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Analysis of Factors Influencing Behavioral Intention Regarding AI Technology for Quality Inspection Using the Technology Acceptance Model at PT XYZ

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Abstract

The development of Artificial Intelligence (AI) technology provides significant opportunities for the manufacturing industry to improve the efficiency and accuracy of quality inspection processes. The implementation of AI in quality inspection is expected to reduce human error and accelerate decision-making. However, the successful adoption of this technology depends largely on user acceptance and intention to use it within the work environment. Many digital transformation initiatives fail to achieve optimal outcomes due to employees' limited perceptions of technological benefits and ease of use. Therefore, this research is important for understanding the factors influencing user acceptance of AI-based quality inspection systems, enabling companies to develop more effective implementation strategies. This study applied the Technology Acceptance Model (TAM) by incorporating the variables of perceived usefulness (PU), perceived ease of use (PEU), perceived enjoyment (PE), perceived cyber risk (PCR), perceived innovativeness in IT (PIIT), self-efficacy (SE), and behavioral intention (BI). The research employed a quantitative approach through questionnaire distribution to employees at PT XYZ who were directly involved in quality inspection activities. The results of the study using the PLS-SEM method showed that the perceived usefulness (PU) variable had the strongest significant effect on behavioral intention (BI). Therefore, strategies to improve technology acceptance should prioritize variables with substantial impacts, particularly by providing training and enhancing employee understanding of the benefits of AI in supporting work performance.

INTRODUCTION

The development of digital technology has driven significant transformation in the manufacturing sector. One of the key technologies underpinning the Industry 4.0 era is Artificial Intelligence (AI), which enables systems to learn from data, recognize patterns, and make autonomous decisions (Abdullah & Almaqtri, 2024; Adelia et al., 2025). AI technology has been increasingly adopted to replace manual inspection systems that previously relied heavily on human labor (Apriliana et al., 2024). According to Schmitt et al. (2020), manual inspection approaches have several limitations, including operator fatigue, variations in perceptions of quality standards, and relatively long inspection times. These limitations may lead to inconsistencies in inspection results and increase the possibility of defective products reaching the distribution stage. The implementation of AI-based systems enables inspection processes to be conducted automatically, in real time, and more objectively, thereby improving consistency and accuracy in product defect detection. Furthermore, Kelly et al. (2023) explained that AI-based machine vision can increase the speed and accuracy of defect detection by more than 90% while significantly reducing operational costs and production time.

AI machine vision is a technology that enables computer systems to replicate human visual capabilities through automated digital processing. In the manufacturing context, AI machine vision functions as a quality inspection system capable of detecting product defects, dimensional inconsistencies, and visual anomalies in a consistent and objective manner (Babić et al., 2021; Mezher et al., 2024). The system operates by utilizing cameras and lenses to capture images of objects moving along production lines, while illumination systems are used to maintain stable image quality and minimize shadows or noise (Zhou et al., 2023). The captured images are then processed using software and image-processing libraries to identify defect patterns based on previously trained datasets. Subsequently, the analysis results are transmitted to control systems, such as conveyors or robotic systems, to perform automated actions, including separating defective products or initiating process corrections. Through the integration of these components, AI machine vision can improve the speed, accuracy, and effectiveness of quality inspection compared with conventional manual methods.

Nevertheless, the successful implementation of AI technology in quality inspection systems is determined not only by algorithm sophistication and system capabilities but also by users' behavioral intentions toward the technology (Hold, 2024). Previous studies have demonstrated that user intention is a critical factor influencing the success or failure of new technology adoption in workplace environments (Entertainment et al., 2021; Chatterjee et al., 2021). Employees who perceive limited benefits or experience difficulties in using new systems tend to demonstrate resistance to change, resulting in suboptimal AI utilization despite successful technical implementation.

Based on an initial pre-survey conducted among 20 respondents involved in the quality inspection process, user intention and satisfaction regarding AI implementation were found to remain relatively low. The findings showed that the indicator "AI makes work easier" obtained the lowest score of 1.9, indicating that most employees had not yet perceived significant benefits from AI systems in supporting inspection activities. Furthermore, the indicator "AI is convenient to use" achieved a score of 2.5, demonstrating that ease of use and operational convenience remained challenges during implementation. Meanwhile, the perception that AI could reduce human error received a score of 2.7, indicating that respondents were not yet fully convinced of AI's contribution to improving inspection accuracy.

Interestingly, the indicator "willing to use AI sustainably" obtained the highest score of 4.2. This finding suggests that although users' initial satisfaction regarding AI benefits and ease of use remained limited, they still demonstrated a tendency to accept and continue using the technology in the long term. This condition reflects an acceptance gap, referring to the difference between the expected technical benefits of a technology and users' psychological readiness to adopt it.

