity result

Variable	Item	Outer Loading	AVE
Confirmation	CON1	0.852	0.658
	CON2	0.750	
	CON3	0.800	
	CON4	0.839	
Continuance Intention	CI1	0.862	0.704
	CI2	0.801	
	CI3	0.853	
Perceived Ease of Use	PEOU1	0.781	0.634
	PEOU2	0.796	
	PEOU3	0.782	
	PEOU4	0.786	
	PEOU5	0.836	
Perceived Usefulness	PU1	0.832	0.672
	PU2	0.809	
	PU3	0.816	
	PU4	0.804	
	PU5	0.839	
Satisfaction	SAT1	0.860	0.702
	SAT2	0.783	
	SAT3	0.863	
	SAT4	0.842	
Trust	T1	0.869	0.730
	T2	0.859	
	T3	0.831	
	T4	0.860	

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4.1.2 Discriminant Validity

Discriminant validity test is carried out by paying attention to the cross loading value. Each item has good consistency on the corresponding variable and is correlated if the cross loading value of the item is more than 0.6 (Janna & Herianto, 2021). Referring to Table 12, the cross loading exceeds 0.6, indicating that the item has good consistency on the corresponding and correlated variables and is eligible for further testing.

Table 12. Cross loading

	CON	CI	PEOU	PU	SAT	T
CON1	**0.852**	0.729	0.760	0.714	0.704	0.690
CON2	**0.750**	0.691	0.726	0.646	0.669	0.649
CON3	**0.800**	0.691	0.735	0.655	0.665	0.618
CON4	**0.839**	0.720	0.772	0.671	0.695	0.682
CI1	0.729	**0.862**	0.754	0.688	0.665	0.686
CI2	0.727	**0.801**	0.736	0.688	0.678	0.686
CI3	0.742	**0.853**	0.747	0.680	0.685	0.709
PEOU1	0.723	0.688	**0.781**	0.632	0.649	0.640
PEOU2	0.735	0.709	**0.796**	0.695	0.671	0.643
PEOU3	0.701	0.712	**0.782**	0.676	0.683	0.638
PEOU4	0.737	0.679	**0.786**	0.676	0.675	0.637
PEOU5	0.777	0.750	**0.836**	0.730	0.720	0.699
PU1	0.642	0.673	0.697	**0.832**	0.758	0.712
PU2	0.704	0.675	0.741	**0.809**	0.758	0.727
PU3	0.682	0.667	0.685	**0.816**	0.767	0.702
PU4	0.671	0.659	0.699	**0.804**	0.759	0.738
PU5	0.697	0.675	0.691	**0.839**	0.763	0.738
SAT1	0.706	0.694	0.731	0.802	**0.860**	0.734
SAT2	0.682	0.653	0.671	0.742	**0.783**	0.723
SAT3	0.721	0.703	0.737	0.796	**0.863**	0.757
SAT4	0.716	0.650	0.720	0.769	**0.842**	0.758
T1	0.703	0.730	0.698	0.768	0.785	**0.869**
T2	0.712	0.699	0.708	0.766	0.773	**0.859**
T3	0.664	0.709	0.675	0.708	0.730	**0.831**
T4	0.704	0.686	0.717	0.773	0.743	**0.860**

4.1.3 Composite Reliability

The composite reliability test is carried out by looking at the Cronbach's alpha and composite reliability values. Variables are declared to have good reliability if they have a Cronbach's alpha value and a composite reliability value of more than 0.7 (Amalia & Arthur, 2023). Based on Table 13, Cronbach's alpha value and a composite reliability value exceed 0.7, indicating that the variable has good reliability and is eligible for further testing.

Table 13. Cronbach's alpha and composite reliability value

Variable	Cronbach's alpha	Composite Reliability
Confirmation	0.826	0.885
Continuance Intention	0.789	0.875
Perceived Ease of Use	0.856	0.897

Variable	Cronbach's alpha	Composite Reliability
Perceived Usefulness	0.878	0.911
Satisfaction	0.858	0.904
Trust	0.877	0.915

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4.2 Evaluation of the Structural Model (Inner Model)

4.2.1 R-Square Test

This test relies on the R^2 values of each endogenous variable to assess the influence of exogenous variables. According to previous research, an $R^2 \geq 0.75$ indicates strong influence, ≥ 0.50 moderate, and ≥ 0.25 weak. (Hair Jr et al., 2021) . Based on Table 14, the R^2 values for CI and SAT exceed 0.75, showing strong influence, while the PU variable, with an R^2 between 0.5 and 0.75, indicates moderate influence.

