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FROM DIGITALIZATION TO INTELLIGENCE: MAPPING AI FORECASTING READINESS OF MSMES IN GREATER JAKARTA

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Abstract
Digital transformation presents both challenges and opportunities for Indonesian micro, small, and medium enterprises (MSMEs) in achieving sustainability performance. This study aims to examine the influence of digital readiness, technology adoption, and institutional support on MSMEs' sustainability performance. A quantitative approach was employed by distributing questionnaires to MSME actors and analyzing the data using structural equation modeling based on partial least square (PLS-SEM). The results indicate that most independent variables have a positive and significant effect on sustainability performance, although certain variables show a negative relationship, which differs from some previous studies. This finding highlights that digital readiness and technology adoption do not always generate uniform effects but are strongly shaped by institutional contexts and internal conditions of MSMEs. Theoretically, this research contributes to the advancement of Institutional Theory and the Natural Resource-Based View (NRBV) by emphasizing digital capabilities as strategic resources for sustaining competitive advantage. Practically, the study suggests that policymakers and stakeholders should enhance digital literacy, infrastructure, and support programs for MSMEs to strengthen their ability to adapt to the digital era. The study concludes that synergy between internal MSME factors and external support is crucial for achieving sustainable business outcomes. Future research is recommended to include moderating variables such as strategic leadership or market orientation to provide deeper insights into the dynamics of MSME digital transformation.

Keywords: MSMEs, Digital Transformation, Digital Readiness, Technology Adoption, Sustainability Performance

1. Introduction

Micro, small, and medium enterprises (MSMEs) are a fundamental pillar of Indonesia's economy, contributing more than 60% to GDP and absorbing approximately 97% of the workforce. Despite their vital role, the level of digital technology adoption among MSMEs remains relatively low. Data from the Ministry of Communication and Informatics show that by early 2020, only 17.1% of approximately 64 million MSMEs in Indonesia were digitally literate and utilized e-commerce channels, while around 81% had not yet been touched by digitalization. Even by mid-2021, only 29% of MSMEs had integrated e-commerce into their business activities, indicating that digital readiness among MSMEs is still weak (Anatan & Nur, 2023).

In fact, digital transformation offers various opportunities for MSMEs to improve performance, innovation, and productivity (OECD, 2021). Digital technologies can help MSMEs reduce operating costs, access wider markets, and make data-driven decisions (OECD, 2021). The Fourth Industrial Revolution (Industry 4.0) and the COVID-19

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pandemic further accelerated the need for MSMEs to adapt digitally in order to survive and remain competitive (Anatan & Nur, 2023).

Accurate forecasting capabilities are crucial for MSME sustainability, especially amid current market uncertainties (Volodina, 2025). Traditionally, many MSMEs rely on simple statistical methods, which are often constrained by limited high-quality data. The application of Artificial Intelligence (AI) in forecasting promises to improve prediction accuracy, helping business owners to project sales and market trends more precisely. This, in turn, can enhance cost efficiency, risk management, and the quality of decision-making in MSMEs (OECD, 2021).

However, AI adoption requires adequate digital readiness. The SME digital gap has become increasingly evident: OECD studies highlight that AI adoption does not occur evenly, with digitally pioneering firms (early adopters) likely to capture most of the benefits, while lagging MSMEs may reap almost none. Evidence shows that MSMEs are far less likely to use data analytics and AI solutions than large enterprises (OECD, 2021). This gap must be urgently addressed to prevent MSMEs from falling further behind. The Indonesian government itself has targeted 30 million MSMEs to join the digital ecosystem by 2023 (Sugihartati, 2023), illustrating the urgency of accelerating digitalization.

Nevertheless, the adoption of AI, such as intelligent forecasting systems, does not occur instantaneously. MSMEs must undergo a transformation process that is often costly and complex, while many still lack awareness, skills, and the data-driven culture required (OECD, 2021). Implementing AI also demands investment in data quality, technological infrastructure, and skilled human resources challenges that can be particularly burdensome for MSMEs (OECD, 2021). Recent studies emphasize that although AI models can significantly reduce forecast errors, their success heavily depends on good data readiness, robust implementation planning, and strong managerial and external support (Volodina, 2025). Without these elements, the potential of AI forecasting for MSMEs is difficult to realize.