Therefore, further analysis is required to examine factors influencing user intention toward AI technology, particularly through the Technology Acceptance Model (TAM) approach, to ensure that technology implementation aligns more effectively with organizational operational requirements.

Based on company operational data related to AI implementation for quality inspection, customer complaints associated with product defects were found to be higher after AI-based inspection compared with manual inspection. Under manual inspection, the percentage of customer complaints ranged from 6.5% to 15.5%, whereas AI-based inspection produced higher complaint rates ranging from 12.4% to 22.3%. These findings indicate that AI implementation in the quality inspection process has not yet generated the expected positive impact, particularly in quality control and defect prevention. Several factors contributing to the high error rate following AI implementation include operators' limited familiarity and skills in operating AI systems, software instability and technical errors, and the limited availability of personnel capable of maintaining and troubleshooting AI systems, resulting in slower problem resolution.

This condition demonstrates a gap between technology implementation and human resource readiness, requiring further analysis of user intention toward AI technology through the Technology Acceptance Model (TAM) approach. According to Ryseff et al. (2024), approximately 80% of corporate AI projects fail to achieve successful implementation. Many artificial intelligence (AI) projects fail not only due to technological limitations but also due to insufficient user intention and acceptance of the implemented systems.

To understand the factors influencing user acceptance of AI technology, one widely applied approach in technology adoption research is the Technology Acceptance Model (TAM) developed by Davis (1989). This model explains that technology adoption is influenced by two primary variables: perceived usefulness (PU) and perceived ease of use (PEOU), which subsequently affect attitude toward using (ATU) and behavioral intention to use (BIU) (Wicaksono, 2022). Through this approach, organizations can analyze how perceived benefits and ease of use influence users' attitudes and intentions to accept and utilize AI technology in daily work activities.

Previous studies have demonstrated that the TAM framework is a valid theoretical model for assessing technology acceptance across various industrial contexts. Gansser et al. (2021) showed that perceived ease of use significantly influences behavioral intention to use AI systems in smart manufacturing environments. Meanwhile, Kelly et al. (2023) highlighted the importance of trust and system reliability as additional determinants that strengthen perceived usefulness of AI technology. These findings indicate that AI acceptance is influenced not only by technical factors but also by psychological and social dimensions among technology users.

In Indonesia, AI adoption in the manufacturing sector continues to face challenges related to digital readiness, human resource capabilities, and organizational culture that may not fully support technological transformation. Rosmasari et al. (2024) demonstrated that the TAM framework is effective for analyzing technology acceptance levels across various sectors, including information systems and digital services. Their findings showed that perceived usefulness and perceived ease of use play important roles as primary determinants of technology acceptance. Therefore, TAM is also relevant for understanding user behavior toward AI technology in manufacturing quality inspection contexts.

The novelty of this research lies in the integration of Personal Innovativeness in IT (PIIT), Self-Efficacy (SE), Perceived Cyber Risk (PCR), and Perceived Enjoyment (PE) as external variables within the Technology Acceptance Model (TAM) framework, specifically in the context of AI adoption for quality inspection in the Indonesian manufacturing sector. Previous studies have primarily focused on core TAM variables or applied the model in different contexts, such as education and digital services. This research extends the TAM framework by incorporating psychological and risk-related factors that are particularly relevant to manufacturing environments, thereby providing a more comprehensive understanding of the factors influencing employees' behavioral intention to use AI technology.

Based on these conditions, this study aimed to analyze the acceptance of AI technology in the quality inspection process at PT XYZ using a modified Technology Acceptance Model (TAM) framework that incorporates additional technology-related factors. The study involved seven variables: Personal Innovativeness in IT (PIIT), Self-Efficacy (SE), Perceived Cyber Risk (PCR), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Perceived Enjoyment (PE), and Behavioral Intention (BI). The PIIT variable represents employees' openness toward AI technology innovation in supporting quality inspection processes, while SE reflects employees' confidence in their ability to operate AI systems effectively. The PCR variable represents users' perceptions of potential risks associated with AI systems, including system errors, software failures, or limitations in AI-based defect detection reliability. The PEU variable reflects employees' perceptions regarding the ease of using AI systems. Meanwhile, the PU variable represents employees' perceptions of the benefits of AI implementation in improving the accuracy, speed, and consistency of quality inspection processes. The PE variable describes users' level of comfort and enjoyment when interacting with AI systems in their daily work, while BI represents employees' intention to continuously use AI technology in quality inspection activities. The collected data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method to examine structural relationships among variables and test the proposed hypotheses.

