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The Paradox of AI Adoption in Emerging Economies: A Structural Equation Analysis of Usage Intensity and SME Performance Evidence from Micro, Small, and Medium Enterprises in Jakarta, Indonesia

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Abstract **Purpose:** The Jakarta Provincial Government aims for 80% of MSMEs to be digitalized by 2025; however, empirical evidence on whether the intensity of Artificial Intelligence (AI) use truly enhances business performance in developing economies remains inconclusive. This study examines the relationship between AI usage intensity and business performance among MSMEs in Jakarta, while accounting for firm size variations. **Method:** A cross-sectional survey was conducted among 300 MSME owners/managers in Jakarta's five administrative regions who had used at least one AI tool in the past 3 months. The Technology Acceptance Model (TAM) was extended with a Resource-Based View (RBV) perspective and firm size variables (micro, small, medium). Data were analyzed using CB-SEM with Maximum Likelihood estimation and FIML to handle missing data. **Results:** The model demonstrated an excellent fit ($\chi^2/df = 1.13$; CFI = 0.993; RMSEA = 0.021; SRMR = 0.018). However, AI usage intensity did not have a significant direct effect on business performance ($\beta = 0.085$; $p = 0.113$). Firm size had a substantial direct effect on performance (small: $\beta = 0.446$, $p < 0.001$; medium: $\beta = 0.548$, $p < 0.001$). Small firms tended to have higher AI usage intensity ($\beta = 0.269$, $p < 0.001$). Nevertheless, mediation analysis confirmed that AI usage did not function as a significant mechanism for improving performance among small or medium firms. **Implications:** The findings indicate the presence of adoption without impact—access to and intensity of AI use alone are insufficient; business value emerges only when complementary resources (dynamic capabilities, data governance, and human resource skills) are available. Policy programs should therefore integrate managerial training and infrastructure financing rather than merely providing technology license subsidies. **Originality/Value:** This study is among the earliest quantitative examinations in the ASEAN context exploring the relationship between AI usage intensity and performance among MSMEs, using a SEM–TAM approach that incorporates firm size as a contingency variable.

Keywords artificial intelligence, SMEs, TAM, SEM, emerging economy, Jakarta

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1. Introduction

Jakarta contributes 17.2% of the national GDP and is home to 495,000 micro, small, and medium enterprises (MSMEs) [1]. The DKI Jakarta government launched the *Jakarta Smart City & SME Digital Leap 2025* program, which aims to have 80% of MSMEs adopt digital technologies, including artificial intelligence (AI), to increase competitiveness. However, Jakarta's MSME AI readiness index (42%) is still well below Singapore's (71%) and Malaysia's (58%) [2]. This readiness gap raises an important question: Does the adoption and use of AI truly improve MSME business performance, or does it create an "adoption paradox" in resource-constrained environments?

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Global evidence provides mixed results. The OECD [3] shows that AI can increase the productivity of manufacturing SMEs by 15–25% in developed countries, but only when supported by adequate analytical capabilities and data infrastructure. This indicates that technology alone is not enough; the quality of complementary resources determines value creation. In developing countries, the uneven distribution of digital infrastructure increases the risk that AI adoption will not automatically lead to improved performance.

The classic Technology Acceptance Model (TAM) [4] explains adoption behavior through perceived usefulness and perceived ease of use, which influence behavioral intention and ultimately actual use. However, most research stops at the intention level, without testing whether the intensity of actual use is related to organizational performance. A meta-analysis by [5] of 147 articles found that only 37% of studies tested the relationship between actual use and performance. This confirms a methodological gap in the post-adoption TAM literature, particularly regarding the role of actual technology use in creating business value.

The context of MSMEs in Jakarta underscores the urgency of examining this gap. According to the Resource-Based View (RBV), technology only creates competitive advantage when combined with complementary assets that are rare and difficult to imitate [6, 7]. In practice, many micro and small MSMEs in Jakarta face limitations in capital, internet bandwidth, and analytical skills. [8] stated that many MSMEs still do not have adequate internet access due to the country's limited digital infrastructure. Without proper infrastructure, the intensity of AI use is often not translated into task-technology fit that is relevant to business processes [9].

Previous research across various countries has yielded similar findings. [10] show that AI adoption only improves the sustainable performance of Saudi SMEs when combined with managerial dynamic capabilities. [11] found that Danish manufacturing SMEs that implemented AI–IoT only succeeded in reducing defect rates if they already had lean process knowledge. [12] also emphasize that organizational factors and managerial interventions (e.g., training, incentives) influence whether AI use actually has an impact, so that intensive use without adequate absorptive capacity tends not to produce performance.