Therefore, research on the level of digital readiness of MSMEs to implement AI forecasting is urgently needed as an initial step in reducing the AI adoption gap in the MSME sector. Although various studies have examined MSMEs' digital readiness, there remains a research gap concerning the specific application of AI technologies for forecasting. Most prior studies in Indonesia focus on the adoption of e-commerce or the digitalization of marketing processes, or they assess e-readiness in a general sense without identifying enabling and inhibiting factors in detail. Studies on MSME readiness for Industry 4.0 typically emphasize manufacturing or industrial technology adoption (Anatan & Nur, 2023), leaving small-scale trade and service MSMEs underrepresented.

To date, there has been no comprehensive study mapping the digital readiness of MSMEs to implement AI for forecasting. Yet, business planning based on intelligent forecasts has substantial potential to enhance MSME competitiveness in a data-driven era. Volodina (2025) notes that there is still a lack of specific guidance for MSMEs on adopting AI in demand forecasting, indicating that this area has received limited research attention. In addition, many technology adoption studies examine only partial aspects (e.g., technological or behavioral factors alone), whereas this study seeks to integrate multiple dimensions of determinants such as literacy, data quality, infrastructure, managerial support, and Technology Acceptance Model (TAM)-based perceptions into a unified AI Forecasting Readiness framework.

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Another research gap lies in the absence of a baseline index that quantitatively measures AI forecasting readiness among MSMEs and categorizes it into practical levels (low–medium–high). Accordingly, this study fills the void by conducting an in-depth assessment of the digital readiness of MSMEs in Greater Jakarta (Jabodetabek) for AI forecasting implementation, while identifying key influencing factors. The resulting baseline is expected to serve as a reference for selecting MSMEs that are ready for AI forecasting pilot projects as well as for designing targeted interventions for those that are still lagging.

Based on the above discussion, the research problem can be formulated as follows: How digitally ready are MSMEs in Greater Jakarta to implement AI for forecasting, and what factors influence their level of readiness?

In other words, this study aims to measure the level of AI Forecasting Readiness among MSMEs and to test the effects of determinants such as current technology adoption, data management practices, digital/financial literacy, IT infrastructure, managerial support, and technology perceptions (perceived usefulness and perceived ease of use) on that readiness. Addressing this question is crucial for determining the initial (baseline) condition of MSME digital transformation in the context of AI, thereby enabling the formulation of appropriate support strategies and policies to enhance their readiness toward successful AI forecasting implementation.

By mapping readiness levels and their leverage factors, this study is expected to generate recommendations on how to accelerate AI adoption among MSMEs in an effective and ethical manner, ultimately strengthening MSME competitiveness and sustainability in the digital economy. Within this background, digital readiness becomes a fundamental prerequisite for MSMEs to leverage advanced technologies such as Artificial Intelligence (AI) in business activities, including sales and demand forecasting.

2. Theoretical Background

This section synthesizes the existing literature to establish the theoretical foundation for examining digital and AI readiness among MSMEs. The review is structured around two key themes: the current state of digital readiness in the Indonesian context, and the dominant theoretical lenses and critical barriers identified in global SME research.

2.1. Digital Readiness of MSMEs: The Indonesian Context

Research on Indonesian MSMEs reveals a growing yet uneven landscape of digital readiness. A study by Panjaitan et al. (2021) on 170 respondents found that digital value creation mediates the relationship between technology readiness and digital capabilities, suggesting that perceived benefits are crucial for leveraging technological infrastructure. However, assessments of readiness levels often indicate significant gaps. For instance, Rafiah et al. (2022), in a study of 113 West Java MSMEs, measured readiness across five dimensions human resources, processes, strategy, technology, and integration. Their findings showed an overall low readiness, with the "people" aspect (human capital, literacy, and openness) being the most prepared, while technological and integration aspects lagged considerably. This points to a paradox where owner/manager willingness may exist, but technical execution remains a hurdle. Conversely, positive prior experience can accelerate readiness. Harmawan (2022) observed that MSMEs in Banyuwangi with existing digital marketing experience demonstrated higher readiness in strategic and managerial aspects for further technological adoption, underscoring the cumulative effect of digital learning.