Table 14. R-square test result

Variable	R^2	Description
Continuance Intention	0.821	Strong
Perceived Usefulness	0.687	Moderate
Satisfaction	0.891	Strong

4.2.2 Q-Square Test

The Q-square test assesses predictive relevance using the Q^2 value of each endogenous variable. A $Q^2 \geq 0.35$ indicates high relevance, ≥ 0.15 moderate, and ≥ 0.02 low. Based on Table 15, the Q^2 values for CI, PU, and SAT exceed 0.35, showing that these variables have strong predictive relevance in the model.

Table 15. Q-square test result

Variable	Q^2	Description
Continuance Intention	0.572	Large
Perceived Usefulness	0.454	Large
Satisfaction	0.617	Large

4.2.3 Effect Size Test

The effect size test uses the f^2 value to measure how much each exogenous variable influences the endogenous variables. An $f^2 \geq 0.35$ indicates a large effect, ≥ 0.15 a moderate effect, and ≥ 0.02 a small effect. Based on Table 16, CON → PU, PEOU → CI, and PU → SAT show large effects. CON → SAT, T → CI, and T → SAT show small effects, while PEOU → SAT, PU → CI, and SAT → CI have f^2 values < 0.02, indicating no effect.

Table 16. Effect size test result

	CON	CI	PEOU	PU	SAT	T
CON				2.191	0.022	
CI						
PEOU		0.565			0.004	
PU		0.002			0.471	
SAT		0.005				
T		0.105			0.107	

4.2.4 Path Coefficient Test

The results of this test depend on the original sample value, t-statistic, and p-value of each hypothesis in this research model. Hypothesis acceptance can be approved by adjusting the criteria, the t-statistic value has a value of more than 1.96, the p-value is less than 0.05, and the original sample value to determine the direction of each hypothesis. Based on Table 17, the accepted hypotheses are H1, H2, H3, H7, H8, and H9 because they have met the acceptance requirements, while hypotheses H4, H5, and H6 are rejected because they do not meet these acceptance requirements.

Table 17. Path coefficient test result

	Hypothesis	Original Sample	T-statistic	P-value	Conclusion
H1	CON → PU	0.829	53.007	0.000	Accepted
H2	CON → SAT	0.132	2.755	0.006	Accepted
H3	PU → SAT	0.556	8.726	0.000	Accepted
H4	PU → CI	0.055	0.561	0.575	Rejected
H5	SAT → CI	-0.089	1.028	0.305	Rejected
H6	PEOU → SAT	0.057	1.130	0.259	Rejected
H7	PEOU → CI	0.652	11.312	0.000	Accepted
H8	T → SAT	0.242	3.586	0.000	Accepted
H9	T → CI	0.321	2.930	0.004	Accepted

4.2.5 Model Fit Test

The results of the model fit test depend on the SRMR, chi-square, and NFI values of this research model. Referring to Table 18, based on the SRMR value ≤ 0.10, the proposed research model meets the criteria and is considered a model with good fit conditions. Meanwhile, based on the chi-square measurement, the model is considered a good fit because it meets the threshold ≥ 0.05 with a value obtained of 1356.608, while based on the NFI measurement, the value obtained is below 0.90, so in this measurement the model does not meet the criteria and is considered a model with marginal fit conditions.

Table 18. Model fit test result

Index	Limit	Value	Description
SRMR	≤ 0.10	0.048	Good fit
Chi-square	≥ 0.05	1356.608	Good fit

Index	Limit	Value	Description
NFI	≥ 0.90	0.837	Marginal fit

4.3 Discussion

Based on the analysis results of the path coefficient test shown in Table 4.8, it is obtained that H1 is accepted with a t-statistics value of 53.007 and a p-value of 0.000. This shows that CON has a significant influence on PU. Therefore, if workers' expectations match the actual experience of using an AI chatbot, it will significantly increase the perceived usefulness for users. In line with Tyas and Azizah (2022) research which states that confirmation has a significant effect on perceived usefulness in the context of using new technology.

Based on the path coefficient test, the correlation between the confirmation and satisfaction variables gets a t-statistics value of 2.755 and a p-value of 0.006 so that the correlation can be accepted with a positive direction. This shows that CON has a significant influence on SAT. Thus, if workers' expectations match the actual experience of using an AI chatbot, the level of user satisfaction will increase significantly. The results of this study are in line with Catherine and Tjokrosaputro (2023) who states that confirmation has a significant effect on satisfaction in the context of new technology adaptation.

