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Continuity of AI-Based Collection System Usage in Credit Billing: The Influence of Employee Perception and Risk Management in Shaping Sustainability Intention

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ABSTRACT

Artificial Intelligence (AI) has transformed operational processes in banking, particularly in customer service and business initiation. However, previous studies have predominantly focused on AI applications in customer-facing banking processes and largely overlooked risk perception as a determining factor in sustained usage intentions. This study examines the back-end operational systems for credit collection and incorporates risk perception of technology adoption through the Expectation Confirmation Model. The study analyzes how user perceptions, including risk perception, influence employees' sustainable intentions toward an AI-based Collection System for credit collection at a large state-owned bank in Indonesia pioneering this technology in back-end banking operations. Data is collected through questionnaires distributed to Collection System users in the bank's billing division. The analysis employed a three-stage methodology: questionnaire preparation and pre-testing, primary analysis using Structural Equation Modeling - Partial Least Square (SEM-PLS) with outer model measurements. The findings demonstrate that user perceptions of AI intelligence, human-like characteristics, usefulness, and positive interaction experiences significantly enhance continued usage intentions. Conversely, high-risk perceptions reduce sustainable adoption intentions. The model exhibits strong predictive power. These results provide actionable insights for banks to enhance AI system design by addressing risk concerns and user perceptions to promote sustainable technology adoption. This study contributes to the literature by analyzing AI implementation in banking back-end processes and identifying risk perception as a critical factor influencing Continuous Intention, extending beyond traditional Expectation Confirmation Model variables and offering new perspectives on AI-based technology adoption in banking contexts.

KEYWORDS *Artificial intelligence (AI), Collection System, Perceive Risk, Continuity Intention, Expectation Confirmation Model (ECM).*

INTRODUCTION

The rapid development in the era of globalization will certainly affect various aspects, ranging from politics, culture, environment, technology, and economics, which are driven by easy access to various information and easy connections. The technological aspect has made rapid progress with the emergence of the internet, which provides easy access for its users. The penetration of internet use is very felt in Indonesia, especially during the COVID-19 pandemic, which encouraged the transformation from the conventional era to the digitalization era.

The development of *artificial intelligence (AI) in the era of digitalization has changed the operational paradigm in the banking sector significantly*. Using artificial intelligence technology or Artificial Intelligence (AI) in the financial industry is not new. The increasing needs of the market that continue to change have driven a transformation in the use of AI in the way financial institutions or banks operate and serve their customers. In the credit acquisition process (front-end), operational paradigm changes such as credit collection also occur in the back-end process (Davenport et al., 2020).

However, in the use of AI technology in the banking industry, including in the credit collection process, it is necessary to pay attention to the factors that affect the intention of its users to continue using the technology. Customer satisfaction is one of the factors that can affect the continuity of the use of AI technology in banking. In previous research, Lee, Tang, and Jiang (2023) analyzed the development of a model for understanding user intentions using Artificial Intelligence (AI)-based mobile banking services. This study integrates AI characteristics—such as intelligence perception and anthropomorphism—with the *Expectation Confirmation Model* (ECM) to explain how AI characteristics affect the confirmation of expectations, satisfaction, usability of perceptions, and, ultimately, the user's ongoing intentions.

In addition, the theory *of the Technology Acceptance Model* (TAM) (Davis, 1989) and the *Unified Theory of Acceptance and Use of Technology* (UTAUT) (Venkatesh et al., 2003) explains that technology adoption is influenced by users' perception of *usefulness* and ease *of use*. Meanwhile, *the Expectation-Confirmation Model* (ECM) (Bhattacherjee, 2001) expands this understanding by emphasizing that the *continuance use* of technology depends on the confirmation *of expectations* and *satisfaction* after the initial adoption phase. On the other hand, *the Risk Management Framework* (ISO 31000) emphasizes the need to mitigate *inherent risks* in implementing new technologies, including operational risks and data security (Purwandari et al., 2023). Integrating these two perspectives is crucial to understanding the *continuance* of the use of AI-based systems.