METHOD

The conceptual model in this study was developed based on a modified Technology Acceptance Model (TAM) framework referring to the research framework proposed by Al-Adwan et al. (2023). This model was selected because it incorporates relevant and comprehensive variables that align with recent developments in technology acceptance research. In this study, Personal Innovativeness in IT, Self-Efficacy, Perceived Cyber Risk, and Perceived Enjoyment were included as external variables influencing the core TAM constructs, namely Perceived Usefulness and Perceived Ease of Use. The integration of these variables enabled the model to capture psychological factors, perceived benefits, usability perceptions, and potential barriers affecting individuals' acceptance of new technologies.

Data were collected through questionnaire distribution using random sampling. The number of respondents was determined based on the sample size guidelines for Partial Least Squares Structural Equation Modeling (PLS-SEM), which recommend a minimum sample size of ten times the number of structural paths or hypotheses in the research model (Hair et al., 2017). The conceptual model consisted of 13 hypotheses; therefore, the minimum required sample size was 130 respondents ($13 \times 10 = 130$). This criterion was applied to ensure sufficient data adequacy for evaluating the structural and measurement models. The collected data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method.

RESULTS AND DISCUSSION

Descriptive Analysis of Respondents

Analysis of respondent characteristics was conducted to provide an overview of the profile of respondents participating in the study. The characteristics analyzed included age, gender, education level, job title, and length of experience using AI machine vision.

Table 1. Characteristics of Research Respondents

Features	**Category**	**Number (People)**	**Percentage (%)**
Age	20–30 years	59	45,4
	31–40 years	40	30,8
	41–50 years	20	15,4
	>50 years old	11	8,5
Gender	Men	122	93,8
	Women	8	6,2
Education Level	SMP	7	5,4
	High School/Vocational School	62	47,7
	D3	7	5,4
	S1	52	40,0
	S2	2	1,5
Departments	Operator	77	59,2
	Supervisor	53	40,8
Length of Use of AI Machine Vision	1–6 months	48	36,9
	6–12 months	82	63,1
Total Respond		**130**	**100**

Based on Table 1, the majority of respondents are employees aged 20–30 years (45.4%), male (93.8%), and have a high school/vocational education level (47.7%). Most of the respondents served as operators (59.2%) and had used AI machine vision for 6–12 months (63.1%). These characteristics show that respondents have sufficient experience in using AI machine vision so that they can provide relevant assessments of the variables studied.

Model Analysis Results Using PLS-SEM

1. Evaluation of the Outer Model

An external model evaluation was carried out to assess the validity and reliability of indicators in measuring latent variables. The assessment was carried out using the outer loading values, Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) to ensure that the measurement model met the feasibility criteria before evaluating the structural model.

Table 2. CA and CR Test Results

Variable Leave	CA	CR	Remarks
BI	0.951	0.968	Reliable
PCR	0.932	0.956	Reliable
OR	0.913	0.945	Reliable
LITTLE	0.943	0.963	Reliable
SILICON	0.942	0.963	Reliable
PU	0.928	0.954	Reliable
SE	0.922	0.951	Reliable

The results of the internal consistency reliability test showed that all variables met the reliability criteria, with Cronbach's Alpha (CA) values of 0.913–0.951 and Composite Reliability (CR) of 0.945–0.968, all of which were above the minimum limit of 0.70. This shows that each construct has excellent internal consistency.

Table 3. Test Results of Outer Loadings Indicators

Variable Leave	Indicator	Outer loadings	Remarks
BI	BI1	0.950	Valid
	BI2	0.955	Valid
	BI3	0.957	Valid
PCR	PCR1	0.940	Valid
	PCR2	0.955	Valid
	PCR3	0.917	Valid
OR	PE1	0.924	Valid
	PE2	0.925	Valid
	PE3	0.920	Valid
LITTLE	PEU1	0.945	Valid
	PEU2	0.947	Valid
	PEU3	0.949	Valid

SILICON	SILICON1	0.947	Valid
	SILICON2	0.952	Valid
	SILICON3	0.941	Valid
PU	PU1	0.943	Valid
	PU2	0.927	Valid
	PU3	0.933	Valid
SE	SE1	0.933	Valid
	SE2	0.916	Valid
	SE3	0.942	Valid

Based on Table 3, the results of the outer loading test showed that all indicators in each latent variable had values above the recommended minimum limit, which was 0.70. The outer loading value of all indicators is in the range of 0.916 to 0.957, which indicates that each indicator has a strong contribution in representing the latent variable being measured. Thus, all indicators in the research model are declared valid and meet the criteria of convergent validity and are still above the minimum limit, so there are no indicators that need to be eliminated.

