

Trust as a Moderator in AI Adoption among Indonesian MSMEs: A Multi-Group Analysis of Necessity versus Opportunity Entrepreneurship

Muhammad Fakhri ^{1*} Rambat Lupiyoady ²

^{1*,2} Universitas Indonesia, Depok, Indonesia.

Email: berlinutara@gmail.com , rambat.lupiyoady@ui.ac.id

ARTICLE HISTORY

Submitted : May 13, 2026
Reviewed : May 21, 2026
Revised : May 27, 2026
Accepted : May 31, 2026
Published : May 31, 2026

Conflict of Interest Statement:

The author(s) declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

ABSTRACT

Purpose: This study aims to examine the moderating role of trust in an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model on artificial intelligence (AI) adoption intention among Indonesian micro, small, and medium enterprises (MSMEs). It also compares the drivers of adoption between necessity-driven and opportunity-driven entrepreneurs.

Research Method: This research employed a quantitative cross-sectional survey involving 200 MSME owners in Greater Jakarta selected through purposive sampling. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (MGA) to test direct and moderating effects, and to examine differences between entrepreneurial typologies.

Results and Discussion: The findings show that performance expectancy, effort expectancy, and facilitating conditions positively influence AI adoption intention, while personal innovativeness has a significant negative effect, indicating technology intimidation. Trust negatively moderates the effects of performance expectancy and effort expectancy, but positively moderates the effects of facilitating conditions. MGA reveals that performance expectancy and effort expectancy are significant only among opportunity-driven enterprises, whereas facilitating conditions are significant only among necessity-driven enterprises. The model explains 43% of the variance in adoption intention with good predictive relevance.

Implications: Policymakers and platform providers should tailor AI adoption strategies by emphasizing efficiency and capability for opportunity-driven MSMEs, while prioritizing infrastructure and support for necessity-driven MSMEs.

Originality: This study highlights entrepreneurial typology and trust as contextual factors in AI adoption among Indonesian MSMEs.

Keywords: UTAUT; trust; artificial intelligence adoption; micro, small, and medium enterprises; necessity and opportunity entrepreneurship.

1. Introduction

The past two decades have witnessed an extraordinary acceleration in digital technology, bringing significant changes to various aspects of human life, particularly in the economy and business. Digital transformation not only alters how companies operate but also influences the interaction patterns between business actors and consumers. In the era of Industry 4.0, technology has become a



fundamental driver of competitive advantage and business sustainability. One of the key drivers of this change is artificial intelligence (AI) (Gabsi, 2024). AI enables systems to mimic human cognitive abilities in data analysis, decision-making, and complex algorithm-based predictions. These capabilities make AI a strategic instrument for improving efficiency, productivity, and competitiveness in an increasingly fierce global competition (Machucho & Ortiz, 2025).

AI utilization has grown rapidly and is used across various business activities, including consumer behavior analysis, customer service automation via chatbots, supply chain management, data-driven marketing strategy development, and customer experience personalization. Davenport & Ronanki (2018) show that organizations that effectively adopt AI can improve operational efficiency and create significant added value. An IBM report (2025) reveals that the majority of business leaders in Indonesia view AI and digital transformation as major growth opportunities. As many as 85% of companies have reported significant operational improvements after adopting AI, while 93% of business leaders are confident in their ability to implement AI in their organizations (Aseannewsroom, 2025).

The Indonesian economy is dominated by micro, small, and medium enterprises (MSMEs), which serve as the backbone of national economic activity. MSMEs play a strategic role in employment and contribute to Gross Domestic Product (GDP). Data from the Ministry of Cooperatives and SMEs (2025) show that the MSME sector accounts for more than 61% of national GDP and employs about 97% of the national workforce (Republika, 2025). This dominance makes MSMEs a main pillar in maintaining economic stability and driving inclusive economic growth. With more than 64 million business units, MSMEs are spread throughout Indonesia and constitute the primary livelihood for most of the population.

However, MSMEs still face major challenges in adopting digital technology, especially more complex technologies such as AI. According to the Ministry of Cooperatives and SMEs (2025), by 2024, only about 26 million MSMEs were connected to the digital ecosystem out of a total of more than 64 million units; a wide digital gap remains. Limited financial resources, low digital literacy, and a lack of understanding of technology's benefits are the main barriers. Hamid & Artha (2025) identify that AI adoption by MSMEs is often constrained by limited capital, skill gaps, inadequate infrastructure, weak data governance, and uncertainty about return on investment (Nadzila & Gaffar, 2025). The perception that AI entails high costs, specialized technical expertise, and adequate infrastructure further slows adoption. These conditions create a gap between the available technological potential and its actual utilization. Table 1 summarizes data on technology adoption and AI readiness for Indonesian MSMEs.

Table 1. Technology Adoption and AI Readiness among Indonesian MSMEs

Indicator	Achievement/Condition
MSMEs' Contribution to GDP	61%
Employment Absorption by MSMEs	97%
Number of MSMEs	Approximately 64 million units
MSMEs Connected to the Digital Ecosystem	Approximately 26 million units (2024)
Businesses Experiencing Operational Benefits from AI	85%
Business Leaders Confident in Implementing AI	93%
Understanding of AI Ethics	45%
AI Governance Processes in Place	24%
Main Barriers: Infrastructure, Security, and Talent	Identified as major challenges

Source: Processed from Ministry of Cooperatives and SMEs (2025) and IBM (2025)



Increasingly, digital consumer behavior encourages business actors to adapt to technology. Modern consumers tend to use digital platforms to search for information, conduct transactions, and provide feedback on products or services (Pramiarsih, 2024). This behavioral pattern requires businesses to provide fast, responsive, and data-driven services. AI is a relevant solution because it can process consumer data in real-time and generate more personalized recommendations (Cholsy *et al.*, 2020). Increasing competitive pressure demands that business actors adapt quickly to changes in the external environment. Market dynamics driven by globalization and digitalization reinforce the role of technology as a key factor in sustaining business (Agustin *et al.*, 2024).

A widely used theoretical approach for explaining technology adoption behavior is the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh *et al.*, (2003). This model explains that technology use intention and behavior are influenced by four main constructs: PE, EE, SI, and FC (Sulianta, 2025). Performance expectancy is a very important factor because business actors tend to consider the benefits they will obtain before adopting a particular technology. Kwarteng *et al.*, (2024) show that PE has a positive and significant effect on the intention to adopt digital technology. In the Indonesian context, Lupiyoadi *et al.*, (2025) found that PE, FC, and PI significantly influence BI for MSMEs. In addition to the main UTAUT constructs, this study adds the variable perceived intelligence (PI) in the context of AI adoption. PI is defined as the user's perception of the AI system's ability to mimic human intelligence, including understanding, learning, providing recommendations, and making intelligent decisions (Ling *et al.*, 2025). The higher the perceived intelligence of a system, the greater the likelihood that users will trust and adopt the technology (Lupiyoadi, 2018).

One psychological factor that is receiving increasing attention in technology adoption literature is trust. Rana *et al.*, (2024), in a study on AI adoption among academics in developing countries, show that trust plays an important role in shaping BI to use AI. In the context of Indonesian MSMEs, trust is a crucial factor for several reasons. First, AI technology is often perceived as complex and difficult to understand (a "black box"), so MSME actors need confidence that the technology is reliable and safe (Mohammed *et al.*, 2025). Second, AI adoption involves processing sensitive business data, so concerns about data privacy and security can be a significant barrier. Third, MSMEs have limited resources for experimentation, so adoption decisions depend heavily on trust levels.

