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Analysis of Factors Influencing Artificial Intelligence Adoption Among MSMEs in Batam City Using the TOE and TAM Approaches

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Abstract: Artificial intelligence (AI) has considerable potential to enhance operational competitiveness, but its adoption among Micro, Small, and Medium Enterprises (MSMEs) remains constrained by structural and perceptual barriers. This study examines the factors influencing AI adoption intention among MSMEs in Batam City using the Technology-Organization-Environment (TOE) framework and Technology Acceptance Model (TAM), with Diffusion of Innovation (DOI) providing additional theoretical support. A sequential explanatory mixed-methods design was employed. Quantitative data were collected from 270 MSME practitioners and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The measurement model met the criteria for convergent validity, discriminant validity, and reliability after the removal of the Environmental Pressure construct due to discriminant validity issues. The structural model showed that all six hypotheses retained in the final model were supported. Technology Readiness and Organizational Support had significant positive effects on Perceived Usefulness and Perceived Ease of Use, while Perceived Usefulness was the strongest direct predictor of AI adoption intention. Qualitative interviews with five MSME practitioners further supported the quantitative findings by indicating that practical operational benefits and internal readiness were important considerations in AI adoption. Based on these findings, MSME managers and policymakers in Batam City should emphasize the practical operational benefits of AI and strengthen digital infrastructure and organizational readiness to support adoption.

Keywords: Artificial Intelligence; MSMEs; Mixed Methods; TOE Framework; Technology Acceptance Model (TAM); PLS-SEM.

1. Introduction

The continued development of the digital economy has changed how businesses operate, compete, and respond to market demands. Micro, Small, and Medium Enterprises (MSMEs) represent a major part of business activity worldwide and contribute substantially to employment and economic development (Costa Melo *et al.*, 2023). In Indonesia, MSMEs also play an important role in national economic activity, contributing more than 60% to Gross Domestic Product (GDP) (Badan Pusat Statistik, 2023) [cek sitasi]. At the same time, the expansion of internet connectivity has created broader opportunities for businesses to adopt digital technologies in marketing, communication, administration, and customer service (Asosiasi Penyelenggara Jasa Internet Indonesia, 2023). These conditions have increased the need for MSMEs to consider technologies that can support daily operations while helping them remain responsive to changes in customer behavior and market competition.

Artificial Intelligence (AI) is one of the digital technologies with growing potential for business operations. Previous studies indicate that AI can support operational efficiency, reduce operational costs, and assist business decision-making (Rehman *et al.*, 2024). AI has also been applied to support new product development, allowing businesses to respond more quickly to changing consumer needs (Cooper, 2025). For MSMEs, AI applications may provide practical benefits in areas such as promotional content creation, customer communication, administrative support, product recommendation, and routine data processing. Nevertheless, the potential benefits of AI do not automatically lead to adoption. MSMEs differ in their technological capabilities, access to resources, managerial support, and perceptions of whether AI is useful and easy to apply in their business activities.

Digital technology adoption among MSMEs remains uneven, particularly when the technology requires capabilities beyond basic digital applications. Compared with larger enterprises, MSMEs often face specific constraints when adopting advanced technologies, including limited financial resources, limited organizational capabilities, and insufficient technological readiness (Faiz *et al.*, 2024; Ulrich & Frank, 2021). In Indonesia, these challenges may also involve infrastructure limitations, adoption costs, and differences in digital literacy among business owners and employees. In Batam City, previous research has reported the use of AI for marketing activities among local MSMEs, while also indicating the need for further support in applying AI to broader business processes (Friadi *et al.*, 2025) [cek sitasi]. This condition suggests that the decision to adopt AI cannot be explained solely by the availability of the technology. MSMEs also need to assess whether the technology is compatible with their existing digital infrastructure, organizational conditions, and operational needs.

Another important issue concerns the ability of MSMEs to evaluate whether a new technology is appropriate for their business context. Because many MSMEs operate with limited resources, adoption decisions are often shaped by practical experience, perceived business value, and the ability of employees or owners to learn and use the technology. Previous studies have emphasized the importance of technological capabilities, organizational conditions, and external factors in understanding technology adoption among SMEs (Arroyabe *et al.*, 2024; Bettoni *et al.*, 2021). However, these factors may not directly influence adoption intention unless users perceive the technology as beneficial and manageable. Therefore, examining AI adoption among MSMEs requires an approach that connects business-level readiness with user-level perceptions.