One of the AI-based systems that has been adopted by Bank X, one of Indonesia's state-owned banks (SOEs), is the Collection System, which aims to improve the operational efficiency of credit collection. However, challenges arise regarding employee perceptions of the new system and potential inherent risks such as algorithm bias, prediction errors, or data privacy violations (Dwivedi et al., 2021). This condition will certainly affect the effectiveness of the collection system, which depends on the *continuance intention* and is influenced by technical and non-technical factors (Bhattacherjee, 2001).

This study aims to analyze and find out how user (employee) perception and risk perception arise with the potential *inherent risk* and how they affect users' sustainable intentions toward the AI-based Collection System at Bank X. The update in this study lies in the analysis of the use of AI in the *back-end process* in banking (credit collection) and the identification of risk perception as a factor that also influences the Sustainable Intention (CI) of the use of the Collection System, in addition to the traditional variables in the *Expectation Confirmation Model (ECM)*.

The results of this research are expected to make a practical contribution to Bank X in optimizing the use of AI-based Collection Systems in the credit collection process and providing strategic recommendations to improve the effectiveness of risk management. In addition, the findings of this study can also serve as a reference for the banking industry in general in adopting AI technology, especially in the context of credit collection and risk management. Thus, the study provides new insights into the banking and technology literature and offers innovative solutions to improve efficiency and security in the credit collection process through AI integration.

Hypothesis Development

According to Polireddi (2024), AI technology has great potential to change how banks manage credit risk, including in the collection process. AI can analyze large amounts of data in real-time, allowing banks to identify patterns and trends that may not be visible to human analysts. This application is especially useful in the retail segment credit collection process, where AI can help identify customers with payment difficulties before the problem occurs. *Innovation Diffusion Theory* (Rogers, 2003) explains that innovation characteristics such as relative advantage, compatibility, and ease of use influence technology adoption. Using AI, banks can analyze customers' historical data, including payment history, transactions, and data from external sources such as social media or utility bills. This knowledge of AI technology allows banks to assess credit risk more accurately and make more informed decisions in the collection process.

The factors that underlie user behavior in the use of the Collection System include the perception of the benefits and ease of use of technology, according to Davis (1989) in the *Technology Acceptance Model* (TAM), as well as the contributing factors of the *Unified Theory of Acceptance and Use of Technology* (UTAUT) developed by Venkatesh et al. (2003). UTAUT identified four main factors influencing the intention to use technology: *performance expectancy*, *effort expectancy*, social support, and facilitating conditions (Venkatesh et al., 2003).

In digital banking, TAM is used to understand how users' perceptions of artificial Intelligence (AI) affect their intention to continue using the service. For example, research by Lee and Chen (2022) shows that the perception of Intelligence (*Perceived Intelligence*) and the perception of anthropomorphism (*Perceived Anthropomorphism*) affect the quality of interaction and user experience, which ultimately influences the intention to continue using AI-based banking services. From some of these theories, a hypothesis is obtained that AI technology knowledge, or *AI technological knowledge* (TK), will have a positive effect on the perception of Intelligence (*Perceived Intelligence*) and the perception of anthropomorphism (*Perceived Anthropomorphism*), which will affect the quality of interaction and user experience.

H1a: *AI technological knowledge* (TK) has a positive effect on *perceived Intelligence* (PI) in the use of AI (collection system) for the credit collection process at Bank X.

H1b: *AI technological knowledge* (TK) has a positive effect on *perceived anthropomorphism* (PA) in the use of AI (collection system) for the credit collection process at Bank X.

Meanwhile, the *Expectation Confirmation Model* (ECM), developed by Oliver (1980), was used as the main approach in this study. ECM has four main components as determinants of sustainable intention to use technology (*expectation, confirmation, satisfaction, and continuance intention*) in the study of Bhatnagar et al. (2024), expanded to include AI features such as *perceived Intelligence* (PI) and *perceived anthropomorphism* (PA) to evaluate the intention to continue using AI-based digital banking services, as well as additional variables such as *interaction quality* (IQU) and *customer/user experience* (USE) to understand better the factors that affect the intention to continue using a technology.