Table 4. AVE Test Results

Variable Leave	AVE	Remarks
BI	0.911	Valid
PCR	0.879	Valid
OR	0.852	Valid
LITTLE	0.897	Valid
SILICON	0.896	Valid
PU	0.873	Valid
SE	0.865	Valid

The value of the Average Variance Extracted (AVE) test on each latent variable showed that all constructs in this study had met the convergent validity criteria. The AVE value of each variable is in the range of 0.852 to 0.911, which means that all variables are able to explain more than 50% of the variance of the indicators. The Behavioral Intention (BI) variable had the highest AVE value of 0.911, while the lowest value was found in the Perceived Enjoyment (PE) variable of 0.852. All AVE values are still above the recommended minimum limit, which is 0.50, so that all variables in the research model are declared valid and feasible to proceed to the next stage.

2. Inner Model Evaluation

Internal model evaluation was carried out to assess the relationship between latent variables and the model's ability to explain dependent variables. The test used R^2, f^2, Q^2, as well as the path coefficient and t-statistics of bootstrapping results to evaluate the structural model and test the research hypothesis.

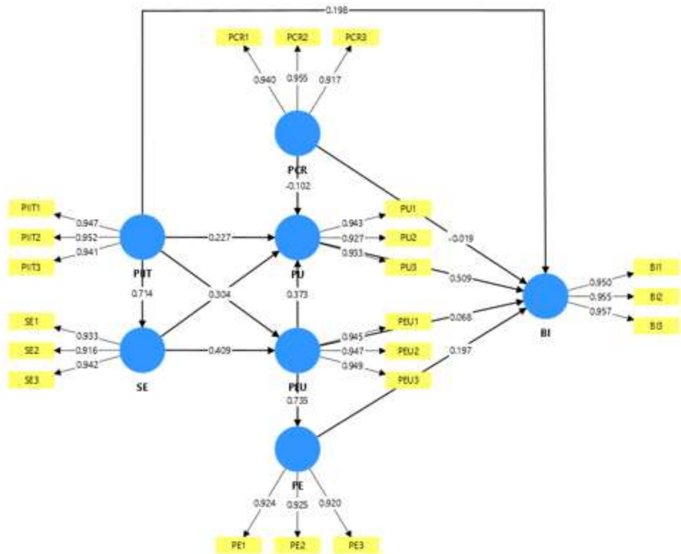

Figure 1. Results of Research Model Evaluation

Table 5. R2 Test Results

Variable endogenous	R2	Remarks
BI	0.767	Strong
OR	0.540	Moderate
LITTLE	0.672	Moderate
PU	0.705	Moderate
SE	0.509	Moderate

The coefficient of determination value (R^2) is used to show the ability of exogenous variables to explain endogenous variables in structural models. Based on the criteria, the R^2 value of 0.75 is categorized as strong, 0.50 is categorized as moderate, and 0.25 is categorized as weak. The test results showed that the Behavioral Intention (BI) variable had an R^2 value of 0.767 which was included in the strong category, which means that the exogenous variables in the model were able to explain 76.7% variation in the intention to use the technology.

Meanwhile, the variables Perceived Enjoyment (PE), Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Self-Efficacy (SE) each had R^2 values of 0.540; 0.672; 0.705; and 0.509 which were in the moderate category. These results show that the research model has a fairly good explainer ability, because most endogenous variables can be explained moderately to strongly by exogenous variables in the structural model

Table 6. F2 Test Results

Relationships Between Latent Variables	f2	Remarks
PCR → BI	0.002	Small effects
PCR → PU	0.035	Small effects
OR → BI	0.073	Small effects

LITTLE → BI	0.005	Small effects
LITTLE → OR	1.173	Huge effect
LITTLE → PU	0.154	Moderate effects
PIIT → BI	0.059	Small effects
SMALL → SMALL	0.338	Moderate effects
PIIT → PU	0.063	Small effects
PIIT → SE	1.037	Huge effect
PU → BI	0.351	Huge effect
IF → LITTLE	0.251	Moderate effects
OR → PU	0.123	Small effects

The relative influence between variables in a structural model can be seen through the effect size value (f^2), which shows the magnitude of the contribution of each exogenous variable to the endogenous variable. Based on the criteria, the f^2 value of 0.02 is categorized as a small effect, 0.15 as a medium effect, and 0.35 as a large effect.

Results in Table 6. shows that the relationship between variables has varying degrees of influence. The largest influence was shown by the relationship between Perceived Ease of Use (PEU) to Perceived Enjoyment (PE) with a value of f^2 of 1.173, Personal Innovativeness in IT (PIIT) to Self-Efficacy (SE) of 1.037, and Perceived Usefulness (PU) to Behavioral Intention (BI) of 0.351. In addition, the relationship between PEU and SE to PEU is in the medium securities category, while the other relationships are in the minor securities category. Overall, these results show that some variables have a more dominant contribution in explaining endogenous variables than others.