The Technology-Organization-Environment (TOE) framework provides a perspective for examining technological, organizational, and environmental conditions that may influence technology adoption. The Technology Acceptance Model (TAM), meanwhile, focuses on user perceptions, particularly Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), as determinants of technology acceptance. Combining these perspectives allows AI adoption to be examined from both organizational conditions and individual perceptions. Although previous studies have applied TOE and TAM to explain digital technology adoption, evidence remains limited regarding their integrated application to AI adoption among MSMEs in the specific context of Batam City. Existing studies in Batam have also tended to focus on practical implementation rather than examining AI adoption through an integrated theoretical model (Friadi *et al.*, 2025) [cek sitasi]. This gap is relevant because local MSMEs may face different combinations of technological readiness, organizational support, and perceived benefits when considering AI adoption.

Based on this research gap, this study examines the factors influencing AI adoption intention among MSMEs in Batam City using an integrated TOE–TAM approach. The study employs a sequential explanatory mixed-methods design to analyze the statistical relationships among the research constructs and to further understand the practical experiences of MSME practitioners. Specifically, this study aims to analyze how technological, organizational, and environmental factors influence Perceived Usefulness and Perceived Ease of Use; examine the effects of Perceived Usefulness and Perceived Ease of Use on the intention to adopt AI; explore practical challenges and experiences related to AI adoption through qualitative interviews; and develop strategic recommendations for MSME practitioners, policymakers, and local stakeholders in Batam City.

2. Related Work

Research on digital innovation adoption among Micro, Small, and Medium Enterprises (MSMEs) has continued to develop as businesses increasingly consider advanced technologies to support their operations. At the global level, recent bibliometric research indicates growing interest in how SMEs acquire knowledge and adopt artificial intelligence (AI) (Ayinaddis, 2025). From an organizational perspective, Ulrich and Frank (2021) found that limitations in human resource capabilities and organizational culture can hinder technology adoption among SMEs in developed countries. In developing-country contexts, Faiz *et al.* (2024) identified factors such as high investment costs and limited digital literacy as important challenges affecting technology adoption.

In Indonesia, MSMEs have also begun exploring practical applications of AI. Friadi (2025) reported the use of AI in marketing activities among MSMEs in Batam, while Novantara *et al.* (2024) examined AI applications in other Indonesian MSME contexts. These studies indicate that AI can support activities such as advertising and marketing efficiency. However, practical adoption alone does not explain why MSMEs decide to adopt AI. The technological conditions of the business, organizational readiness, and user perceptions also need to be considered when examining adoption intention. The Technology-Organization-Environment (TOE) framework provides a basis for examining how technological, organizational, and environmental conditions influence technology adoption. The Technology Acceptance Model (TAM), in contrast, focuses on users' perceptions of a technology, particularly Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).

Combining these perspectives allows technology adoption to be examined from both organizational conditions and user perceptions. In addition, the Diffusion of Innovation (DOI) theory provides supporting concepts for understanding how characteristics of an innovation may shape its acceptance. In this study, DOI is used as an additional theoretical perspective rather than as a separate structural framework in the empirical model. Previous studies have applied TOE and TAM to different technology adoption contexts. Truong (2022), for example, examined the combination of TOE and TAM in explaining digital technology adoption among SMEs. Haq *et al.* (2025) also examined an integrated TOE–TAM model in a smart technology adoption context. However, these studies differ from the present study in terms of technology, organizational scale, and research setting. The present study focuses specifically on AI adoption among MSMEs in Batam City and combines quantitative PLS-SEM analysis with qualitative interviews to examine both statistical relationships and the practical experiences of MSME practitioners. Therefore, the contribution of this study is primarily related to the application of an integrated TOE–TAM perspective to AI adoption in the Batam MSME context, supported by qualitative evidence.