H2 : *Perceived Anthropomorphism - PA has a positive effect on Interaction Quality (IQU) in the use of an AI-based Collection System for the credit collection process at Bank X*

H3 : *Perceived Anthropomorphism - PA has a positive effect on Interaction Quality (IQU) in the use of an AI-based Collection System for the credit collection process at Bank X*

H4 : *Interaction Quality (IQU) has a positive effect on the confirmation results (CON) regarding user experience that meets or exceeds initial expectations in the use of AI-based collection systems in the credit collection process at Bank X*

The Unified Theory of Acceptance and Use of Technology – UTAUT (Venkatesh et al., 2003) provides a framework for understanding how user satisfaction and social factors affect sustainable intentions in the use of technology. Then, according to research conducted by Rahman et al. (2022), customer perception of the use of AI in banking services is greatly influenced by factors such as trust, security, and transparency. Customers are more comfortable with human interaction, especially in sensitive situations like credit collection. Therefore, banks need to ensure that the use of AI in the billing process does not reduce the customer experience or raise concerns regarding the privacy and security of data obtained from the confirmation results of using the Collection System.

H5 : *Confirmation- CON has a positive effect on Perceived Usefulness (PU) in the use of AI (collection system) for the credit collection process at Bank X*

H6 : *Confirmation- CON has a positive effect on User Experience (USE) in the use of AI-based collection systems in the credit collection process at Bank X*

H8 : *Perceived Usefullnes (PU) has a positive effect on Continuance Intention (CI) in the use of AI (collection system) for the credit collection process at Bank X*

In addition, a study by Garg et al. (2021) shows that customers are more likely to accept AI technology if they understand its benefits and feel it can improve service efficiency. The findings apply to users or employees who use the technology daily. Effective education and communication from management is essential to increase the acceptance of Bank X employees to the use of AI-based Collection Systems in the credit collection process.

H9 : *User Experience (USE) has a positive effect on Continuance Intention (CI) in the use of AI (collection system) for the credit collection process at Bank X*

In addition to user perception, risk management is also a critical factor in using AI. According to Durst et al. (2023), banks must manage various risks, including operational and credit risks, to ensure the reliability of AI-based Collection Systems. This condition is undoubtedly a new challenge in the risk management area of Bank X regarding this collection system application. One of them is risks related to data security and privacy, where with the massive use of the Collection System by Bank X employees, banks must ensure that customer data is well protected and that their AI systems are not vulnerable to cyberattacks. In addition, banks also need to ensure that the AI algorithms used do not contain biases that can unfairly influence billing decisions. This argument will be tested through an independent *perceived risk* (PI) variable that reflects user concerns regarding security and privacy when banking transactions through mobile devices. These risks can affect the level of intent of AI users (collection systems), even reduce user satisfaction levels, and, ultimately, reduce the intention of users (employees) to continue using AI technology (collection systems).

H7 : *Perceive Risk (PR) has a negative effect on User Experience (USE)*

H10 : *Perceive Risk (PR) has a negative effect on the continuous intention (CI) in the use of AI for the credit collection process at Bank X*