Table 7. Q2 Test Results

Variable endogenous	**Q^2**	**Remarks**
SE	0.504	Has predictive relevance
LITTLE	0.585	Has predictive relevance
OR	0.330	Has predictive relevance
PU	0.544	Has predictive relevance
BI	0.543	Has predictive relevance

The predictive ability of the structural model was evaluated using the predictive relevance (Q^2) value. The results in Table 7 show that all endogenous variables have a Q^2 value above 0, which indicates that the model has predictive relevance and is able to predict observational data well.

Table 8. Hypothesis Test Results

Hipotesis	T statistics	P values	Path Coefficients	Remarks
PCR → BI	0.476	0.634	-0.019	Insignificant, negative
PCR → PU	2.116	0.034	-0.102	Signifikan, negative
OR → BI	3.210	0.001	0.197	Significant, positive
LITTLE → BI	0.712	0.477	0.068	Insignificant, positive
LITTLE → PE	17.780	0.000	0.735	Significant, positive
LITTLE → PU	4.935	0.000	0.373	Significant, positive
PIIT → BI	2.843	0.004	0.198	Significant, positive
PIIT → LITTLE	6.818	0.000	0.476	Significant, positive
SILICON → PU	2.600	0.009	0.227	Significant, positive
PIIT → SE	17.563	0.000	0.714	Significant, positive
PU → BI	7.401	0.000	0.509	Significant, positive
IF → LITTLE	5.119	0.000	0.409	Significant, positive
OR → PU	3.382	0.001	0.304	Significant, positive

Based on Table 8, the results show that there are eleven relationships that have a significant effect and two relationships that do not have a significant effect in the research model. The results of testing each hypothesis are as follows.

1. Personal Innovativeness in IT (PIIT) had a positive and significant effect on Self-Efficacy (SE) with a path coefficient value of 0.714, a t-statistics value of 17.563, and a p-value of 0.000.
2. Personal Innovativeness in IT (PIIT) had a positive and significant effect on Perceived Usefulness (PU) with a path coefficient value of 0.227, a t-statistics value of 2.600, and a p-value of 0.009.
3. Personal Innovativeness in IT (PIIT) had a positive and significant effect on Perceived Ease of Use (PEU) with a path coefficient value of 0.476, a t-statistics value of 6.818, and a p-value of 0.000.
4. Personal Innovativeness in IT (PIIT) had a positive and significant effect on Behavioral Intention (BI) with a path coefficient value of 0.198, a t-statistics value of 2.843, and a p-value of 0.004.
5. Self-Efficacy (SE) had a positive and significant effect on Perceived Usefulness (PU) with a path coefficient value of 0.304, a t-statistics value of 3.382, and a p-value of 0.001.
6. Self-Efficacy (SE) had a positive and significant effect on Perceived Ease of Use (PEU) with a path coefficient value of 0.409, a t-statistics value of 5.119, and a p-value of 0.000.
7. Perceived Cyber Risk (PCR) had a negative and significant effect on Perceived Usefulness (PU) with a path coefficient value of -0.102, a t-statistics value of 2.116, and a p-value of 0.034.

8. Perceived Cyber Risk (PCR) had no significant effect on Behavioral Intention (BI) with a path coefficient value of -0.019, a t-statistics value of 0.476, and a p-value of 0.634.
9. Perceived Ease of Use (PEU) had a positive and significant effect on Perceived Usefulness (PU) with a path coefficient value of 0.373, a t-statistics value of 4.935, and a p-value of 0.000.
10. Perceived Ease of Use (PEU) had a positive and significant effect on Perceived Enjoyment (PE) with a path coefficient value of 0.735, a t-statistics value of 17.780, and a p-value of 0.000.
11. Perceived Ease of Use (PEU) had no significant effect on Behavioral Intention (BI) with a path coefficient value of 0.068, a t-statistics value of 0.712, and a p-value of 0.477.
12. Perceived Usefulness (PU) had a positive and significant effect on Behavioral Intention (BI) with a path coefficient value of 0.509, a t-statistics value of 7.401, and a p-value of 0.000.
13. Perceived Enjoyment (PE) had a positive and significant effect on Behavioral Intention (BI) with a path coefficient value of 0.197, a t-statistics value of 3.210, and a p-value of 0.001.

H1: Personal Innovativeness in IT (PIIT) has a significant positive effect on Self-Efficacy (SE)

The test results showed a t-statistical value of 17.563 and a p-value of 0.000, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.714$) which indicates a positive direction, and an effect size value of f^2 of 1.037 which is included in the category of large effects. These results suggest that employees who are more open to new technologies tend to have higher levels of confidence in using AI systems. Individuals who are more open to new technologies are usually more active in learning system features, trying out various functions, and not afraid to make mistakes in the learning stage. This condition makes them more quickly master the system and feel able to operate it independently.