Table 1. Comparison of Previous Studies

Authors (Year)	Focus / Approach	Methods & Dataset	Main Results	Limitations
Ulrich and Frank (2021)	Barriers to AI adoption, particularly human resources and organizational culture	Quantitative; survey of SMEs in Germany	Human resource limitations and internal organizational resistance were identified as important barriers	Focused on a developed-country context
Rehman *et al.* (2024)	Drivers of technology adoption using the TOE framework	Quantitative; PLS-SEM	Technological, organizational, and environmental factors were associated with adoption intention	Focused on metaverse technology rather than AI
Enshassi *et al.* (2025)	Drivers and barriers of AI adoption in SME digital marketing	Quantitative; survey of SMEs in Malaysia	Identified technological and organizational factors associated with AI adoption, together with operational barriers	Focused primarily on digital marketing applications
Haq *et al.* (2025)	Integration of TOE and TAM in smart technology adoption	Quantitative; large-scale business sector	The integrated model was effective in explaining technology adoption intention	Focused on large-scale manufacturing rather than MSMEs
Friadi (2025)	Practical implementation of AI in MSME marketing	Qualitative; case study of MSMEs in Batam	AI applications supported marketing activities and operational efficiency	Did not empirically test an integrated technology adoption model

Proposed Research	AI adoption determinants using an integrated TOE–TAM perspective, with DOI as additional theoretical support	Mixed methods; PLS-SEM and semi-structured interviews involving MSMEs in Batam	Examines the relationships between technological and organizational factors, user perceptions, and AI adoption intention	Findings are limited to the MSME context of Batam City

3. Methodology

This section describes the research methods used to examine the factors influencing artificial intelligence (AI) adoption among Micro, Small, and Medium Enterprises (MSMEs) in Batam City. The study employed a mixed-methods approach combining quantitative and qualitative techniques. The quantitative phase used Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the relationships among the research constructs, while semi-structured interviews were conducted in the qualitative phase to further interpret and contextualize the quantitative findings.

3.1 Research Design

This study employed a mixed-methods approach using a sequential explanatory design. The research began with a quantitative phase in which data were collected through a structured questionnaire to examine the relationships among variables derived from the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM). The quantitative findings were then followed by a qualitative phase using semi-structured interviews. This stage was conducted to provide additional explanations for the quantitative results, clarify findings that required further interpretation, and capture the practical experiences of MSME practitioners in adopting AI. The integration of both phases allowed the study to combine statistical analysis with contextual information from MSME practitioners.

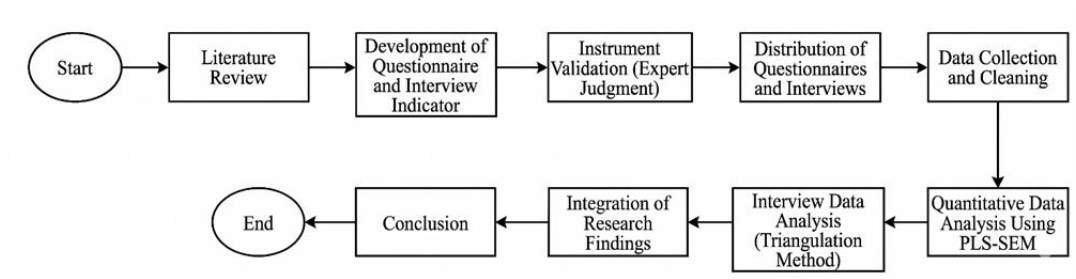

Figure 1. Sequential Explanatory Research Flowchart

3.2 Population, Sampling, and Data Collection

The research population consisted of registered MSMEs operating in the economic zones of Batam City. Purposive sampling was used to select MSME owners, managers, and staff who had basic knowledge of digital technology. A minimum of 200 responses was targeted based on the sample-size consideration adopted for PLS-SEM (Hair *et al.*, 2019). The final dataset consisted of 270 valid responses. Quantitative data were collected using a structured questionnaire with a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire initially included indicators for the constructs specified in the proposed research model. For the qualitative phase, five MSME practitioners were selected through purposive sampling based on their active involvement in daily business operations, previous use of basic digital platforms, and representation of different MSME sectors. Semi-structured interviews were conducted using questions related to operational challenges, the practical utility of AI, and barriers to learning and adoption. Each interview lasted approximately 30–45 minutes. The interview transcripts were analyzed thematically by identifying relevant codes, grouping them into themes, and relating the themes to the quantitative findings.