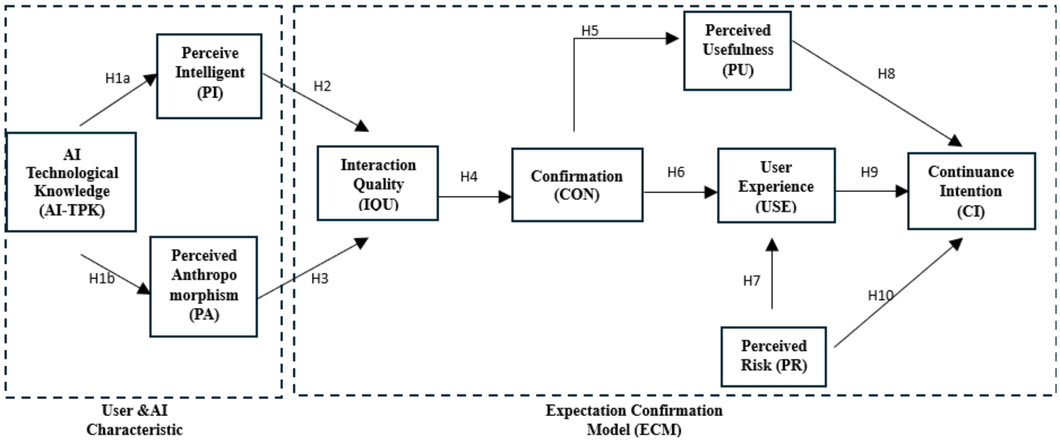

Figure 1. Research Model

Source: Data processed by researchers, 2025

RESEARCH METHOD

Data Collection & Sample

The methodology of this study uses a quantitative approach that was developed comprehensively under the guidelines of Zou and Xu (2023) and follows the best practices suggested by Hair, Page, and Brunsveld (2019). Primary data was collected by distributing online questionnaires to employees using the AI-based Collection System in Bank X's retail credit collection unit. The use of electronic media in the distribution of questionnaires is expected to speed up the data collection process and facilitate data processing and analysis because the collected data can be directly exported to Excel files and analyzed statistically.

The population in this study is Bank X employees who are on duty or function in a credit collection unit and use the AI-based Collection System in their daily work with a working time of more than 3 months. The first stage is a series of procedures to ensure that the research instrument is of good quality before it is used in the main data collection. *Wording tests* and *pre-tests* are used to ensure that each question item can measure the variables in question accurately and consistently.

Measurement

The first stage, the questionnaire preparation stage, was carried out as a *pre-test* in the form of a validity and reliability test on 50 respondents to understand the basic characteristics of the research sample. For the validity test, 2 test methods will be used, namely the convergent validity test to assess whether there is a strong relationship between two different sources in response to the same measurement instrument and discriminant validity to assess the unrelated between two different concepts, which is reflected in the non-correlation between the two. The acceptable mean result of extracted variance (AVE) is 0.50 or higher (Hair et al., 2021). Meanwhile, the reliability test will use *the composite reliability* and *Cronbach alpha* methods applied to a group of indicators that measure a particular construct. A construct is considered reliable if the value of composite reliability and Cronbach's alpha is > 0.70 (Hair et al., 2019).

In the second stage, namely the main analysis stage, testing will be carried out on the data that has been collected using the Structural Equation Modeling - Partial Least Square *(SEM-PLS)* analysis recommended by Hair et al. (2017), where PLS-SEM has advantages over CB-SEM in certain situations, such as when the sample size is small, the data distribution is abnormal, or there are indicators with formative measurements. SEM is a statistical method used to evaluate and test the causal relationship between constructs or variables that interact with each other. CB-SEM focuses more on a confirmatory approach, while PLS-SEM relies on predicting the strength of relationships between variables. According to Hair et al. (2017), there are two types of models in conducting analysis using the SEM model, namely the *outer model, which assesses the relationship between indicator variables and related constructs, and the inner model,* which is used to analyze the relationship between constructs. The analysis will be carried out using R Studio to build an "*outer model*" to evaluate the validity and reliability of the research construct.

The third stage is structural model measurement and hypothesis testing. For structural model measurement, an "*inner model*" will be used to assess the relationship between research variables, which will involve testing the R-Square value to assess the predictive ability of the model and F-Square to measure the effect of the size of a latent variable, which is a variable that cannot be measured directly because of its abstract or physically unobservable nature and is commonly called an indicator. Then, Q-Square to test the predictive relevance of the model, and PLS Predict to measure the accuracy of the model's predictions.

Meanwhile, for hypothesis testing, the *bootstrapping* method is used, which is a non-parametric statistical technique used to estimate the sampling distribution of a statistic by resampling (repeated sampling) from the existing dataset (Efron & Tibshirani, 1993). This method is used to see the significance of the relationship between variables with bootstrapping (*p-value* < 0.05) to determine whether the research hypothesis can be accepted or rejected based on the statistical significance that has been determined.

RESULT AND DISCUSSION

After conducting a pre-test of 50 respondents with valid and reliable test results, the study continued by distributing questionnaires to the billing division of Bank X employees who used the Collection System with a total population of 821 employees. Hair et al. (2022) stated that the minimum sample size can be determined from 10 times the maximum number of indicators leading to latent variables in the research model. In this research model, the largest number of indicators is 3, namely the *Continuance Intention* (CI) variable. So, the minimum sample size calculation used in this study is 3 times 10, which is 30 samples. However, this study will use data from 274 samples from the population using the random sampling method with a Likert scale used to assess specifically.