The findings of this study are in line with the Technology Acceptance Model (TAM) proposed by (Davis, 1989), which explains that user characteristics play an important role in shaping acceptance of a technology. Users who have readiness and interest in new technology will more easily build confidence in their abilities when using the system. The results of this study are also supported by (Gansser & Reich, 2021) which states that the acceptance of Artificial Intelligence is not only influenced by the characteristics of the technology, but also by the readiness of the individual to adopt it. In addition, (Jöhnk et al., 2021) explains that individual readiness is one of the main factors for the successful implementation of AI in organizations, as more innovative individuals tend to have digital competence and a higher sense of confidence in using technology.

H2: Personal Innovativeness in IT (PIIT) has a significant positive effect on Perceived Usefulness (PU)

The test results showed a t-statistical value of 2.600 and a p-value of 0.009, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.227$) indicating a positive direction, as well as an effect size value of f^2 of 0.063 which is included in the category of small effects. Employees who are more open to new technologies tend to better understand the potential benefits of using AI systems. Individuals who are open to new technologies not only see technology as an auxiliary tool, but also as an opportunity to improve quality, reduce errors, and speed up work processes.

The results of this study support the theory of the Technology Acceptance Model (TAM) developed by (Davis, 1989), which states that perceived usefulness is the main factor that determines the acceptance of a technology. The greater the benefits that users feel, the higher their tendency to accept the technology. These findings are also consistent with research (Chatterjee et al., 2021) which suggests that individual characteristics have an effect on the perception of the benefits of AI in the manufacturing sector. (Kelly et al., 2023) Through systematic review, it is also concluded that openness to innovation is one of the important determinants in forming a positive perception of Artificial Intelligence. Therefore, companies not only need to provide advanced technology, but also build a culture of innovation and improve employees' digital literacy so that the benefits of using AI can be optimally understood.

H3: Personal Innovativeness in IT (PIIT) has a significant positive effect on Perceived Ease of Use (PEU)

The test results showed a t-statistical value of 6.818 and a p-value of 0.000, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.476$) which indicates a positive direction, and an effect size value of f^2 of 0.338 which is included in the category of moderate effects. This suggests that employees who are open to new technologies tend to find AI systems easier to use. Such individuals are usually quicker to understand the procedures for using and the features of AI systems. As a result, the perception of the ease of use of the system is higher than employees who tend to be less familiar with new technology.

These results are in accordance with the TAM theory developed by (Davis, 1989), which explains that the perception of ease of use is an important factor in the acceptance of technology. Research (Selim et al., 2023) and (Gansser & Reich, 2021) It also shows that the characteristics of individuals who are open to innovation will increase the perception of the ease of use of technology, including in the implementation of AI in the industrial environment.

H4: Personal Innovativeness in IT (PIIT) has a significant positive effect on Behavioral Intention (BI)

The test results showed a t-statistical value of 2.843 and a p-value of 0.004, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.198$) indicating a positive direction, as well as an effect size value of f^2 of 0.059 which is included in the category of small effects. These findings indicate that employees who are open to new technologies tend to have higher intentions to use AI systems. Individuals who are open to new technologies usually have a high level of curiosity and are not hesitant to try new systems, making it easier to accept technology-based changes.

These findings are in line with research (Al-Adwan et al., 2023) which states that individual characteristics play a role in increasing the intention to use technology. In addition, (Kelly et al., 2023) also explained that individual readiness for innovation is one of the factors that encourage the acceptance and use of Artificial Intelligence in organizational and manufacturing environments.

H5: Self-Efficacy (SE) has a significant positive effect on Perceived Usefulness (PU)

The test results showed a t-statistical value of 3.382 and a p-value of 0.001, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.304$) indicating a positive direction, and an effect size value of f^2 of 0.123 which is included in the category of small effects. Employees who have self-confidence in using the system are likely to feel greater benefits from AI technology. When users feel that they are able to operate the system well, they can make optimal use of the technology features, so that the benefits of the system become more real.

These findings are in line with the Technology Acceptance Model (TAM) presented by (Davis, 1989), which explains that the perception of benefits is a major factor in the acceptance of technology. Users who feel capable of operating a system will be more likely to realize the benefits provided by the technology. The results of this study are also supported by (Al-Adwan et al., 2023) which states that the ability of individuals to use technology contributes to the formation of a perception of benefits on digital platforms. In addition, (Gansser & Reich, 2021) explained that user confidence is an important factor in increasing positive perception of the use of Artificial Intelligence. Therefore, increasing employee competence and self-confidence through training and mentoring is an important step so that the benefits of AI can be felt optimally.