3.3 Research Constructs and Measurement Items

The research constructs were measured using indicators adapted from previous studies. Technology Readiness (VT) and Organizational Support (VO) represented technological and organizational conditions, while Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) represented users' perceptions of AI. Intention to Adopt AI (IAI) represented the behavioral intention to adopt AI. Environmental Factors/Environmental Pressure (VL) were included in the initial research model and were evaluated during the measurement-model assessment.

Table 2. Research Constructs and Indicators

Construct	Code	Indicator Description	Source
Technology Readiness (VT)	VT1	Availability and quality of digital devices for business operations	Rehman *et al.* (2024)
	VT2	Reliability and speed of internet connectivity	Faiz *et al.* (2024)
	VT3	Digital technology infrastructure supporting AI operations	Faiz *et al.* (2024)
	VT4	Compatibility of existing technology with AI tools	Rehman *et al.* (2024)
Organizational Support (VO)	VO1	Top management support for digital innovation	Rehman *et al.* (2024)
	VO2	Availability of financial resources for technology adoption	Faiz *et al.* (2024)
	VO3	Employee willingness and digital culture within the business	Faiz *et al.* (2024)
	VO4	Provision of basic training or guidance for new platforms	Rehman *et al.* (2024)
Perceived Usefulness (PU)	PU1	AI improves operational efficiency and speeds up tasks	Enshassi *et al.* (2025)
	PU2	AI enhances marketing and business decision-making	Enshassi *et al.* (2025)
	PU3	AI provides tangible benefits to the business	Enshassi *et al.* (2025)
Perceived Ease of Use (PEOU)	PEOU1	AI tools are easy to learn and operate	Enshassi *et al.* (2025)
	PEOU2	The interface of AI applications is clear and understandable	Enshassi *et al.* (2025)
	PEOU3	The AI system is flexible to interact with	Enshassi *et al.* (2025)
Intention to Adopt AI (IAI)	IAI1	Intention to use AI for future business operations	Rehman *et al.* (2024)
	IAI2	Plan to integrate AI into daily administrative or marketing tasks	Rehman *et al.* (2024)
	IAI3	Willingness to recommend AI tools to other business owners	Rehman *et al.* (2024)

3.4 Conceptual Framework and Research Model

The conceptual framework combines the TOE and TAM perspectives to examine AI adoption among MSMEs. The TOE framework is used to represent technological and organizational conditions, while TAM is used to examine users' perceptions of AI through Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In the proposed model, technological, organizational, and environmental factors are hypothesized to influence PU and PEOU, which subsequently influence Intention to Adopt AI (IAI). The measurement model was assessed using PLS-SEM to evaluate the reliability and validity of the research instrument. Convergent validity was assessed using Average Variance Extracted (AVE), while discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, following established procedures for PLS-SEM analysis (Mohd Dzin & Lay, 2021).