To provide an overview of the characteristics of the respondents in this study, the following is a demographic analysis based on the table presented. Respondent profiles include information about gender, age, last education, length of employment, and current position in the organization. This data is important to understand the characteristics of the sample and how demographic factors can affect the study's results.

Table 1. Respondent Profile

Category Demographics	Category	Frequency	Percentage
Gender	Man	92	33,6
	Woman	182	66,4
Age	< 25 Years	32	11,7
	25 - 34 Years	144	52,6
	35 - 44 Years	94	34,3
	45 - 54 Years	4	1,5
Final Education	Diploma	30	10,9
	Graduate	3	1,1
	Bachelor	241	88,0
Long Time Working	< 1 Year	47	17,2
	1 - 3 Years	45	16,4
	4 - 6 Years	30	10,9
	7 - 10 Years	55	20,1

Category Demographics	Category	Frequency	Percentage
	> 10 Years	97	35,4
Current position	*Desk Collector*	182	66,4
	Field Collector	35	12,8
	Junior Manager	24	8,8
	Team Leader/Manager/Senior Manager	33	12,0

Source: Data processed by researchers, 2025

Measurement Model Analysis *(Outer Model)*

Furthermore, the data collected is continued with analysis using Structural Equation Modeling - Partial Least Squares (PLS-SEM) with a measurement model (outer model), which measures the relationship between existing indicators and the latent variable in question. In this analysis, an evaluation was carried out on the validity and reliability of existing constructs and how each indicator can accurately represent latent variables. In addition, testing the measurement model is also important to ensure that the data used in this study meets the necessary criteria to produce valid and reliable conclusions. The outer model will be assessed by loading factors, Average Variance Extracted (AVE) values, and other relevant reliability components.

Convergent validity can be seen through *the outer loading* and AVE values. The *outer loading value* is considered valid if it is greater than 0.70, and the AVE value is considered valid if it is greater than 0.50.

Table 2. AVE Test Results

Indicator	Outer Loadings	AVE
Copyright © 2019 TPK1. All Rights Reserved.	0,773	
AI - TPK2	0,891	
AI - TPK3	0,892	
AI - TPK4	0,906	**0,743**
AI - TPK5	0,905	
AI - TPK6	0,823	
AI - TPK7	0,834	
PI1	0,877	
PI2	0,899	
PI3	0,919	**0,819**
PI4	0,915	
PI5	0,914	
PA1	0,858	
PA2	0,892	
PA3	0,858	**0,778**
PA4	0,892	
PA5	0,910	
IQU1	0,874	
IQU2	0,919	**0,834**
IQU3	0,917	
IQU4	0,924	

Indicator	Outer Loadings	AVE
IQU5	0,932	
CON1	0,903	**0,862**
CON2	0,945	
CON3	0,937	
PU1	0,913	**0,828**
PU2	0,851	
PU3	0,942	
PU4	0,931	
USE1	0,915	**0,873**
USE2	0,927	
USE3	0,960	
PR1	0,898	**0,800**
PR2	0,900	
CI1	0,949	**0,908**
CI2	0,957	

Source: Data processed by researchers, 2025

The validity of the discriminator in the SEM-PLS can be measured from the *Fornell-Larcker Criterion* value. Measurements with this criterion ensure that a construct (latent variable) is unique and does not overlap with other constructs in the model (Fornell & Larcker, 1981). The test results show that the *Fornell-Larcker Criterion* value of each construct has been higher than the correlation between the other constructs in the model (which can be seen from the top diagonal). Thus, it can be stated that all items and constructs are valid.