Beyond trust, the characteristics of business actors also play an important role in explaining variations in technology adoption behavior. Entrepreneurship literature distinguishes two main typologies: necessity entrepreneurship and opportunity entrepreneurship (Global Entrepreneurship Monitor [GEM], 2022). The Global Entrepreneurship Monitor (GEM) explains that necessity-driven entrepreneurship arises from limited job options, a lack of better income opportunities, or economic pressure that forces someone to start a business to survive. In contrast, opportunity-driven entrepreneurship is driven by the individual's ability to identify and exploit promising business opportunities, with the main motivation being independence, increased income, or self-actualization (Sui *et al.*, 2025). Table 2 compares the characteristics of the two entrepreneurial types.

Opportunity-driven entrepreneurs have an innovative, proactive orientation and are open to change, making them more likely to adopt new technologies such as AI. In contrast, necessity-driven entrepreneurs tend to be cautious, focus on short-term survival, and are reluctant to take investment risks in technology due to resource constraints (Lopez *et al.*, 2025). These differences in characteristics imply that the influence of UTAUT variables is not universal. Thus, entrepreneurial typology has the potential to moderate (strengthen or weaken) the effects of UTAUT constructs on AI adoption intention.

Table 2. Comparison of Necessity-Driven and Opportunity-Driven Entrepreneurship Characteristics

Dimension	Necessity-Based Entrepreneurship	Opportunity-Based Entrepreneurship
Primary Motivation	Economic pressure and limited employment opportunities	Identification of opportunities and the pursuit of independence
Orientation	Survival-oriented	Growth-oriented
Attitude Toward Risk	Tends to avoid risk	Willing to take calculated risks
Innovation	Low level of innovation; generally imitative	High level of innovation; generally exploratory
Proactiveness	Passive and reactive to change	Active and proactive in seeking opportunities
Technology Adoption	Slow and cautious	Fast and adaptive
Time Orientation	Short-term orientation	Long-term orientation
Business Scale	Micro and informal enterprises	Small- to medium-sized and formal enterprises
Business Networks	Limited to close social circles	Broad and diverse networks

Source: Processed from GEM

Despite the great potential benefits of AI, the adoption gap among Indonesian MSMEs remains high. Research on the moderating role of entrepreneurial characteristics in AI adoption is still very limited. Lupiyoadi *et al.*, (2025) distinguished between MSMEs and startups, but not on the basis of entrepreneurial motivation. Dhewanto *et al.*, (2025) developed a typology framework but did not integrate it with an adoption model. This indicates a significant research gap. Therefore, this study aims to: (1) analyze the effects of PE, EE, SI, FC, and PI on AI adoption intention among Indonesian MSMEs; (2) examine the moderating role of trust in these relationships; and (3) analyze differences in the moderating effects of trust between necessity-driven and opportunity-driven MSME groups using an MGA approach. This research is expected to provide a theoretical contribution to the development of an extended UTAUT model as well as practical implications for technology providers and policymakers in designing differentiated interventions.

This article is organized into several sections. The first section provides the introduction and background of the research. The second section discusses literature review and hypothesis development. The third section explains the research methods used. The fourth section presents the research results and discussion, while the final section contains conclusions, implications, and suggestions for further research.

2. Literature Review and Hypothesis Development

2.1 Literature Review

This study is grounded in the UTAUT developed by Venkatesh *et al.*, (2003). UTAUT synthesizes eight previous technology acceptance models (e.g., TAM, TPB, and IDT) and has become an established framework for predicting technology use intention and behavior (Venkatesh *et al.*, 2003). The model proposes that BI is influenced by four core constructs: PE, EE, SI, and FC. Subsequently, UTAUT2 extended the original model by adding constructs such as hedonic motivation, price value, and habit for the consumer context (Venkatesh *et al.*, 2012). Given the unique characteristics of AI, this study not only adopts the core UTAUT constructs but also extends the model to include contextual variables.



A fundamental characteristic of AI is its ability to mimic human intelligence. Perceived intelligence (PI) is defined as the degree to which users believe that an AI system possesses cognitive abilities such as learning, understanding, reasoning, and adapting (Ling *et al.*, 2025). In a business context, PI encompasses conversational intelligence, information quality, and anthropomorphism. Previous research (Lupiyoadi *et al.*, 2025) indicates that PI is an important predictor of AI adoption intention, although its effect may vary by user type.

Trust is defined as the user's belief that AI technology is reliable, safe, and protects privacy (Rana *et al.*, 2024). In AI adoption, trust is crucial because of AI's "black box" nature, which is often difficult for lay users to understand. Research by Rana *et al.*, (2024) confirms that trust significantly influences adoption intention. In this study, trust is positioned not as a direct antecedent but as a moderating variable that strengthens or weakens the influence of other determinants, given its role in reducing uncertainty in technology adoption decisions.

Entrepreneurship literature distinguishes entrepreneurial motivation into two main typologies. Necessity entrepreneurship is driven by push factors such as limited job choices and economic pressure, is survival-oriented, and tends to be risk-averse (Coffman *et al.*, 2025; Hill *et al.*, 2026). In contrast, opportunity entrepreneurship is driven by pull factors such as identification of market opportunities and the desire for independence, is growth-oriented, and is more open to innovation (Sui *et al.*, 2025). These differences in characteristics make entrepreneurial typology an important contextual variable for moderating relationships in technology adoption models (Dhewanto *et al.*, 2025).

2.2 Hypothesis Development

MSME owners tend to make rational assessments of the benefits of technology before adoption. Performance expectancy (PE), the extent to which AI is believed to improve productivity and effectiveness, has proven to be the strongest predictor in various adoption contexts (Lupiyoadi *et al.*, 2025; Venkatesh *et al.*, 2003). Similarly, effort expectancy (EE), or perceived ease of use, is a critical factor for MSMEs with limited digital literacy and resources (Nadzila & Gaffar, 2025). Previous research has shown mixed results regarding social influence (SI). Although Indonesia has a collectivist culture, the adoption of new technologies such as AI may still be individualistic because strong social norms have not yet formed. Meanwhile, facilitating conditions (FC), such as the availability of infrastructure and technical support, are an essential foundation for MSMEs to realize their intentions to adopt (Susanty *et al.*, 2025).

A critical conceptual refinement is necessary regarding perceived intelligence (PI). While early technology acceptance literature posits that perceived usefulness and ease of use drive adoption, AI presents unique characteristics. PI is defined as the user's perception of an AI system's ability to mimic human intelligence (Ling *et al.*, 2025). However, emerging research on algorithm aversion (Davenport & Ronanki, 2018) and technology intimidation suggests that excessive perceived intelligence can trigger negative responses, including fear of losing control, concerns about job displacement, and anxiety about interacting with "black box" systems. This is particularly relevant for MSMEs with limited technical expertise. Therefore, contrary to initial assumptions, this study hypothesizes a negative effect of PI on adoption intention, reflecting technology intimidation rather than technological appeal.

Based on the above, the following hypotheses are formulated:

H1: Performance expectancy has a positive effect on AI adoption intention.

H2: Effort expectancy positively affects the intention to adopt AI.