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2.2. Theoretical Frameworks and Critical Barriers to Advanced Technology Adoption

Globally, technology adoption in SMEs is frequently analyzed through established frameworks like the Technology–Organization–Environment (TOE) and the Technology Acceptance Model (TAM). The TAM constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are consistently validated as primary determinants of adoption intention in MSME contexts (Nurqamarani et al., 2021). However, moving from intention to actual adoption of advanced technologies like Artificial Intelligence (AI) reveals a complex web of interconnected barriers that extend beyond individual perceptions.

Recent systematic analyses highlight a stark reality. Sanchez et al. (2025), reviewing 71 studies, identified 27 distinct challenges for AI adoption in industrial MSMEs, with low digital maturity, poor data quality/availability, and insufficient AI knowledge being paramount. Notably, over 90% of MSMEs in these studies had no AI applications, and internal knowledge gaps were a recurring theme. Trinugroho et al. (2022) corroborate the importance of internal capabilities, finding that technological knowledge, market demand, and owner education significantly influence readiness for digital financial technologies.

These barriers can be categorized into technological, organizational, and strategic constraints:

1) Technological & Data Constraints: Inadequate IT infrastructure, legacy systems, and fragmented data practices are foundational barriers that prevent AI integration (Peretz-Andersson et al., 2024; Sanchez et al., 2025). Basic digital maturity, such as experience with ERP systems, is positively correlated with the capacity to adopt more advanced innovations.
2) Organizational & Human Capital Constraints: Managerial skepticism, low innovation acceptance among employees, and a general resistance to change are frequently cited organizational hurdles (Proietti & Magnani, 2025; Sanchez et al., 2025). The absence of internal champions or skilled personnel to bridge technical and operational gaps further impedes progress.
3) Strategic & Perceptual Constraints: A pervasive lack of strategic clarity regarding AI's relevance, coupled with concerns over high costs, unclear Return on Investment (ROI), and implementation risks, stifles initiative (Proietti & Magnani, 2025; Sanchez et al., 2025). This is compounded by a knowledge gap, as evidenced by a study of Italian SMEs where fewer than 14% used AI, and only 11% were familiar with generative AI tools.

2.3. Synthesis and Identified Research Gap

The literature converges on the critical role of factors such as basic technology adoption, data readiness, digital/financial literacy, managerial support, and the core TAM constructs (PU and PEOU) in determining MSMEs' innovation readiness. However, a salient gap emerges: while studies extensively catalog barriers and affirm the importance of foundational readiness (like digital marketing or ERP use), there is limited integrated research examining how these foundational stages specifically, prior experience with commonplace digital tools directly shape the perceptions of usefulness and ease of use, and subsequently the practical readiness, for adopting sophisticated, next-generation technologies like AI-based predictive systems. This study seeks to address this gap by investigating the pathway from basic digital adoption to AI readiness within the Indonesian MSME context.

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3. Methods

3.1 Research Design

This study employs a descriptive quantitative approach complemented by associative analysis. This design is chosen to systematically measure MSMEs' readiness levels and to test the relationships among digital readiness variables and the implementation of AI-based forecasting.

3.2 Research Scope and Object

The research subjects are MSME owners or managers operating in the trade, services, and small-scale manufacturing sectors within the Greater Jakarta area (Jakarta, Bogor, Depok, Tangerang, and Bekasi). The research object is the digital readiness of MSMEs to implement AI for forecasting.

3.3 Population, Sample, and Sampling Technique

The sampling technique used is purposive sampling. The study targeted a minimum sample size of 100 respondents, selecting MSMEs that have had a transaction recording system in place for at least six months.