Table 3. Results of the Discriminant Validity Test

	TPK	PI	PA	IQU	CON	PU	USE	PR	CI
TPK	0,862								
PI	0,642	0,905							
PA	0,745	0,768	0,882						
IQU	0,714	0,753	0,877	0,913					
CON	0,639	0,685	0,808	0,831	0,929				
PU	0,712	0,680	0,838	0,857	0,869	0,910			
USE	0,707	0,689	0,831	0,842	0,855	0,886	0,934		
PR	0,537	0,397	0,468	0,493	0,560	0,580	0,560	0,953	
CI	0,693	0,652	0,793	0,801	0,785	0839	0,872	0,600	0,953

Source: Data processed by researchers, 2025

Then, the constructs are tested to ensure the consistency and stability of the measurement of a latent variable (construct). Reliability indicates the extent to which the indicators or items used to measure such constructs produce non-random results if the measurements are repeated under the same conditions (Hair et al., 2022). The reliability of the construct can be seen through Cronbach's Alpha and Composite Reliability values. Constructs have good reliability if Cronbach's Alpha value is greater than 0.6 and the Composite Reliability value is greater than 0.7.

Table 4. Construct Reliability Test Results

	Cronbach's Alpha	*Composite Reliability (rhoC)*
TPK	0,942	0,953
PI	0,945	0,958
PA	0,929	0,946
IQU	0,950	0,962
CON	0,920	0,949
PU	0,930	0,951
USE	0,927	0,954
PR	0,898	0,936
CI	0,899	0,952

Source: Data processed by researchers, 2025

The results of the above test show that *the values of Cronbach's Alpha* and *Composite Reliability* of each construct have met the criteria. Thus, it can be stated that all items and constructs are valid.

Structural Model Analysis (*Inner Model*)

The structural model describes the relationship between the constructs being tested and how much influence the independent variables exert on the dependent variables. In this analysis, a test was carried out on the strength and direction of the relationship between variables through path *analysis* and assessing the obtained path coefficient. The purpose of structural model analysis is to test the validity of the underlying theory of the research model and ensure that the identified relationships between variables can be explained empirically. In addition, an evaluation of *goodness-of-fit* will also be carried out to ensure the model fits with the existing data.

First, a collinearity test was carried out using indicators such as *Variance Inflation Factor* (VIF) and *Tolerance* to evaluate how much influence there is between independent variables, with the following results:

Table 5. Collinearity Test Results

	TPK	**PI**	**PA**	**IQU**	**CON**	**PU**	**USE**	**PR**	**CI**
TPK									
PI									
PA									
IQU		2,438	2,438						
CON									
PU									
USE									
PR									
CI						4,998	4,805	1,946	

Source: Data processed by researchers, 2025

Based on the table above, it can be seen that the VIF value for each construct variable is less than 5.0. Therefore, all variables do not have symptoms of multicollinearity and can be used in subsequent analyses.

Then, a determination coexistence test (R Square) was carried out to predict the accuracy of the construct in the structural model. The R-square value criterion is 0.67, 0,33, and 0.19, which were declared high, medium, and low (Hair et al., 2017). To strengthen the prediction of the R-square value, adjusted R-square measurements were made for more than one independent variable.

Table 6. Determination Coefficient Test Results

	PI	PA	IQU	WITH	PU	USE	THERE
R^2	0,412	0,556	0,784	0,690	0,755	0,731	0,797
Adj. R^2	0,410	0,554	0,783	0,689	0,755	0,730	0,794

Source: Data processed by researchers, 2025

a. The PI construct has an R-square of 0,412, which can be classified as having a medium level of prediction accuracy. This means that the PI construct affects the dependent construct by 41,2%, while other factors outside the research model influence the remaining 58,8%.
b. The PA construct has an R-square of 0,556, which can be classified as having a medium level of prediction accuracy. This means that the PA construct affects the dependent construct by 55,6%, while other factors outside the research model influence the remaining 44,4%.
c. The IQU construct has an R-square of 0.784, which can be classified as having a high level of prediction accuracy. This means that the IQU construct affects the dependent construct by 78,4%, while other factors outside the research model influence the remaining 22,6%.
d. The CON construct has an R-square of 0,690, which can be classified as having a high level of prediction accuracy. This means that the CON construct affects the dependent construct by 69%, while other factors outside the research model influence the remaining 31%.
e. PU construct has an R-square of 0,755, which can be classified as having a high level of prediction accuracy. This means that PU constructs affect dependent constructs by 75,5%, while other factors outside the research model influence the remaining 24,5%.
f. The USE construct has an R-square of 0.731, which can be classified as having a high level of prediction accuracy. This means that the USE construct affects the dependent construct by 73,1%, while other factors outside the research model influence the remaining 26,9%.
g. The CI construct has an R-square of 0.794, which can be classified as having a high level of prediction accuracy. This means that the CI construct affects

the dependent construct by 79,7%, while other factors outside the research model influence the remaining 20,3%.