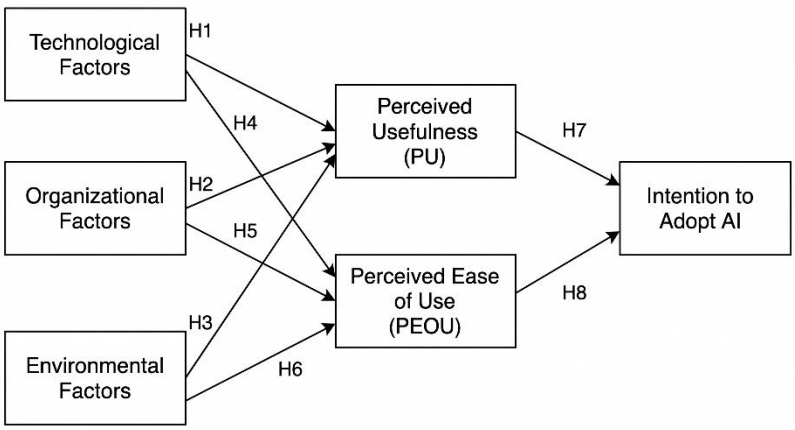

Figure 2. Research Model of AI Adoption for MSMEs

Based on the conceptual framework and proposed research model, the following hypotheses were formulated:
H1: Technology Readiness (VT) positively influences Perceived Usefulness (PU) of AI.
H2: Organizational Support (VO) positively influences Perceived Usefulness (PU) of AI.
H3: Environmental Factors (VL) positively influence Perceived Usefulness (PU) of AI.
H4**:** Technology Readiness (VT) positively influences Perceived Ease of Use (PEOU) of AI.
H5: Organizational Support (VO) positively influences Perceived Ease of Use (PEOU) of AI.
H6: Environmental Factors (VL) positively influence Perceived Ease of Use (PEOU) of AI.
H7: Perceived Usefulness (PU) positively influences Intention to Adopt AI (IAI).
H8: Perceived Ease of Use (PEOU) positively influences Intention to Adopt AI (IAI).

4. Result and Discussion

4.1 Results

The quantitative analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. A bootstrapping procedure with 5,000 subsamples was used to assess the significance of the structural paths. Before evaluating the structural model, the measurement model (outer model) was assessed to examine the reliability and validity of the research constructs. A total of 270 valid responses were obtained from MSME practitioners in Batam City. The respondents were primarily operational employees (47.2%) and business owners (39.0%), providing perspectives from both individuals involved in business decision-making and those involved in daily operations. In terms of business duration, 46.3% of the respondents represented businesses operating for 0–3 years, while 33.3% represented businesses operating for 3–5 years. These characteristics indicate that a substantial proportion of the sampled MSMEs were relatively young businesses.

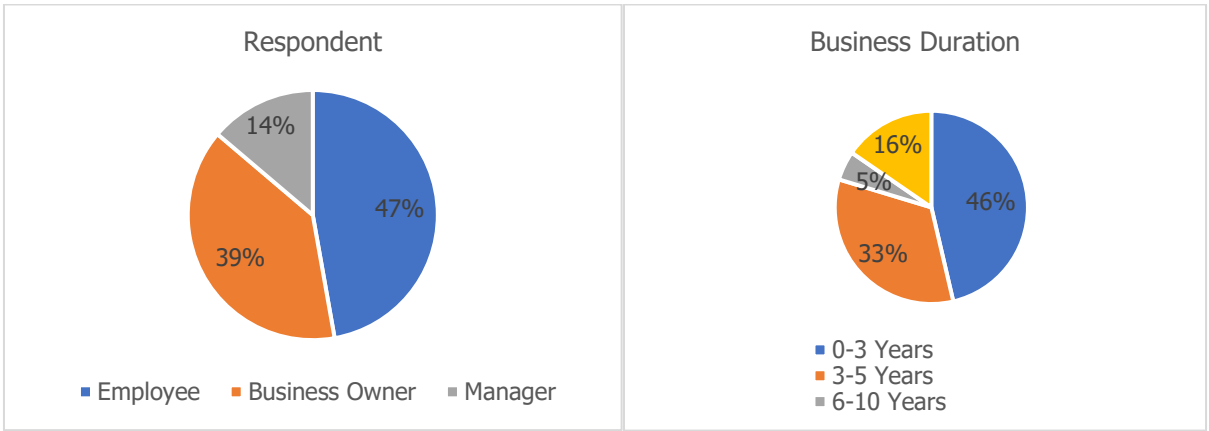

Figure 3. Demographic Profile of MSME Respondents Based on Organizational Role (Left) and Business Duration (Right) (N = 270).

4.1.1 Indicator Elimination and Measurement Model Validation

The initial measurement model was evaluated based on the outer loadings, convergent validity, discriminant validity, and internal consistency reliability. During the assessment, PEOU3 was removed from

the model because its measurement performance did not meet the required criteria, including an issue with cross-loading and outer loading. The Environmental Pressure (VL) construct was also removed from the final model because it failed to satisfy the discriminant validity criteria. This result indicates that the VL indicators did not demonstrate sufficient empirical distinction from the other constructs in the measurement model. Therefore, VL was excluded from the subsequent structural model assessment, and hypotheses H3 and H6 were not tested in the final structural model. After the removal of PEOU3 and VL, the remaining measurement model satisfied the specified evaluation criteria. The outer loadings of the retained indicators exceeded the 0.70 threshold. The Average Variance Extracted (AVE) values for all retained constructs were above 0.50, indicating adequate convergent validity. Cronbach's Alpha and Composite Reliability values also exceeded 0.70, indicating satisfactory internal consistency reliability.