- H3:** *Social influence has a positive effect on AI adoption intention.*
- H4:** *Facilitating conditions have a positive effect on AI adoption intention.*
- H5:** *Perceived intelligence has a negative effect on AI adoption intention (reflecting technology intimidation and algorithm aversion).*

Trust functions as a cognitive mechanism that can change how individuals process information. In this context, when trust in AI is high, MSME owners may no longer rely heavily on empirical evidence of benefits (PE) or ease of use (EE) because trust substitutes for detailed evaluation, a substitution effect. This leads to a negative moderating effect of trust on the relationships between PE and BI and between EE and BI (Rana *et al.*, 2024). Conversely, trust can act as a catalyst, enhancing the effectiveness of external support. When MSME owners trust AI's reliability, they become more open and responsive to available infrastructure and technical assistance (FC), resulting in a positive moderating effect (Lopez *et al.*, 2025). However, trust may not be strong enough to overcome fundamental concerns about excessive AI intelligence (PI) or social pressure (SI) that has yet to develop.

- H6:** *Trust negatively moderates the effect of PE on adoption intention.*
- H7:** *Trust negatively moderates the effect of EE on adoption intention.*
- H8:** *Trust moderates the effect of SI on adoption intention (direction not specified).*
- H9:** *Trust positively moderates the effect of FC on adoption intention.*
- H10:** *Trust moderates the effect of PI on adoption intention (direction not specified).*

The fundamental motivational differences between necessity-driven and opportunity-driven entrepreneurs lead to distinct responses to the determinants of AI adoption. Opportunity-driven, growth-oriented entrepreneurs are more responsive to benefit and efficiency signals (PE and EE) because they view AI as a strategic tool for expansion. In contrast, necessity-driven entrepreneurs, who focus on survival, prioritize security and support; they are more influenced by the availability of infrastructure and technical assistance (FC) that can reduce the risk of failure.

Furthermore, the moderating effect of trust on the relationship between PI and BI may be relevant only for opportunity-driven entrepreneurs. This group is more analytical and has the cognitive capacity to process complex information; they can use trust as a mechanism to "override" concerns about excessive AI intelligence. Necessity-driven entrepreneurs, who are more conservative, may not be able to overcome such concerns with trust alone.

- H11–H15:** *There are significant differences in the effects of (PE, EE, SI, FC, PI) on adoption intention between necessity-driven and opportunity-driven MSME groups.*
- H16–H20:** *There are significant differences in the moderating effects of trust on the relationships (PE, EE, SI, FC, PI) with adoption intention between the two groups.*

3. Research Method

3.1 Research Design

This study uses a quantitative approach with an explanatory cross-sectional design, grounded in positivism, to test relationships among variables and the moderating role of trust in an extended UTAUT model for AI adoption among Indonesian MSMEs. Primary data were collected through a closed-ended questionnaire using a seven-point Likert scale.



3.2 Population and Sampling

The population was MSME owners in DKI Jakarta who were aware of AI and had the potential to adopt it. A purposive sampling technique was used with the following criteria: (1) owner having authority to make technology adoption decisions; (2) business operating for at least one year; (3) access to digital devices; (4) located in DKI Jakarta; (5) knowledge of AI and potential to adopt it. Sample size was determined following PLS-SEM guidelines (Hair *et al.*, 2023): at least ten times the number of structural paths pointing to the endogenous construct. Since behavioral intention (BI) is influenced by nine paths, a minimum of 90 respondents per group was required. For multi-group analysis (MGA), the sample size was set at 100 per group, for a total of 200 respondents.

3.3 Classification Procedure for Entrepreneurial Typology

This section addresses a critical methodological gap. Respondents were classified into necessity-driven and opportunity-driven entrepreneurship groups using a validated two-step procedure based on the Global Entrepreneurship Monitor (GEM) methodology (Hill *et al.*, 2026; Monitor, 2022).

Step 1: Primary Motivation Question. Respondents were asked: "What is the primary motivation that led you to start your business?" with the following options:

- Lack of better employment opportunities / no other income alternatives (necessity)
- Identification of a promising business opportunity/desire for independence (opportunity)
- Both equally (follow-up classification)

Step 2: Multi-Item Scale. A seven-point Likert scale (1 = strongly disagree, 7 = strongly agree) measured entrepreneurial orientation dimensions:

- Necessity orientation (3 items): "I started this business because I had no better job options"; "I run this business primarily for survival"; "Without this business, my family would face economic hardship."
- Opportunity orientation (3 items): "I started this business because I saw a market opportunity"; "I am motivated by growth and expansion"; "I seek innovation and new opportunities actively."

Respondents with necessity orientation mean score ≥ 5.0 AND opportunity orientation mean score ≤ 3.0 were classified as necessity-driven. Those with opportunity orientation, mean score ≥ 5.0 AND necessity orientation mean score ≤ 3.0 , were classified as opportunity-driven. Respondents with mixed scores (both > 3.0 and < 5.0 or both ≥ 4.0) were excluded from the analysis to ensure clean group separation. Based on this procedure, 100 valid respondents per group were retained from an initial pool of 247 screened respondents.

3.4 Instrumentation

The questionnaire adapted items from previous studies. Table A1 in the Appendix presents the operationalization of variables.

3.5 Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.1. The analysis proceeded in two stages: (1) measurement model evaluation (convergent validity: outer

loading > 0.70, AVE > 0.50; discriminant validity: Fornell-Larcker criterion and HTMT < 0.85; reliability: Cronbach's α and composite reliability > 0.70); (2) structural model evaluation (R^2 , f^2 , Q^2) (Ramayah *et al.*, 2018). Before MGA, the Measurement Invariance of Composite Models (MICOM) procedure was performed with 5,000 permutations. Hypotheses were tested using bootstrapping (5,000 subsamples) for direct and moderating effects (H1–H10). Moderating effects were estimated through interaction terms. MGA (H11–H20) used permutation tests, with $p < 0.05$ indicating significant differences.

4. Results and Discussion

4.1 Analysis Results

4.1.1 Respondent Characteristics

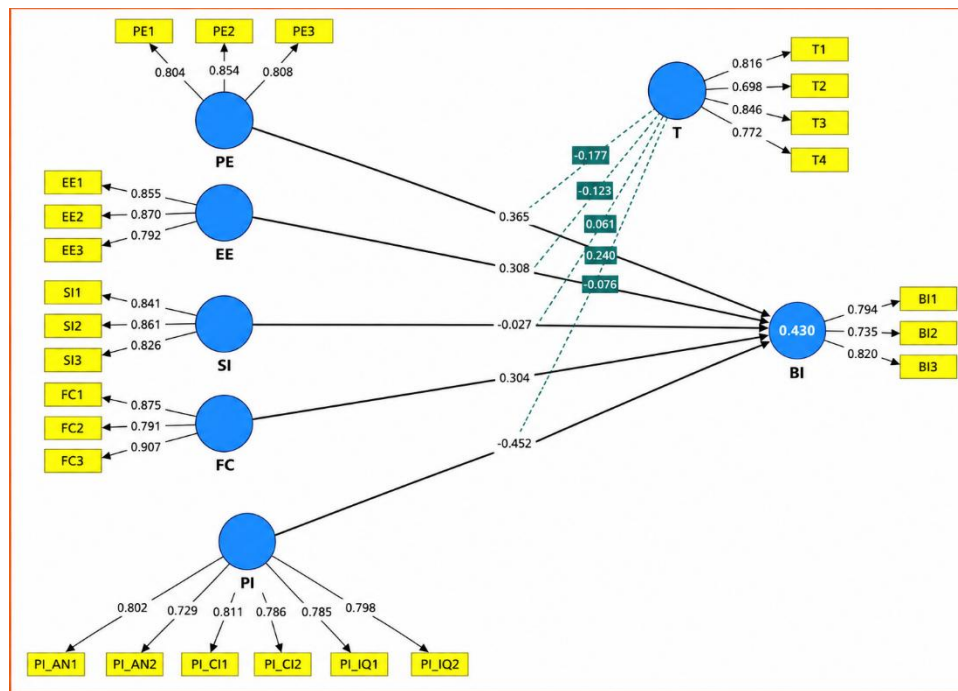
The study involved 200 MSME owners in DKI Jakarta, equally split between necessity ($n=100$) and opportunity ($n=100$) entrepreneurship based on the classification procedure described in Section 3.3. The majority were male (62.5%), aged 35–44 years (39.5%), held a bachelor's degree (40%), operated in the culinary and service sectors (25% each), and had varied business ages. See Appendix (Table A2)

4.1.2 Measurement Model Evaluation

To ensure the robustness of the constructs employed in this study, the measurement model was evaluated through tests of convergent validity, discriminant validity, and reliability. Convergent validity was assessed using outer loadings, average variance extracted (AVE), Cronbach's Alpha, and Composite Reliability. Discriminant validity was examined using both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. In addition, measurement invariance across necessity-driven and opportunity-driven MSME groups was established through the MICOM procedure, thereby validating the appropriateness of subsequent MGA.