3.4 Data Collection Techniques

Primary data were collected using a questionnaire with a 5-point Likert scale (1–5), distributed online (Google Forms) and offline via direct visits to MSMEs. The study was conducted from March to July 2025. Secondary data, including government policy documents, official statistics from the Ministry of Cooperatives and SMEs, and reports from organizations such as the OECD and ERIA on MSME digitalization, were used to support the contextual analysis.

3.5 Operational Definitions of Variables and Research Instrument

The research instrument is a questionnaire developed based on theoretical reviews and prior empirical studies. It measures:

1) Independent Variables: Technology adoption, data quality, digital/financial literacy, IT infrastructure, managerial support, and technology perceptions (perceived usefulness and perceived ease of use).
2) Dependent Variable: Readiness for the implementation of AI-based forecasting. The questionnaire was tested for validity and reliability through a pilot test, with Cronbach's alpha ≥ 0.70 used as the reliability threshold.

3.6 Data Analysis Technique

Data analysis was conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS).

4. Results and Discussion

4.1 Measurement Model Results

The evaluation of the measurement model confirms the validity and reliability of the research instrument. As shown in the research model (Figure 1), almost all indicator loadings for the constructs (X1 to X6 and Y) exceed 0.8, approaching 0.95, which indicates strong convergent validity (Hair et al., 2019).

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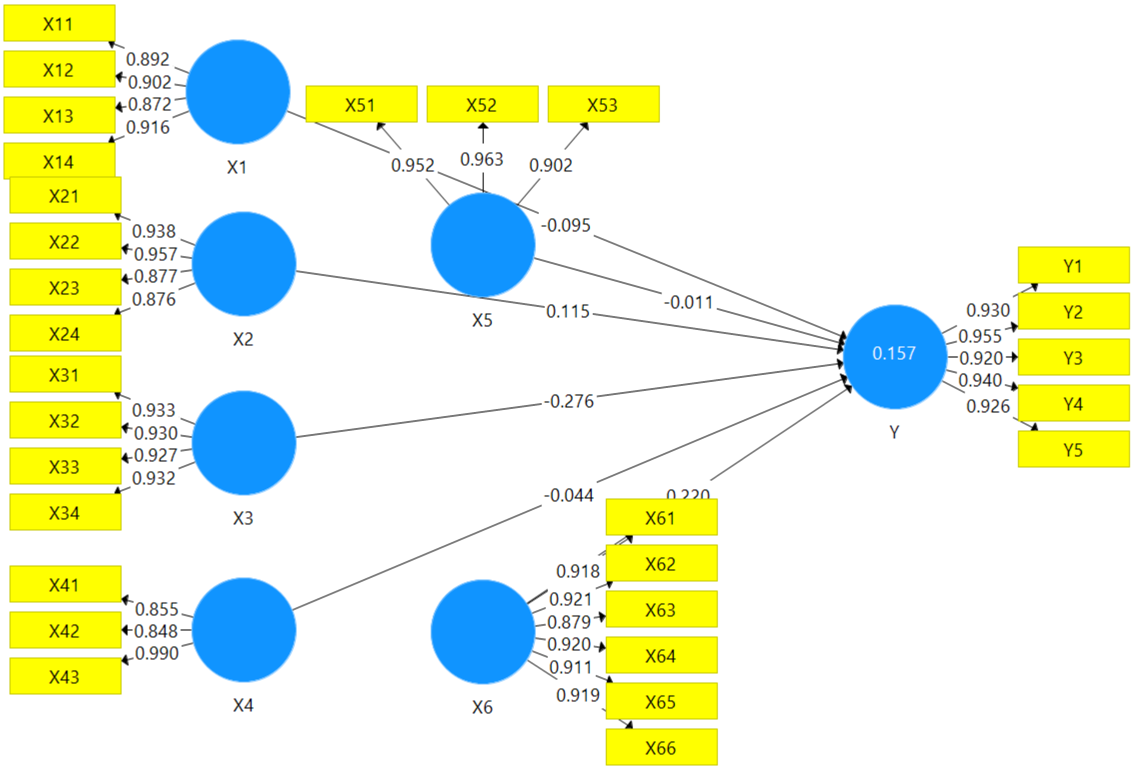

Figure 1. Research Model

4.2 Structural Model and Hypothesis Testing Results

The structural model assessment reveals the direction and strength of the relationships between the exogenous constructs (X1–X6) and the endogenous construct (Y), as illustrated by the path coefficients in Figure 2.