Then, a hypothesis test was implemented to test the significance of the coefficient of the path, with the criterion that the t-statistical value must be greater than 1,657 to be considered significant. In addition, if the *confidence interval* (CI) does not include the number 0, the relationship between these variables can also be considered significant. This analysis aims to ensure that the relationships identified in the structural model are valid and reliable and to test the hypotheses proposed in this study.

Table 7. Direct Impact Test Results

	Original East.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI
TPK →PI	0,642	0,644	0,045	15,170	0,552
TPK →PA	0,745	0,748	0,035	21,441	0,673
TPK →IQU	0,667	0,670	0,038	17,480	0,590
TPK →CON	0,554	0,556	0,043	12,844	0,462
TPK →PU	0,482	0,484	0,044	10,868	0,393
TPK →USE	0,474	0,476	0,043	11,018	0,383
TPK →CI	0,371	0,397	0,046	8,646	0,307
PI →IQU	0,194	0,195	0,054	3,623	0,094
PI →CON	0,161	0,162	0,043	3,731	0.078
PI →PU	0,140	0,140	0,038	3,689	0.069
PI →USE	0,138	0,138	0,038	3,639	0,067
PI →CI	0,108	0,115	0,032	3,539	0,055
PA →IQU	0,728	0,726	0,053	13,824	0,611
PA → CON	0,604	0,603	0,054	11,129	0,497
PA →PU	0,525	0,524	0,052	10,037	0,424
PA →USE	0,517	0,516	0,050	10,366	0,419
PA →CI	0,404	0,430	0,051	8,496	0,332
IQU →CON	0,831	0,829	0,028	29,665	0, 773
IQU →PU	0,722	0,721	0,037	19,527	0,646
IQU →USE	0,710	0,709	0,036	19,556	0,636
CON → PU	0,869	0,869	0,021	41,625	0,827
CON → USE	0,855	0,855	0,024	36,028	0,803
PR → USE	0,210	0,213	0,071	2,971	0,086
CON →CI	0,712	0,712	0,046	15,619	0,618
PU →CI	0,262	0,267	0,082	3,181	0,126
USE →CI	0,566	0,562	0,088	6,441	0,387
PR →CI	0,131	0,131	0,054	2,423	0,027

Source: Data processed by researchers, 2025

Based on the direct influence test results, the path analysis showed that all path coefficients showed a significant relationship, requiring *a t-statistical* value greater than 1.657 and a sustainability use interval (CI) that did not include 0. The results of the path analysis conducted show that the research model supports the hypothesis proposed.

Hypothesis Testing

Hypothesis testing is an important step in data analysis to test the truth of a previously submitted conjecture or statement. In the context of this study, hypothesis testing was carried out to evaluate the relationships between variables that have been analyzed through direct path coefficients. This test aims to ascertain whether the relationships between the variables proposed in the theoretical model have statistical significance. In hypothesis testing, *the t-statistics* value must be greater than 1,657.

Table 8. Hypothesis Test Results

No	Hypothesis Statement	Path	*Original Sample*	Nilai *t-statistics*	Research Results
H1a	Knowledge about AI technology has a positive effect on the Perception of Intelligence	TPK→PI	0.642	15.170	Hypothesis Accepted
H1b	Knowledge of AI technology has a positive effect on the Perception of Anthropomorphism	TPK→PA	0.745	21,441	Hypothesis Accepted
H2	Perceived intelligence has a positive effect on Interaction Quality	PI→IQU	0.194	3,623	Hypothesis Accepted
H3	Perceived anthropomorphism has a positive effect on Interaction Quality	PA→IQU	0.728	13,824	Hypothesis Accepted
H4	Interaction Quality has a positive effect on confirmation	IQU→CON	0.831	29,665	Hypothesis Accepted
H5	Confirmation has a positive effect on perceived usefulness	CON →PU	0.869	41,625	Hypothesis Accepted
H6	Confirmation has a positive effect on User Experience	CON →USE	0.739	36,028	Hypothesis Accepted
H7	Perceived risk has a negative effect on User Experience	PR → USE	0,173	2,696	Hypothesis Not Accepted
H8	Perceived usefulness has a positive effect on Continuance Intention	PU→CI	0,262	3,181	Hypothesis Accepted
H9	User Experience has a positive effect on Continuance Intention	USE→CI	0,566	6,411	Hypothesis Accepted
H10	Perceived risk has a negative effect on Continuance Intention	PR→CI	0,131	2,423	Hypothesis Not Accepted