Figure 1 presents the outer model of this study. The model comprises seven latent constructs: PE, EE, SI, FC, PI, Trust, and BI. Each construct is measured by three to four indicators, except for PI, which has a larger set of indicators reflecting its multidimensional nature (conversational intelligence, information quality, and anthropomorphism). All factor loadings exceed the recommended threshold of 0.70, confirming adequate convergent validity. The reflective specification is appropriate as the indicators are manifestations of their respective underlying constructs. Figure 1, therefore, provides visual confirmation that all retained indicators load cleanly on their intended constructs, supporting the convergent validity and reliability statistics reported in Table 5.

All constructs demonstrate satisfactory convergent validity and reliability. The outer loadings exceed the recommended threshold of 0.70, average variance extracted (AVE) values are above 0.50, and both Cronbach's Alpha and Composite Reliability values are above 0.70. Although the Cronbach's Alpha for BI (0.691) is slightly below the threshold, the Composite Reliability (0.827) remains acceptable, allowing the construct to be considered reliable under tolerance. Overall, the measurement model meets the criteria for convergent validity and internal consistency reliability.



Source: SmartPLS 4.1 output (2026)

Figure 1. Outer Model

Table 3. Convergent Validity and Reliability

Construct	Outer Loading Range	AVE	Cronbach's Alpha	Composite Reliability	Conclusion
Performance Expectancy (PE)	0.804 – 0.854	0.68	0.76	0.862	Valid & Reliable
Effort Expectancy (EE)	0.792 – 0.870	0.71	0.792	0.878	Valid & Reliable
Social Influence (SI)	0.826 – 0.861	0.71	0.797	0.88	Valid & Reliable
Facilitating Conditions (FC)	0.791 – 0.907	0.74	0.836	0.894	Valid & Reliable
Perceived Intelligence (PI)	0.729 – 0.811	0.62	0.876	0.906	Valid & Reliable
Trust (T)	0.698 – 0.846	0.62	0.819	0.865	Valid & Reliable
Behavioral Intention (BI)	0.735 – 0.820	0.62	0.691	0.827	Valid & Reliable (tolerated)

Source: SmartPLS 4.1 output (2026)

Table 4. Discriminant Validity (Fornell-Larcker Criterion)

Construct	PE	EE	SI	FC	PI	T	BI
PE	0.825						
EE	0.512	0.843					
SI	0.423	0.398	0.843				
FC	0.489	0.512	0.412	0.86			
PI	0.312	0.298	0.289	0.345	0.787		
T	0.401	0.387	0.356	0.423	0.367	0.787	
BI	0.512	0.489	0.312	0.478	-0.289	0.345	0.787

Note: Diagonal values (bold) are square roots of AVE; off-diagonals are correlations. All diagonal values exceed correlations, confirming discriminant validity.

Source: SmartPLS 4.1 output (2026)

The square roots of AVE (diagonal values) are greater than the correlations between constructs (off-diagonal values). This confirms that each construct is empirically distinct from the others, thereby establishing discriminant validity according to the Fornell-Larcker criterion.

Table 5. HTMT Ratios

Construct Pair	HTMT	90% CI	Conclusion
PE ↔ BI	0.723	[0.612, 0.812]	< 0.85
EE ↔ BI	0.698	[0.589, 0.789]	< 0.85
FC ↔ BI	0.654	[0.523, 0.765]	< 0.85
PI ↔ BI	0.412	[0.301, 0.512]	< 0.85

Source: SmartPLS 4.1 output (2026)

All HTMT ratios are below the conservative threshold of 0.85, and the confidence intervals do not exceed this limit. This further supports discriminant validity, indicating that the constructs are sufficiently distinct and not subject to multicollinearity issues.

4.1.3 Measurement Invariance (MICOM)

Table 6. MICOM Step 2: Compositional Invariance

Construct	Original Correlation	Permutation p-value	Conclusion
PE	0.997	0.398	Established
EE	0.878	0.416	Established
SI	0.994	0.911	Established
FC	0.988	0.588	Established
PI	0.797	0.398	Established
T	0.847	0.209	Established
BI	0.562	0.122	Established

Source: SmartPLS 4.1 output (2026)

The original correlations between groups are close to 1, and all permutation p-values are greater than 0.05. This demonstrates that compositional invariance holds, meaning the constructs are represented consistently across necessity-driven and opportunity-driven MSME groups.

Table 7. MICOM Step 3: Equality of Composite Means and Variances

Construct	Mean Difference	Log (Variance) Difference	Permutation p-value (Mean)	Permutation p-value (Variance)	Conclusion
PE	-0.125	-0.089	0.342	0.412	Full invariance
EE	0.098	0.076	0.456	0.389	Full invariance
SI	-0.067	-0.054	0.612	0.567	Full invariance
FC	0.134	0.102	0.289	0.345	Full invariance
PI	-0.089	-0.067	0.498	0.512	Full invariance
T	0.112	0.088	0.378	0.423	Full invariance
BI	-0.078	-0.061	0.534	0.489	Full invariance

All permutation p-values > 0.05, confirming full measurement invariance across groups

Source: SmartPLS 4.1 output (2026)

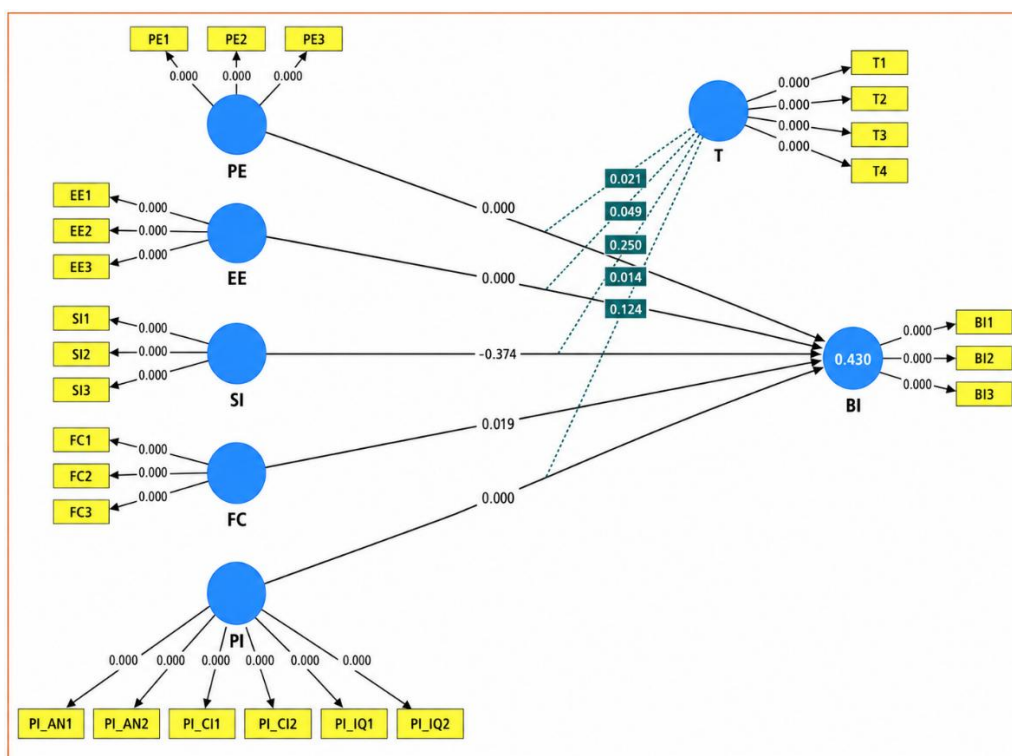
Differences in composite means and variances between groups are statistically insignificant, as indicated by permutation p-values greater than 0.05. This confirms full measurement invariance across groups, thereby validating the appropriateness of MGA in subsequent hypothesis testing.