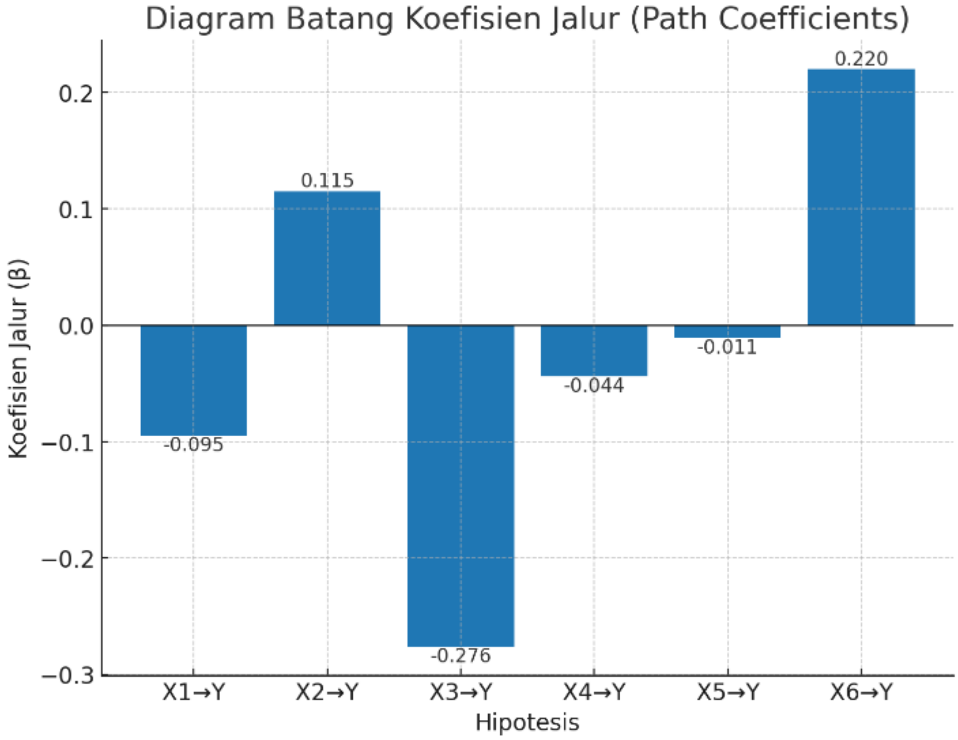

Figure 2. Path Coefficients

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The results of the hypothesis testing are summarized in Table 1. The model explains 15.7% of the variance in Y ($R^2 = 0.157$), which is considered a low-to-moderate explanatory power, suggesting other factors beyond the studied variables influence Y.

Table 1. Hypothesis Testing Results

Hypothesis	Relationship	Path Coefficient (β)	T-Statistic	P-Value	Conclusion
H1	X1 → Y	–0.095	1.119	0.264	Not significant (rejected)
H2	X2 → Y	0.115	1.237	0.217	Not significant (rejected)
H3	X3 → Y	–0.276	4.313	0.000	Significant (accepted)
H4	X4 → Y	–0.044	0.397	0.692	Not significant (rejected)
H5	X5 → Y	–0.011	0.108	0.914	Not significant (rejected)
H6	X6 → Y	0.220	2.559	0.011	Significant (accepted)

Source: processed data (2025)

Based on Table 1, two hypotheses are supported:

1) H3 (X3 → Y) has a significant negative effect ($\beta = -0.276$, $p < 0.001$). This indicates that an increase in X3 significantly decreases Y.
2) H6 (X6 → Y) has a significant positive effect ($\beta = 0.220$, $p < 0.05$). This indicates that X6 plays an important role in enhancing Y. Conversely, hypotheses H1, H2, H4, and H5 are rejected as their effects are not statistically significant ($p > 0.05$).