Source: Data processed by researchers, 2025

From the table above, all proposed hypotheses are accepted, with the requirement that the *t-statistics* value of each test is greater than 1.657. Figure 2 below shows the path coefficient values of each hypothesized relationship in the research model processed by R Studio.

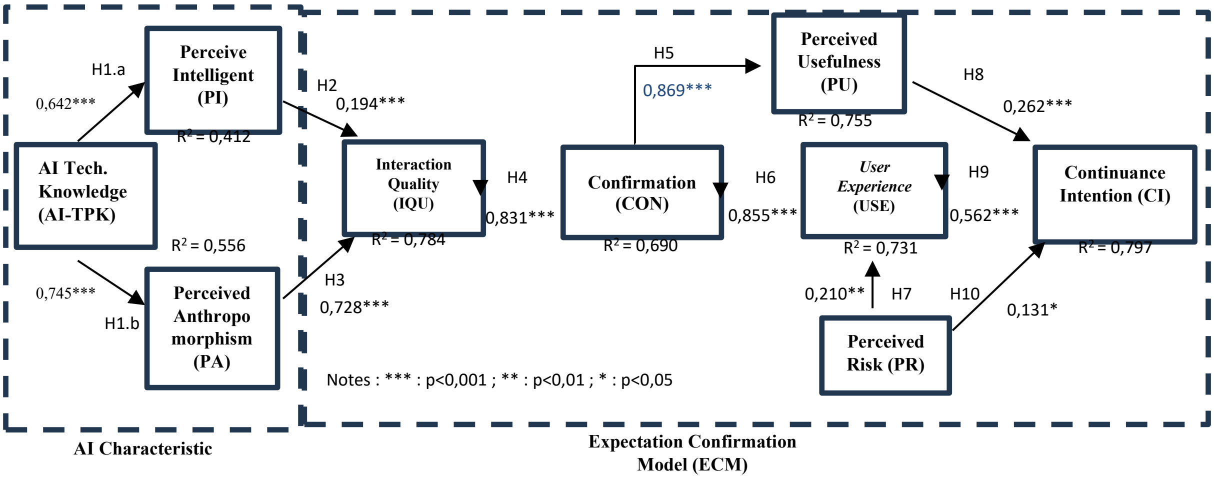

Figure 2. Hypothesis test results

Source: Data processed by researchers, 2025

CONCLUSION

This study confirms that users' knowledge of AI technology (TPK-AI) significantly improves perceived Intelligence (PI) and the human nature of AI (PA), which in turn strengthens interaction quality (IQU). Good interaction quality has a positive impact on expectation confirmation (CON) and perceived usefulness (PU), with CON as a key driver of positive user experience (USE), user experience, and perceived usefulness enhancing continuance intention (CI), supporting the integration of TAM and ECM models. From a risk management perspective, the findings related to perceived risk did not significantly affect either user experience or user continuance intention (hypotheses are not accepted). This result contradicts the conventional assumption that risk perception is always a significant obstacle in technology adoption. However, this condition is highlighted by the study by Kim, Ferris, and Lee (2017). They state that in the context of high trust and substantial benefits, which seems to prevail in the Bank X context, perceived risk can be minimized and does not serve as a significant barrier to the continued use of technology. The results of this study can provide practical implications for Bank X to improve user education and more humanized AI design while still considering risk management to support adoption and maintain positive trust in the use of AI-based Collection Systems in credit collection. The study's limitations include specific scopes and cross-sectional data, so further research is recommended to explore additional factors and longitudinal approaches.

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