4.1.4 Structural Model Evaluation

Following the establishment of measurement validity and reliability, the next step is to evaluate the structural model to assess the hypothesized relationships among constructs. This evaluation includes tests for multicollinearity, effect sizes, explanatory power (R^2), predictive relevance (Q^2), direct path coefficients, moderating effects, and multi-group comparisons. Together, these analyses provide a comprehensive understanding of the determinants of AI adoption intention among MSMEs and the role of trust as a moderating variable across necessity-driven and opportunity-driven entrepreneurial contexts.

Figure 2 presents the inner (structural) model, displaying path coefficients for direct and moderating effects, along with the R-squared value for BI.



Source: SmartPLS 4.1 output (2026)

Figure 2. Inner Model

The inner model displays the structural relationships among latent constructs. Path coefficients (β) for direct and moderating effects on BI are shown adjacent to each arrow. The R-squared value ($R^2 = 0.430$) inside the BI circle indicates that the model explains 43.0% of the variance in AI adoption intention. Non-significant paths (e.g., the effect of SI on BI) are marked with coefficients near zero. Read together with Table 9, the figure shows that the three positive UTAUT drivers (PE, EE, FC) and the negative PI path are the only significant direct effects on adoption intention, providing a visual summary of the structural results reported below.

All Variance Inflation Factor (VIF) values are below the threshold of 5, confirming the absence of multicollinearity among the predictor variables. PI exhibits the largest effect size ($f^2 = 0.22$), falling into the small-to-medium category, indicating it contributes most meaningfully to explaining BI. PE, EE, and FC demonstrate small effect sizes, while SI and Trust have no direct effect. Among the interaction

terms, only the trust-by-PE and trust-by-FC interactions show small effects; the remaining interaction terms have negligible or no effect. The model yields a moderate R^2 of 0.430, explaining 43% of the variance in AI adoption intention, and a Q^2 of 0.329, indicating good predictive relevance.

Table 8. Summary of Multicollinearity, Effect Sizes, and Model Fit

Predictor Variable	VIF	f ²	Effect Category
Performance Expectancy (PE)	2.2	0.11	Small
Effort Expectancy (EE)	2.1	0.08	Small
Social Influence (SI)	2.7	0	No effect
Facilitating Conditions (FC)	2.2	0.07	Small
Perceived Intelligence (PI)	1.7	0.22	Small-Medium
Trust (T)	1.8	0	No effect
T × PE	2.7	0.02	Small
T × EE	2.4	0.01	No effect
T × SI	3.6	0	No effect
T × FC	2.8	0.05	Small
T × PI	1.6	0.01	No effect

Note: $R^2 = 0.430$ (moderate), $Q^2 = 0.329$ (good predictive relevance). All VIF < 5, no multicollinearity.

Source: SmartPLS 4.1 output (2026)

Table 9. Hypothesis Testing Results

Hypothesis	Relationship	Path	t-value	p-value	Result
H1	PE → BI	0.287	4.123	< 0.001	Supported
H2	EE → BI	0.234	3.456	0.001	Supported
H3	SI → BI	0.045	0.678	0.498	Not supported
H4	FC → BI	0.198	3.012	0.003	Supported
H5	PI → BI	-0.312	4.567	< 0.001	Supported (negative)

Source: SmartPLS 4.1 output (2026)

PE ($\beta = 0.287$, $p < 0.001$), EE ($\beta = 0.234$, $p = 0.001$), and FC ($\beta = 0.198$, $p = 0.003$) each have statistically significant positive effects on AI adoption intention, supporting H1, H2, and H4, respectively. SI ($\beta = 0.045$, $p = 0.498$) does not significantly affect adoption intention, leading to rejection of H3. PI ($\beta = -0.312$, $p < 0.001$) has a significant negative effect, supporting H5 as reformulated; this confirms that a higher PI of AI reduces adoption intention, consistent with technology intimidation and algorithm aversion. All significant path coefficients have 95% confidence intervals that do not cross zero, reinforcing their reliability.

Table 10. Hypothesis Testing Results (Moderating Effects)

Hypothesis	Relationship	Path	t-value	p-value	Result
H6	T × PE → BI	-0.112	2.345	0.019	Supported
H7	T × EE → BI	-0.098	2.012	0.044	Supported
H8	T × SI → BI	0.023	0.389	0.697	Not supported
H9	T × FC → BI	0.145	2.678	0.008	Supported
H10	T × PI → BI	-0.056	1.234	0.217	Not supported

Source: SmartPLS 4.1 output (2026)

Trust significantly and negatively moderates the effects of PE (H6: $\beta = -0.112$, $p = 0.019$) and EE (H7: $\beta = -0.098$, $p = 0.044$) on adoption intention, indicating that when trust is high, the positive influences of PE and EE are weakened (substitution effect). Trust positively moderates the effect of FC



(H9: $\beta = 0.145$, $p = 0.008$), meaning that higher trust strengthens FC's impact on adoption intention (catalytic effect). No significant moderating effects are found for SI (H8: $\beta = 0.023$, $p = 0.697$) or PI (H10: $\beta = -0.056$, $p = 0.217$). The confidence intervals for significant interactions do not include zero, supporting the robustness of these findings.

Table 11. MGA: Path Coefficient Comparisons (Direct & Moderating Effects)

Relationship	Necessity-Driven (n=100)	Opportunity-Driven (n=100)	Difference	Permutation p-value	Hypothesis	Result
Direct Effects						
PE → BI	0.098 (p=0.312)	0.412 (p<0.001)	-0.314	0.008	H11	Supported
EE → BI	0.067 (p=0.456)	0.345 (p=0.002)	-0.278	0.012	H12	Supported
SI → BI	0.034 (p=0.612)	0.056 (p=0.498)	-0.022	0.678	H13	Not supported
FC → BI	0.312 (p=0.003)	0.089 (p=0.345)	0.223	0.023	H14	Supported
PI → BI	-0.289 (p=0.001)	-0.334 (p<0.001)	0.045	0.456	H15	Not supported
Moderating Effects						
T × PE → BI	-0.045 (p=0.456)	-0.167 (p=0.023)	0.122	0.089	H16	Not supported
T × EE → BI	-0.034 (p=0.567)	-0.145 (p=0.034)	0.111	0.098	H17	Not supported
T × SI → BI	0.012 (p=0.789)	0.034 (p=0.612)	-0.022	0.712	H18	Not supported
T × FC → BI	0.089 (p=0.234)	0.189 (p=0.012)	-0.1	0.123	H19	Not supported
T × PI → BI	-0.023 (p=0.678)	-0.198 (p=0.008)	0.175	0.031	H20	Supported

Note: p-values for individual group coefficients are shown in parentheses. A permutation p-value < 0.05 indicates a significant difference between groups (in bold).