4.3 Discussion

The findings offer nuanced insights into the determinants of MSMEs' readiness for AI-based forecasting (Y). The significant positive role of X6 underscores the critical importance of internal organizational capabilities and resources. This aligns strongly with the Resource-Based View (Barney, 1991), which posits that unique, valuable, and hard-to-imitate internal resources are foundational for building competitive advantage. In this context, X6 representing factors like managerial support or technological perceptions acts as such a strategic resource that directly enhances readiness for advanced technology adoption. This result corroborates prior studies emphasizing the centrality of internal readiness and positive technology perceptions (Nurqamarani et al., 2021; Panjaitan et al., 2021; Sanchez et al., 2025).

Conversely, the significant negative influence of X3 presents a critical counterpoint. This suggests that certain external pressures or specific internal factors (e.g., perceived costs, complexity) can act as substantial barriers, effectively hindering readiness. This finding can be interpreted through Institutional Theory (DiMaggio & Powell, 1983), where coercive or mimetic pressures might induce resistance or lead to ceremonial, rather than substantive, adoption efforts, thereby negatively impacting genuine readiness. This result contrasts with several studies that generally report positive linear relationships between digital readiness constructs and performance outcomes (e.g., OECD, 2021; Rafiah et al., 2022). The discrepancy highlights the context-dependent nature of digital transformation, particularly in the complex urban environment of Greater Jakarta, where specific constraints (represented by X3) may outweigh potential benefits.

The non-significant effects of X1, X2, X4, and X5 indicate that these variables, while theoretically relevant, may not be primary direct drivers of AI readiness in the studied context. They might function as necessary foundational conditions or indirect enabbers rather than active catalysts. This implies that for managers and policymakers, a focused strategy that strengthens positive drivers (X6) and actively mitigates key barriers (X3) would be more effective than a scattergun approach addressing all potential factors equally.

4.4 Theoretical and Practical Implications

Theoretically, this study contributes by integrating the Resource-Based View and Institutional Theory to provide a balanced explanation of digital readiness. It confirms the enabling role of internal resources while also highlighting how specific institutional or contextual factors can create counterproductive resistance.

Practically, the findings suggest that intervention programs for MSMEs in Greater Jakarta should be highly targeted. Efforts should prioritize:

1) Enhancing X6: Through training to improve digital literacy and demonstrations of AI utility to bolster perceived usefulness and ease of use.
2) Mitigating X3: By addressing specific pain points such as simplifying technology access, providing cost subsidies, or clarifying regulatory frameworks to reduce its negative impact. The moderate R^2 value implies that future research should incorporate additional variables, such as ecosystem support, competitive intensity, or more granular measures of technology infrastructure, to better explain AI readiness among MSMEs.

5. Conclusion

This study demonstrates that digital readiness, technology adoption, and institutional support play significant roles in promoting MSME sustainability performance in Indonesia. The hypothesis tests indicate that some independent variables positively and significantly affect sustainability performance, in line with earlier studies emphasizing the importance of digital transformation for MSMEs. However, the results also reveal differences from prior research, particularly regarding certain internal factors that, within the Indonesian MSME context, exhibit negative relationships. These findings enrich the literature by highlighting that the impacts of digital readiness and technology adoption are not homogeneous but heavily shaped by institutional contexts and resource conditions.

Theoretically, this study contributes to the development of Institutional Theory by showing that external institutional pressures are instrumental in accelerating digital conformity, which in turn enhances MSME sustainability. It also strengthens the Natural Resource-Based View (NRBV) perspective by framing digital capabilities as strategic resources that support sustainable competitive advantage.

In practical terms, the findings imply the need for more targeted policies and support programs to enhance MSME digital readiness, improve technological literacy, and expand access to digital infrastructure. For MSME practitioners, the results emphasize the importance of building internal digital capabilities and leveraging institutional support to reinforce sustainable competitiveness in the face of digital era challenges and AI adoption.

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