Table 3. Construct Reliability and Validity

Construct	Cronbach's Alpha	rho_a	rho_c	AVE
IAI	0.795	0.796	0.880	0.709
PEOU	0.716	0.755	0.873	0.776
PU	0.765	0.771	0.867	0.686
VO	0.822	0.824	0.883	0.655
VT	0.882	0.891	0.918	0.738

All retained constructs exceeded the recommended thresholds for internal consistency reliability and convergent validity.

Table 4. Discriminant Validity (HTMT Ratio)

	IAI	PEOU	PU	VO	VT
IAI					
PEOU	0.748				
PU	0.859	0.880			
VO	0.871	0.719	0.796		
VT	0.757	0.657	0.841	0.840	

4.1.2 Structural Model Evaluation

After the measurement model met the required criteria, the structural model was evaluated using the coefficient of determination (R^2), path coefficients, t-statistics, and p-values. A significance level of 5% ($p < 0.05$) and a t-statistic threshold of 1.96 were used to assess the significance of the structural relationships. The R^2 values were 0.518 for Perceived Usefulness (PU), 0.351 for Perceived Ease of Use (PEOU), and 0.485 for Intention to Adopt AI (IAI). These values indicate that the model explains 51.8% of the variance in PU, 35.1% of the variance in PEOU, and 48.5% of the variance in IAI. The final structural model contained six tested paths. All six paths were statistically significant and supported their respective hypotheses. H3 and H6 were not included in the final structural path analysis because the Environmental Pressure (VL) construct had previously been removed due to insufficient discriminant validity.

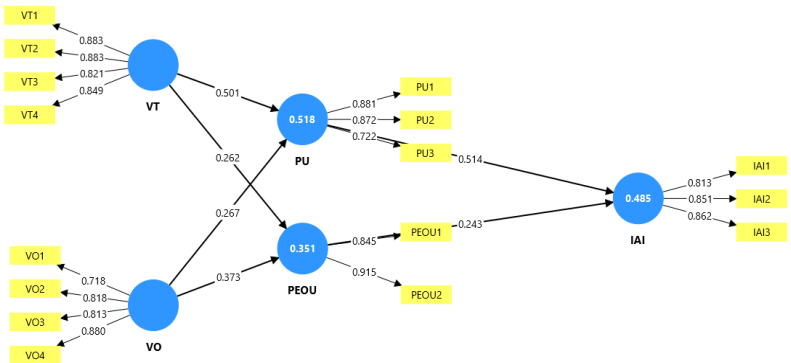

Figure 4. PLS-SEM Structural and Measurement Model Output (Algorithm Results).

Table 5. Hypothesis Testing Outcomes

Hypothesis	Structural Path	β	T Statistics	P Values	Result
H1	VT → PU	0.501	7.157	< 0.001	Supported
H2	VO → PU	0.267	3.094	0.002	Supported

H4	VT → PEOU	0.262	4.135	< 0.001	Supported
H5	VO → PEOU	0.373	5.456	< 0.001	Supported
H7	PU → IAI	0.514	8.569	< 0.001	Supported
H8	PEOU → IAI	0.243	4.089	< 0.001	Supported

4.2 Discussion

The results show that Technology Readiness (VT) has a significant positive relationship with Perceived Usefulness (PU) ($\beta = 0.501$, $t = 7.157$, $p < 0.001$) and Perceived Ease of Use (PEOU) ($\beta = 0.262$, $t = 4.135$, $p < 0.001$). Among the predictors of PU in the final model, VT has the largest path coefficient. This result indicates that the technological conditions available within an MSME are associated with how useful and easy AI is perceived to be. The finding is consistent with Rehman *et al.* (2024), who reported the relevance of existing digital capabilities in technology adoption. The qualitative interviews provide additional context for this relationship. Participants described their existing use of digital platforms such as messaging applications, social media, and digital cashier systems as a foundation for trying AI-based tools. One participant explained, "In our daily operations, we are already active on Instagram, TikTok, and digital cashier applications. Because our digital foundation is set, exploring AI tools to generate content ideas and marketing materials feels highly relevant and significantly saves our time during marketing campaigns" (Participant 3 – Coffee Shop Manager). This response suggests that familiarity with existing digital tools may make the transition to AI-based applications easier for some MSME practitioners.