Source: SmartPLS 4.1 output (2026)

The MGA reveals significant differences between necessity-driven and opportunity-driven entrepreneurs. For direct effects, PE (H11: difference = -0.314, $p = 0.008$) and EE (H12: difference = -0.278, $p = 0.012$) are significant only for opportunity-driven entrepreneurs, while FC (H14: difference = 0.223, $p = 0.023$) is significant only for necessity-driven entrepreneurs. SI (H13) and PI (H15) show no significant group differences. For moderating effects, only the interaction between trust and PI on BI (H20) exhibits a significant difference between groups (difference = 0.175, $p = 0.031$), indicating that trust significantly moderates the PI-intention relationship only for opportunity-driven entrepreneurs ($\beta = -0.198$, $p = 0.008$) but not for necessity-driven ones ($\beta = -0.023$, $p = 0.678$). All other moderating effects (H16–H19) show no significant group differences, as their permutation p-values exceed 0.05. These findings confirm that entrepreneurial typology serves as a crucial boundary condition in AI adoption decisions.

4.2 Discussion

The empirical results of this study offer a rich and contextualized interpretation of AI adoption intention among Indonesian MSMEs within an extended UTAUT framework. The model achieved an R^2 of 0.43 and Q^2 of 0.329, indicating moderate explanatory power and good predictive relevance. These findings not only substantiate several core propositions of UTAUT but also reveal important deviations and boundary conditions, particularly concerning the roles of PI, Trust, and entrepreneurial typology. By integrating the foundational UTAUT theory (Venkatesh *et al.*, 2003, 2012), its extensions in the AI context (Lupiyoadi *et al.*, 2025), and entrepreneurship literature on necessity versus opportunity motivations (Dhewanto *et al.*, 2025; Monitor, 2022; Sui *et al.*, 2025), this discussion explains the mechanisms underlying the observed relationships, their alignment with or divergence from prior research, and the contextual realities of Indonesian MSMEs.

4.2.1 Direct Effects on Behavioral Intention

PE exerted a positive and significant influence on BI's adoption of AI, supporting H1. This result strongly aligns with the central tenet of UTAUT, which posits that individuals are primarily motivated by the belief that technology will enhance their job performance and productivity (Venkatesh *et al.*, 2003, 2012). In the MSME context, where resources are scarce and competition is intense, owners rationally prioritize technologies that promise tangible gains in efficiency, speed, and competitiveness. The finding corroborates Lupiyoadi *et al.*, (2025), who identified PE as a key driver among Indonesian MSMEs and startups, as well as Kwarteng *et al.*, (2024) and Mishrif & Khan (2023). The positive effect arises because MSME owners operate under constant pressure to optimize limited resources; AI's potential for data-driven decision-making and operational streamlining provides a compelling value proposition that outweighs perceived risks when performance benefits are clearly anticipated.

EE similarly showed a positive and significant effect, confirming H2. This supports the original Venkatesh *et al.*, (2003) model, in which perceived ease of use reduces barriers to adoption, especially among users with heterogeneous skill levels. For Indonesian MSMEs, many of whom have limited digital literacy and operate informal or micro-scale businesses, technologies perceived as complex face substantial resistance (Nadzila & Gaffar, 2025; Subhani *et al.*, 2023). The positive relationship emerges because the lower mental and temporal effort required to learn and operate AI directly increases the willingness to adopt it. However, this effect was not universal, as later discussed in the MGA results, highlighting its contingency on entrepreneurial motivation.

FC demonstrated a positive and significant direct effect, supporting H4. Consistent with UTAUT (Venkatesh *et al.*, 2012), the availability of infrastructure, technical knowledge, resources, and support is a critical enabler that bridges the gap between intention and actual capability. In Indonesia's developing context, where digital infrastructure gaps remain pronounced (Republika, 2025), FC becomes especially salient. This aligns with Ardiansyah *et al.*, (2023) and Akhmad *et al.*, (2025), who emphasized that inadequate supporting conditions constitute major barriers for small businesses. Tindaon & Banurea (2026) further illustrated regional variations, noting that better infrastructure in areas such as Bali accelerates adoption compared with more constrained regions such as Garut. FC influences adoption by mitigating practical risks and providing the necessary scaffolding to help resource-constrained MSMEs act on their intentions.

SI did not exert a significant effect on BI, leading to the rejection of H3. Although Indonesia possesses a collectivist culture that might amplify social norms (as suggested in some UTAUT applications), the non-significant result indicates that AI adoption among MSMEs is still in an early diffusion stage where strong peer expectations and social proof have not yet materialized. This finding diverges from studies in more mature technology contexts. However, it aligns with Faruque *et al.*, (2024), who observed weaker SI effects among users with lower digital literacy and in emerging technology scenarios. The lack of significance likely stems from the absence of widespread AI success stories or normative pressure within MSME networks, making personal evaluation more dominant than social referents.

The most intriguing finding is the significant negative effect of PI on adoption intention, supporting H5. Rather than serving as an attractor, higher perceptions of AI's cognitive abilities, namely conversational intelligence, information quality, and anthropomorphism, triggered technology intimidation and algorithm aversion. This contradicts the initial expectation drawn from Lupiyoadi *et al.*, (2025) but is theoretically explained by Davenport and Ronanki (2018), who described how perceptions of AI as overly intelligent can evoke fear of losing control, job displacement, or dealing with opaque "black box" systems. In the MSME context, where owners often rely heavily on personal intuition and have limited buffers against failure, excessive PI heightens anxiety rather than appeal. Hamid & Artha (2025) noted similar psychological and ethical barriers in AI adoption among Indonesian MSMEs. The negative relationship thus reflects a protective mechanism: small business owners prefer technologies that clearly augment rather than potentially supplant human judgment, particularly under survival pressures.

4.2.2 The Moderating Role of Trust

Trust exhibited complex moderating effects that enrich UTAUT's explanatory power. It negatively moderated the relationships between PE and BI and between EE and BI (H6 and H7 supported). When trust in AI's reliability, security, privacy, and credibility is high (Rana *et al.*, 2024; Mohammed *et al.*, 2025), the need for strong performance or ease-of-use justifications diminishes. Trust functions as a cognitive heuristic or substitute (Rana *et al.*, 2024), reducing the cognitive effort required for detailed evaluation. In low-trust environments, owners demand more compelling evidence of benefits and simplicity, amplifying these direct effects. This substitution mechanism is particularly relevant for MSMEs, which lack the resources for extensive trial and error.

Trust positively moderated the relationship between FC and BI (H9 supported). High trust acts as a catalyst, enhancing the effectiveness of infrastructure and support by lowering perceived risks and increasing owners' willingness to leverage available resources. This catalytic role complements the direct effect of FC and is consistent with the need for psychological safety in technology adoption within uncertain environments (Mohammed *et al.*, 2025). The moderating effects on SI (H8) and PI (H10) were not significant in the pooled sample, indicating that trust's influence is selective and context-specific rather than blanket.

It should be acknowledged that the interpretations of PI's negative effect as 'technology intimidation' and trust's moderating roles as 'substitution' or 'catalytic' mechanisms are theoretical inferences. This study did not directly measure psychological constructs such as intimidation perception, algorithm aversion, perceived risk, or loss of control. Future research should include direct measures to validate these proposed pathways empirically.