H6: Self-Efficacy (SE) has a significant positive effect on Perceived Ease of Use (PEU)

The test results showed a t-statistical value of 5.119 and a p-value of 0.000, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.409$) which indicates a positive direction, and an effect size value of f^2 of 0.251 which is included in the category of moderate effects. This shows that the higher the confidence of employees in using technology, they will tend to judge AI systems as easy to use. Confidence in one's abilities makes employees not easily feel anxious or afraid of making mistakes when using the system. As a result, psychological barriers in the use of technology are reduced, so the perception of ease of use increases.

The results of this study support the TAM theory developed by (Davis, 1989), which explains that the perception of ease of use is influenced by the user's ability to interact with technology. These findings are also consistent with research (Shin et al., 2022) which shows that self-efficacy has an important role in increasing the perception of ease of use in the implementation of new technologies. In addition, (Selim et al., 2023) explains that individuals who have a high level of confidence will more easily accept Industry 4.0 technology because they feel able to learn and operate the system independently.

H7: Perceived Cyber Risk (PCR) has a significant negative effect on Perceived Usefulness (PU)

The test results showed a t-statistical value of 2.116 and a p-value of 0.034, so the relationship was declared significant. This relationship has a path coefficient value of (β = -0.102) indicating a negative direction, and an effect size value of f^2 of 0.035 which is included in the category of small effects. This shows that the higher the perception of cyber risk, the perception of the benefits of AI systems tends to decrease. In the context of AI implementation in the industry, concerns about system errors, detection failures, or operational glitches can reduce employees' confidence in the usefulness of the technology. When a system is considered risky, users tend to doubt the benefits produced, resulting in lower perceptions of the usefulness of the technology.

These findings are in line with research (Kelly et al., 2023) which states that risk perception is one of the factors that affect the acceptance of Artificial Intelligence, especially when users still have concerns about the reliability and security of the system. (Ryseff et al., 2024) also explains that various AI projects often experience implementation obstacles due to low user confidence in the stability of the system and the potential risks that may arise during its use. Therefore, companies need to improve the reliability of AI systems through continuous testing, regular system maintenance, and the provision of clear information regarding the safety and reliability of AI so that the perception of the benefits of technology can increase.

H8: Perceived Cyber Risk (PCR) has no significant negative effect on Behavioral Intention (BI)

The test results showed that Perceived Cyber Risk (PCR) had no significant effect on Behavioral Intention (BI), with a path coefficient value of -0.019, a t-statistics value of 0.476, and a p-value of 0.634. The effect size value of 0.002 shows that the influence of this variable is so small that it is not able to explain the employee's intention in using AI machine vision. These findings indicate that perception of cyber risk is not the main factor that determines the intention to use AI in the quality inspection process. Employees still have the desire to use AI systems despite the perception of risks, as they are more aware of the benefits obtained from the use of the technology in supporting their daily work.

The results of this study show that in a manufacturing environment, the use of AI machine vision is seen as an operational necessity rather than as an option to use technology voluntarily. This condition causes risk perception to not be the main consideration in forming the intention of use. In addition, (Chatterjee et al., 2021) stated that in the implementation of AI in the manufacturing sector, the perception of the benefits of technology has a more dominant influence on the intention of use than the perception of risk. The results of this study also strengthen the finding that Perceived Cyber Risk plays a more indirect role through Perceived Usefulness, so companies need to focus their AI implementation strategies on increasing the real benefits felt by users while maintaining the security and reliability of the system so that trust in technology is maintained.

H9: Perceived Ease of Use (PEU) has a significant positive effect on Perceived Usefulness (PU)

The test results showed a t-statistical value of 4.935 and a p-value of 0.000, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.373$) indicating a positive direction, and an effect size value of f^2 of 0.154 which is included in the category of moderate effects. Easy-to-use systems tend to be considered more useful by employees. When the system does not require a great deal of effort to understand or operate, users can focus more on the results of the work produced. In quality inspection, the ease of use of AI systems can speed up the inspection process and reduce operator errors.

Research (Shin et al., 2022) shows that ease of use makes a positive contribution to the perception of benefits in the implementation of technology. In addition, (Al-Adwan et al., 2023) It also found that ease of use is one of the important factors in increasing the perception of user benefits to digital technology. Therefore, companies need to ensure that machine vision AI systems have a simple, easy-to-understand, and user-friendly interface so that the benefits of technology can be felt to the fullest.