Organizational Support (VO) also has a significant positive relationship with Perceived Usefulness (H2: $\beta = 0.267$, $t = 3.094$, $p = 0.002$) and Perceived Ease of Use (H5: $\beta = 0.373$, $t = 5.456$, $p < 0.001$). The stronger coefficient for VO → PEOU suggests that organizational conditions may be particularly relevant to how easily respondents perceive AI technology can be learned and used. This finding is consistent with the role of organizational readiness reported in previous technology adoption studies (Aripradono *et al.*, 2024; Haq *et al.*, 2025). The qualitative findings provide further context for this relationship. One participant described the importance of organizational willingness to learn when staff members experience difficulties with new technologies: "Our team uses marketplaces and Instagram for online promotions, but some of our staff still experience heavy difficulties in fully understanding new technology features. However, we believe AI has vast potential for our future, and we remain highly open to learning these systems to support our business growth" (Participant 4 – Fashion Retail Staff). This response indicates that willingness to learn and organizational support may help MSME employees deal with difficulties when encountering new digital technologies.

The results further show that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) both have significant positive relationships with Intention to Adopt AI (IAI). PU has a path coefficient of 0.514 ($t = 8.569$, $p < 0.001$), while PEOU has a path coefficient of 0.243 ($t = 4.089$, $p < 0.001$). The coefficient for PU is approximately 2.1 times that of PEOU, indicating that perceived usefulness has a stronger direct relationship with AI adoption intention among the respondents. This result suggests that the expected business benefits of AI may be more influential than ease of use when MSME practitioners consider adopting AI. The finding is consistent with Enshassi *et al.* (2025), which reported the relevance of perceived business benefits in AI adoption. The qualitative interviews provide additional context for this result. One participant stated, "Even though some features of AI still feel very confusing and complicated to learn, I am still highly interested in using it. The practical benefits I experience in increasing efficiency and finding new promotional ideas quickly are far more important than the initial difficulties of learning the system" (Participant 1 – Food Stall Owner). Another participant similarly emphasized the importance of operational value: "Using AI definitely requires a clear process of learning and adaptation. But as long as the technology clearly helps our operational development and increases job efficiency, its overall usefulness is far more critical than whether it is easy to use or not" (Participant 5 – Home-based Culinary Owner). These responses support the quantitative result by indicating that perceived operational value may outweigh initial difficulties in learning AI tools.

The Environmental Pressure (VL) construct requires a different interpretation because it was removed during the measurement-model assessment after failing to meet the discriminant validity criteria. Consequently, H3 and H6 were not tested in the final structural model. Therefore, the removal of VL should not be interpreted as evidence that environmental pressure has no effect on AI adoption. Instead, the result indicates that the environmental construct, as operationalized in the questionnaire, could not be empirically distinguished from the other constructs in the measurement model. This limits the extent to which conclusions can be drawn about the role of external competitive pressure, market trends, or other environmental conditions in AI adoption among the respondents. The qualitative interviews nevertheless provide some contextual information regarding the relative importance of internal business needs. One participant explained, "Our technology use is still very simple, mainly using WhatsApp to communicate with our customers. We do not use AI often because we lack the knowledge on how to operate it. We do not care about market trends or what others do; however, we are completely willing to learn and adopt AI the moment its specific benefits become clear for our own small business" (Participant 2 – Gorengan Vendor). This response suggests that at

least some respondents focus on internal knowledge and perceived business benefits when considering AI adoption. However, because the VL construct was not retained in the structural model, this qualitative observation should be treated as contextual evidence rather than statistical evidence that environmental pressure has no effect.