Based on the analysis of the path coefficient test, it is found that H3 is accepted with a t-statistics value of 8.726 and a p-value of 0.000. This shows that PU has a significant influence on SAT. Therefore, if workers believe that the use of AI chatbots provides real benefits in supporting their work, the level of satisfaction felt will increase significantly. In line with Irfansyah (2021) research which states that perceived usefulness has a significant effect on satisfaction in the context of analyzing system user responses.

Based on the results of the path coefficient correlation of the perceived usefulness and continuance intention variables, the t-statistics value is 0.561 and the p-value are 0.575 so that the correlation is rejected. This shows that PU does not have a significant influence on CI. Thus, although workers believe that the use of AI chatbots provides benefits in supporting their work, the perceived usefulness does not significantly affect their intention to continue using AI chatbots. This contradicts Pradana and Pradana and Yolanda (2024) research, which actually states that perceived usefulness has an influence on users' desire to continue using. However, the results of this study are in line with Kurniawan (2018) who states that perceived usefulness does not have a significant effect on continuance intention in the context of application use for users in Indonesia.

Based on the analysis of the path coefficient test, it is found that H5 is rejected with a t-statistics value of 1.028 and p-value of 0.305. This shows that SAT has no significant effect on CI. Therefore, although workers are satisfied with the use of AI chatbots in supporting their work, this satisfaction does not significantly affect their intention to continue using the technology. This statement contradicts the findings from Putri and Puspawati (2024) research which found that satisfaction has an influence on users' desire to continue using the system they use. However, this study is in line with Judoprajitno (2024) research which states that satisfaction does not have a significant effect on continuance intention in the context of analyzing the sustainability of technology use.

Based on the results of the path coefficient correlation, the variable perceived ease of use and satisfaction gets a t-statistics value of 1.130 and a p-value of 0.259 so that the correlation is rejected. This shows that PEOU does not have a significant influence on SAT. Thus, although workers perceived that using the chatbot was easy and did not require much effort, the perceived ease did not significantly affect their level of satisfaction with the experience of using the AI chatbot. This finding shows a contradiction to the research results from Saputra and Wikantari (2024) who found that perceived ease of use has an influence on user satisfaction. However, the results of this study are in line with Prasetia and Suwitho (2022) who states that perceived ease of use does not have a significant effect on satisfaction in the context of using applications for users in Indonesia.

Based on the analysis of the path coefficient test, it is found that H7 is accepted with a t-statistics value of 11.312 and a p-value of 0.000. This shows that PEOU has a significant influence on CI. Therefore, if workers feel that using an AI chatbot is easy and does not require much effort, then their intention to continue using the technology will increase significantly. In line with Ashfaq et al. (2020) research which states that perceived ease of use has a significant effect on continuance intention in the context of chatbot user analysis.

Based on the path coefficient test, the correlation between the trust and satisfaction variables gets a t-statistics value of 3.586 and a p-value of 0.000 so that the correlation can be accepted with a positive direction. This shows that T has a significant influence on SAT. Thus, if workers have a high level of trust in the AI chatbot, the level of satisfaction felt will increase significantly. The results of this study are in line with Pribadi (2020) who states that trust has a significant effect on satisfaction in the context of using e-commerce systems.

Based on the analysis of the path coefficient test, it is found that H9 is accepted with a t-statistics value of 2.930 and a p-value of 0.004. This shows that T has a significant influence on CI. Therefore, if workers have a high level of trust in AI chatbots, then their intention to continue using the technology will increase significantly. In line with Koesasih et al. (2024) research which states that trust has a significant effect on continuance intention in the context of evaluating the sense of sustainability of application users.

5. Conclusion

Continuance intention remains underexplored in Information Systems research. Therefore, the Extended Expectation Confirmation Model incorporating perceived ease of use and trust is proposed to examine factors influencing ongoing AI chatbot use at work.

The smooth interaction between users and AI chatbots during work activities makes users want to continue using AI chatbots at work as they used to do before. In addition, users who believe that the responses provided by AI chatbots can be trusted tend to feel that AI chatbots need to be used in the future to help user work productivity. Users who believe in the safety and transparency of AI chatbots make these users want to continue using AI chatbots in assisting their work. However, perceived usefulness and satisfaction were found to have no significant impact on continuance intention.

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