H10: Perceived Ease of Use (PEU) has a significant positive effect on Perceived Enjoyment (PE)

The test results showed a t-statistical value of 17.780 and a p-value of 0.000, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.735$) which indicates a positive direction, and an effect size value of f^2 of 1.173 which is included in the category of large effects. These results show that the easier the AI system is to use, the higher the level of comfort felt by employees. In a manufacturing work environment that demands speed and precision, a system that is not complex and easy to understand will reduce the cognitive load on the user. When the system does not cause operational difficulties, users will feel more comfortable and unburdened while using it.

The results of this study are also consistent with the research (Gansser & Reich, 2021) which explains that the ease of use of AI contributes to an increase in positive user experiences in interacting with technology. In addition, (Kelly et al., 2023) stated that a comfortable user experience is one of the factors driving the acceptance of Artificial Intelligence.

H11: Perceived Ease of Use (PEU) does not have a significant positive effect on Behavioral Intention (BI)

The test results showed a t-statistical value of 0.712 and a p-value of 0.477, so the relationship was declared not statistically significant. A path coefficient value of ($\beta = 0.068$) indicates a positive direction, but an effect size value of f^2 of 0.005 which belongs to the very small effect category indicates that the effect is not significant in the model. Ease of use plays a more role as an indirect factor that affects other variables, such as Perceived Usefulness or Perceived Enjoyment, which ultimately determines the intention of use. This means that employees may not necessarily increase usage intent just because the system is easy to use, but because the convenience makes the system feel more useful or more convenient. In addition, when the user has reached a certain level of familiarity with the system, the ease of use can be considered a "given" or a minimum standard. In these conditions, convenience is no longer a significant differentiating factor in forming intentions/intentions, because users' attention is more focused on the extent to which the system provides added value to performance.

This finding is different from the basic concept of TAM put forward by (Davis, 1989), which states that perceived ease of use can affect behavioral intent both directly and indirectly. These findings also indicate that perceived ease of use plays a more indirect role as an indirect factor through perceived usefulness and perceived enjoyment in forming behavioral intentions. Therefore, companies should not only focus on simplifying systems, but also ensuring that AI provides tangible benefits to improving productivity and job quality.

H12: Perceived Usefulness (PU) has a significant positive effect on Behavioral Intention (BI)

The test results showed a t-statistical value of 7.401 and a p-value of 0.000, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.509$) indicating a positive direction, and an effect size value of f^2 of 0.351 which is included in the category of large effects. This shows that the perception of the benefits of the system is a major factor that influences the intention to use AI technology. When employees feel that the system is able to improve inspection accuracy, reduce errors, and speed up work processes, then the intention/intention to use the technology will increase significantly.

This finding is very much in line with the Technology Acceptance Model (TAM) theory developed by (Davis, 1989), which places perceived usefulness as the main factor in determining the acceptance of technology. The results of this study are also consistent with the research (Al-Adwan et al., 2023) which shows that the perception of benefits is a predictor in increasing the intention to use technology.

H13: Perceived Enjoyment (PE) has a significant positive effect on Behavioral Intention (BI)

The test results showed a t-statistical value of 3.210 and a p-value of 0.001, so the relationship was declared significant. This relationship has a path coefficient value of ($\beta = 0.197$) which indicates a positive direction, and an effect size value of f^2 of 0.073 which is included in the category of small effects. This shows that the convenience of using AI systems also influences employees' intention to use them. A user-friendly, non-confusing, and non-workload-free user experience can form a positive attitude towards technology, thereby increasing usage intent/intent.

These findings support the development of a Technology Acceptance Model which explains that intrinsic factors, such as convenience and enjoyment in using technology, also influence user acceptance. (Gansser & Reich, 2021) explained that perceived enjoyment is one of the important factors in the Artificial Intelligence acceptance model because it is able to improve the user experience of technology. Therefore, companies need to improve the quality of user experience through a stable system, intuitive interface, and simple operational processes so that the use of AI machine vision not only provides benefits, but also creates a more comfortable and enjoyable work experience for employees.

CONCLUSION

Based on the results of the study, it can be concluded that employees' intention to use Artificial Intelligence (AI) technology in the quality inspection process was significantly influenced by Personal Innovativeness in IT, Self-Efficacy, Perceived Usefulness, and Perceived Enjoyment. Perceived Usefulness was identified as the most dominant factor influencing Behavioral Intention, while Perceived Ease of Use and Perceived Cyber Risk did not have direct effects but still contributed indirectly through Perceived Usefulness. Therefore, companies should focus on strengthening employees' perceptions of AI benefits by demonstrating the technology's actual contributions to improving inspection accuracy, operational efficiency, and the reduction of human error. Future research is recommended to incorporate additional relevant variables, expand research objects across different organizations or industries, increase the number of respondents to improve representativeness, and apply alternative analytical approaches to obtain a more comprehensive understanding of the factors influencing technology acceptance.

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