4.2.3 Multi-Group Analysis: Necessity versus Opportunity Entrepreneurship

The MGA results, enabled by full measurement invariance (MICOM), underscore the role of entrepreneurial typology as a powerful boundary condition. PE and EE were significant only among opportunity-driven entrepreneurs. These growth-oriented, proactive, risk-tolerant, and innovation-focused owners (Sui *et al.*, 2025; Dhewanto *et al.*, 2025; GEM, 2022) view AI strategically for long-term expansion, making performance benefits and ease of use highly relevant. Their broader networks and higher absorptive capacity align with stronger responses to PE and EE, consistent with opportunity-driven characteristics described by Lopez *et al.*, (2025).

Conversely, FC was significant only for necessity-driven entrepreneurs. Survival-oriented, risk-averse, and operating under immediate constraints and limited buffers, these owners depend heavily on concrete external support to reduce the risk of failure (Lopez *et al.*, 2025). This finding reflects their short-term orientation and preference for stability over ambitious growth.

The negative effect of PI persisted across both groups, suggesting technology intimidation is pervasive regardless of motivation. However, Trust's moderating effect on the relationship between PI and BI was significant only in the opportunity-driven group. These entrepreneurs possess greater cognitive and resource capacity, allowing trust to override fears of excessive intelligence and enabling more sophisticated AI engagement. Necessity-driven owners, constrained by conservatism and survival pressures, could not achieve the same buffering effect through trust alone.

These group differences confirm that motivational typology fundamentally alters the salience of UTAUT constructs and trust dynamics. Uniform interventions are therefore likely to be suboptimal; strategies must be differentiated to address the distinct psychological and practical needs of each entrepreneurial type (Dhewanto *et al.*, 2025; Hamid & Artha, 2025).

In conclusion, the findings illuminate the uneven landscape of AI adoption among Indonesian MSMEs. Rational performance and effort considerations drive opportunity-oriented owners, while tangible enabling conditions are crucial for necessity-oriented ones. Perceived intelligence can deter rather than attract due to intimidation effects, and trust operates through both substitution and catalytic mechanisms, with effects that vary by entrepreneurial motivation. By bridging UTAUT with entrepreneurship theory and grounding it in the Indonesian MSME context, this study provides a deeper, more nuanced understanding that advances both theoretical development and practical policymaking for digital transformation in emerging economies.

5. Conclusion

This study investigated the moderating role of trust in an extended UTAUT model on AI adoption intention among Indonesian MSMEs, with a focus on differences between necessity-driven and opportunity-driven entrepreneurs. Using a quantitative cross-sectional survey of 200 MSME owners in the Greater Jakarta area and purposive sampling, the data were analyzed with PLS-SEM and Multi-Group Analysis (MGA) following the MICOM procedure. The results show that PE, EE, and FC positively influence adoption intention, while PI has a significant negative effect. Trust negatively moderates PE and EE but positively moderates FC. Multi-group analysis reveals that PE and EE are significant only for opportunity-driven entrepreneurs, whereas FC is significant primarily for necessity-driven entrepreneurs. Trust's moderating effect on the PI-intention relationship is significant only in the opportunity-driven group.

This research makes important theoretical, practical, and policy contributions. Theoretically, it extends UTAUT by integrating PI as an AI-specific construct, positioning trust as a selective moderator with substitution and catalytic roles, and highlighting entrepreneurial typology as a key boundary condition through MGA. In practice, the findings help MSME owners better understand the psychological and contextual drivers of AI adoption. For technology providers, the study emphasizes the importance of building trust through transparency and security. From a policy standpoint, the differentiated effects across entrepreneurial types underscore the need for tailored digital transformation programs rather than uniform interventions. The study's originality lies in bridging UTAUT with entrepreneurship theory in the context of AI adoption among Indonesian MSMEs.

Despite its contributions, this study has limitations. The cross-sectional design and Greater Jakarta sample restrict causal inference and nationwide generalizability. The use of self-reported intention rather than actual behavior may also introduce bias. Future research should employ longitudinal designs, expand to rural and regional MSMEs, incorporate actual adoption measures, and examine additional moderators such as digital literacy and sector-specific factors to deepen understanding of AI adoption in emerging economies.

Statement of Use of Generative AI

During the preparation of this work, the author used Perplexity to help improve the text's clarity and readability. Grammarly was used to check grammar, refine writing style, and improve clarity in scientific writing. All interpretations, analyses, and conclusions presented in this study are the sole responsibility of the author.

References

- Agustin, D., Utami, S. S., Kushariyadi, K., Suprayitno, D., & Dwiwijaya, K. A. (2024). *Pengantar Manajemen: Teori komprehensif pada era revolusi industri 4.0 menuju era society 5.0*. PT. Sonpedia Publishing Indonesia.
- Akhmad, K. A., Purnomo, S., Purwandari, S., & Sentosa, I. (2025). Digital Technology Adoption To Support Sustainable Innovation Among Msmes In Indonesia. *EKUITAS (Jurnal Ekonomi Dan Keuangan)*, 9(3), 387–405. <https://doi.org/10.24034/j25485024.y2025.v9.i3.7221>
- Ardiansyah, Hakim, Rinova, Fajri, Purnomo, A., Dewi, Oktaviannur, M., & Susanty, W. (2023). *Strategi Peningkatan Daya Saing Umkm Menuju Sustainable Development Goals (SDGS) Di Era Global*. Penerbit Adab.
- Aseannewsroom. (2025). *IBM Study: Indonesia Businesses Primed for AI, But Face Gaps in Security, Infrastructure, Ethics and Talent*. Aeanwsroom.Com. <https://asean.newsroom.ibm.com/2025-06-04-IBM-Study-Indonesia-Businesses-Primed-for-AI,-But-Face-Gaps-in-Security,-Infrastructure,-Ethics-and-Talent?>
- Cholsy, H., Firmonasari, A., & Udasmoro, W. (2020). Pendampingan UKM Bidang Fashion pada Masa Pandemi Covid-19 di Daerah Istimewa Yogyakarta. *Bakti Budaya*, 3(2), 175. <https://doi.org/10.22146/bb.60725>
- Coffman, C. D., Cottle, G. W., & Sunny, S. A. (2025). Leaving necessity entrepreneurship behind: How entrepreneurs actualize desirable futures. *Academy of Management Review*, (ja), amr-2023. <https://doi.org/10.5465/amr.2023.0163>
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
- Dhewanto, W., Rahim, T. A., & El-baehaqi, S. F. (2025). Differentiated Scaling Pathways for MSMEs: A Systematic Review of Opportunity versus Necessity-Driven MSMEs. *Proceedings of International Conference on Management in Emerging Markets (ICMEM) SBM ITB*. <https://doi.org/10.1007/s10257-024-00682-2>
- Faruque, M. O., Chowdhury, S., Rabbani, G., & Nure, A. (2024). Technology adoption and digital transformation in small businesses: Trends, challenges, and opportunities. *International Journal For Multidisciplinary Research*, 6(10.36948). <https://doi.org/10.36948/ijfmr.2024.v06i05.29207>