Overall, the combined quantitative and qualitative findings indicate that existing technological capabilities and organizational support are associated with users' perceptions of AI usefulness and ease of use. Technology Readiness has the strongest relationship with Perceived Usefulness among the predictors examined, while Organizational Support has a stronger relationship with Perceived Ease of Use. These findings are broadly consistent with previous studies emphasizing the importance of technological and organizational conditions in digital technology adoption (Rehman *et al.*, 2024; Haq *et al.*, 2025). The results also indicate that Perceived Usefulness has a stronger relationship with AI adoption intention than Perceived Ease of Use. The qualitative interviews support this pattern by emphasizing practical benefits such as operational efficiency, content generation, and marketing support. For the sampled MSMEs, the expected value of AI appears to be an important consideration when deciding whether to adopt the technology. At the same time, the findings regarding Environmental Pressure require cautious interpretation because the VL construct was removed due to insufficient discriminant validity. Future research should consider refining the measurement of environmental factors and testing the construct using indicators that are empirically distinct from technological and organizational conditions. The qualitative phase also has limitations because the interviews followed the quantitative phase and primarily provided additional explanations and context for the statistical findings. Future studies could employ a concurrent mixed-methods design to examine quantitative and qualitative evidence simultaneously and identify areas of convergence or divergence. In addition, the cross-sectional design captures respondents' perceptions at one point in time and therefore cannot determine how AI adoption intentions change over a longer period.

5. Conclusion and Recommendations

This study examined the factors associated with the intention to adopt Artificial Intelligence (AI) among Micro, Small, and Medium Enterprises (MSMEs) in Batam City by integrating the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM). Based on data from 270 respondents, the findings show that Technology Readiness and Organizational Support are positively related to Perceived Usefulness and Perceived Ease of Use. Technology Readiness shows the strongest relationship with Perceived Usefulness, while Organizational Support has a stronger relationship with Perceived Ease of Use. Perceived Usefulness and Perceived Ease of Use are also positively related to Intention to Adopt AI, with Perceived Usefulness showing the stronger relationship. These results indicate that MSME practitioners' intention to adopt AI is closely associated with the expected operational and business benefits of the technology, while ease of use remains relevant in supporting acceptance. The qualitative findings strengthen this interpretation by showing that participants considered existing digital capabilities, organizational willingness to learn, and practical business benefits when discussing AI adoption. The findings also require careful interpretation regarding the Environmental Pressure construct. This construct was removed from the final model because it did not meet the required discriminant validity criteria. Therefore, this study cannot determine whether environmental factors have a significant or insignificant relationship with AI adoption intention. The qualitative interviews suggest that several participants placed greater emphasis on internal business needs and practical benefits than on external pressure, but these observations should be treated as contextual evidence rather than statistical evidence. The final structural model only evaluates the relationships among the retained constructs, so the role of Environmental Pressure should be re-examined in future studies using more distinct and reliable indicators.

This study contributes to the discussion of AI adoption among MSMEs by linking technological readiness, organizational support, user perceptions, and adoption intention in the context of Batam City. The integrated TOE–TAM approach helps explain how business-level conditions are connected to individual perceptions of AI, while the sequential explanatory mixed-methods design provides additional practical context through interviews with MSME practitioners. However, the findings should be interpreted within the scope of the research design and sample. Because the study was conducted only in Batam City, the results may not be directly generalizable to MSMEs in other regions with different economic conditions, digital infrastructure, and levels of technological readiness. In addition, the cross-sectional design captures respondents' perceptions at one point in time and cannot explain how AI adoption intention may change as MSMEs gain more experience with AI tools. For MSME practitioners, the findings suggest the importance of strengthening basic digital capabilities, building organizational willingness to learn, and identifying AI applications that provide clear operational benefits. Training initiatives may focus on practical uses of AI, such as content generation, marketing support, administrative tasks, customer communication, and other activities related to daily business

operations. For policymakers and local stakeholders, AI-related digitalization programs should emphasize practical and economic benefits while also providing digital literacy support and adequate infrastructure. Future research may expand the study to MSMEs in other regions, apply longitudinal designs to observe changes in adoption intention over time, and refine the measurement of Environmental Pressure to determine whether external factors play a significant role when represented by empirically distinct indicators.

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