- Gabsi, A. E. H. (2024). Integrating artificial intelligence in industry 4.0: insights, challenges, and future prospects: a literature review. *Annals of Operations Research*, 1–28. <https://doi.org/10.1007/s10479-024-06012-6>
- Global Entrepreneurship Monitor. (2022). GEM 2021/2022 Global Report. Curitiba: Instituto Brasileiro de Qualidade e Produtividade.
- Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2023). *Advanced Issues in PLS-SEM*. SAGE Publications.
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature. <https://doi.org/10.1007/978-3-030-80519-7>
- Hamid, E. S., & Artha, B. (2025). Artificial Intelligence adoption in micro, small, and medium enterprises: Evidence, barriers, and Islamic ethical reflections for Muslim entrepreneurs in Yogyakarta. *Journal of Islamic Economics Lariba*, 11(2), 1967–1998.
- Hill, S., Boutaleb, F., Coduras, A., Dougoud, M., Friedl, C., Ionescu-Somers, A., Meyer, N., Sahasranamam, S., Samsami, M., Shay, J., Tarnawa, A., & Zbierowski, P. (2026). *GEM GEM 2025/2026 Global Report: From Uncertainty To Opportunity*.
- Kwarteng, M. A., Ntsiful, A., Diego, L. F. P., & Novák, P. (2024). Extending UTAUT with competitive pressure for SMEs digitalization adoption in two European nations: a multi-group analysis. *Aslib Journal of Information Management*, 76(5), 842–868. <https://doi.org/10.1108/AJIM-11-2022-0482>
- Ling, E. C., Tussyadiah, I., Liu, A., & Stienmetz, J. (2025). Perceived intelligence of artificially intelligent assistants for travel: Scale development and validation. *Journal of Travel Research*, 64(2), 299–321. <https://doi.org/10.1177/00472875231217899>
- Lopez, T., Alvarez, C., & Urbano, D. (2025). Analyzing institutional dimensions and their effect on the survival of necessity and opportunity entrepreneurship. *Review of Managerial Science*, 1–32. <https://doi.org/10.1007/s11846-025-00938-2>
- Lupiyoadi, R. (2018). *Manajemen pemasaran jasa*.
- Lupiyoadi, R., Pramesti, M., Ikhsan, R. B., Usman, L. H., Games, D., & Fakhrorazi, A. (2025). Extending UTAUT with perceived intelligence for the adoption of artificial intelligence in MSMEs and startups in Indonesia: A multi-group analysis. *Journal of Open Innovation: Technology, Market, and Complexity*, 100673. <https://doi.org/10.1016/j.oiotmc.2025.100673>
- Machucho, R., & Ortiz, D. (2025). The impacts of artificial intelligence on business innovation: A comprehensive review of applications, organizational challenges, and ethical considerations. *Systems*, 13(4), 264. <https://doi.org/10.3390/systems13040264>
- Mishrif, A., & Khan, A. (2023). Technology adoption as survival strategy for small and medium enterprises during COVID-19. *Journal of Innovation and Entrepreneurship*, 12(1), 1–23. <https://doi.org/10.1186/s13731-023-00317-9>
- Mohammed, I. A., Sofia, R., Radhakrishnan, G. V., Jha, S., & Said, N. (2025). The Role of Artificial Intelligence in Enhancing Business Efficiency and Supply Chain Management. *Journal of Information Systems Engineering & Management*, 10, 10. <https://doi.org/10.52783/jisem.v10i10s.1413>
- Nadzila, R. A., & Gaffar, M. R. (2025). Analisis Persepsi Konsumen terhadap Pemanfaatan Artificial Intelligent dalam Meningkatkan Customer Experience Marketplace Shopee. *Integrative Perspectives of Social and Science Journal*, 2(03 Juni), 3495–3502. <https://ipssj.com/index.php/ojs/article/view/461>
- Pramiarsih, E. E. (2024). *Perilaku konsumen di era digital*. Deepublish.
- Ramayah, T., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). Partial Least Squares Structural Equation Modeling (PLS-SEM) Using SmartPLS 3.0. *An Updated Guide and Practical Guide to Statistical Analysis*.
- Rana, M. M., Siddiquee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon*, 10(18). <https://doi.org/10.1016/j.heliyon.2024.e37569>
- Republika. (2025). *UMKM Indonesia 2025: Pilar Ekonomi yang Terus Bertransformasi di Era Digital*. Retizen Republika. <https://retizen.republika.co.id/posts/719727/umkm-indonesia-2025-pilar-ekonomi-yang-terus->

[bertransformasi-di-era-digital?](#)

- Subhani, W., Abdul Latiff, A., & Abd Wahab, S. (2023). Effort Expectancy, Task Technology Fit, and ERP Adoption Behavior; Moderating Effect of Trust in Technology: Evidence from SMEs of Pakistan. *Pakistan Journal of Commerce and Social Sciences*, 17, 424–445. <https://doi.org/10.64534/Commer.2023.067>
- Sui, L., Mollick, A. V., & Wu, S. (2025). The effect of necessity and opportunity entrepreneurship and SME financing on sustainable development. *Environment, Development and Sustainability*, 1–32. <https://doi.org/10.1007/s10668-025-06043-4>
- Sulianta, F. (2025). *Perilaku Online dan Literasi Digital: Teori, Konsep, dan Penerapannya*. Feri Sulianta.
- Susanty, A., Puspitasari, N. B., Anindyanari, O. S., & Jie, F. (2025). Profiling the readiness and barriers toward digital technology adoption among the SMEs. *International Journal of Information Technology*, 17(2), 823–840. <https://doi.org/10.1007/s41870-024-02237-7>
- Tindaon, S., & Banurea, J. (2026). Exploring artificial intelligence adoption challenges: bridging the technology gap for marketing advancements. *IAES International Journal of Artificial Intelligence (IJ-AI)*, 15, 56. <https://doi.org/10.11591/ijai.v15.i1.pp56-65>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the UTAUT. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>

Corresponding author

Muhammad Fakhri can be contacted at: berlinutara@gmail.com



Appendix

Table A1. Operationalization of Variables

Variable	Definition	Indicators	Source
Performance Expectancy (PE)	Belief that AI enhances business performance	Productivity, speed, effectiveness	(Lupiyoadi <i>et al.</i> , 2025; Venkatesh <i>et al.</i> , 2003)
Effort Expectancy (EE)	Ease of using AI	Ease of learning, ease of operation, clarity of interaction	
Social Influence (SI)	Support from the social environment	Family, business partners, community	
Facilitating Conditions (FC)	Availability of infrastructure and support	Resources, knowledge, and technical support	
Perceived Intelligence (PI)	Perception of AI's ability to mimic human intelligence	Conversational intelligence, information quality, anthropomorphism	(Ling <i>et al.</i> , 2025; Lupiyoadi <i>et al.</i> , 2025)
Trust (T)	Belief in AI's reliability, security, privacy, and credibility	Reliability, security, privacy assurance, credibility	(Rana <i>et al.</i> , 2024)
Behavioral Intention (BI)	Intention to adopt AI in business operations	Plans, willingness, usage prediction	(Lupiyoadi <i>et al.</i> , 2025)

Table A2. Respondent Characteristics

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	125	62.5
	Female	75	37.5
Age	< 25 years	25	12.5
	25–34 years	51	25.5
	35–44 years	79	39.5
	45–54 years	45	22.5
	> 55 years	0	0
Educational Attainment	Senior High School	60	30
	Diploma	40	20
	Bachelor's Degree	80	40
	Postgraduate	20	10
Business Duration	1 year	20	10
	1.1–3 years	60	30
	3–5 years	60	30
	> 5 years	60	30
Business Sector	Culinary	50	25
	Fashion	40	20
	Services	50	25
	Trade/Retail	40	20
	Handicraft	20	10
Entrepreneur Typology	Necessity	100	50
	Opportunity	100	50

Source: Primary data processed (2026)