The OECD meta-analysis literature [13] even shows that the effect of AI on productivity is size-dependent: micro and small MSMEs need external support mechanisms (subsidies, mentoring, training) for AI adoption to be effective. Conversely, medium MSMEs have higher absorptive capacity because they can build data pipelines and cross-functional teams. Thus, company size has the potential to be an essential contingency factor that moderates the relationship between AI usage intensity and business performance.

Based on this background, this study proposes two main research questions:

- **RQ1:** Does AI usage intensity have a positive effect on the business performance of MSMEs in Jakarta?
- **RQ2:** Does company size strengthen or weaken this relationship?

This research has a dual contribution. Theoretically, this study extends TAM by incorporating a company-size contingency variable and integrating the RBV perspective to explain the paradox of AI adoption in the context of limited resources. Methodologically, this study examines the relationship between actual use and performance using a Covariance-Based Structural Equation Modeling (CB-SEM) approach based on Full Information Maximum Likelihood (FIML). Based on a sample of 300 SMEs in Jakarta, this study provides the first quantitative evidence in ASEAN on the role of complementary conditions and company size in determining the business value of AI. This contributes to the literature on information computing and statistics by demonstrating that post-adoption TAM testing requires a rigorous SEM approach to verify the real impact of technology in a developing economy context.

2. Literature Review and Hypothesis Development

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) posits that perceived usefulness (PU) and perceived ease of use (PEOU) influence behavioral intention, which, in turn, affects actual use [4]. This model is widely used to examine technology adoption across various contexts, but most research stops at the intention stage and rarely tests the relationship between actual use and performance [5].

In the context of AI, post-adoption studies emphasize that usage intensity is a significant predictor of organizational performance. [14] show that actual AI usage improves decision quality only when supported by data governance and analytical skills. [10] also find that AI usage intensity in Saudi SMEs improves sustainable performance, particularly through dynamic capabilities.

This study expands TAM by focusing the analysis on the post-adoption relationship—namely, from AI usage intensity to business performance—using Covariance-Based SEM in the context of Jakarta MSMEs.

2.2. Resource-Based View (RBV) and Task-Technology Fit (TTF)

The Resource-Based View (RBV) argues that competitive advantage arises from a bundle of resources that are scarce, difficult to imitate, and non-substitutable [6]. In the context of AI, successful implementation depends on complementary assets such as quality data, analytical skills, cloud infrastructure, and a culture of knowledge sharing [11, 7]. Without these assets, technology does not generate economic rents.

In line with the RBV, the Task-Technology Fit (TTF) theory asserts that technology improves performance only when it is appropriate to the task at hand [9]. In MSMEs, the fit between AI and business processes mediates the relationship between usage intensity and performance. Without high TTF, usage intensity becomes meaningless, as organizations are unable to absorb the value of the adopted technology.

2.3. Company Size as a Size Variable (Main Effect)

Micro and small SMEs often face the liability of smallness: limited capital, time, and access to AI talent. [13] emphasize that the impact of AI on productivity is size-dependent: micro-SMEs require external support mechanisms, while larger SMEs have greater capacity to build data pipelines and cross-functional teams.

The results of this study show that company size does not significantly moderate the relationship between AI usage intensity and business performance. Therefore, company size is treated as a direct effect on business performance (main effect).

2.4. Hypothesis Development

The literature on technology adoption often assumes that the intensity of technology use will enhance organizational performance by improving efficiency, decision quality, or market access. However, theoretical and empirical evidence shows that the relationship between technology use and performance is often conditional: the real benefits of usage intensity mainly emerge when organizations have adequate complementary resources and capabilities, such as data governance, analytical skills, task–technology fit, absorptive capacity, and dynamic capabilities. [6, 8, 13, 14, 15, 3]. Considering this evidence, the hypothesis tested in this study is formulated while acknowledging the potential conditional nature of the hypothesized effects.

- **H1**: The intensity of AI use is positively related to the business performance of SMEs in Jakarta.
- **H2**: Company size is positively related to the business performance of SMEs in Jakarta (micro ¡ small ¡ medium).

3. Methodology

This study employs a quantitative–positivist approach with a cross-sectional survey design. The main objective is to examine the causal relationship between the intensity of AI use and MSMEs' business performance, as well as the moderating effect of company size. Covariance-Based Structural Equation Modeling (CB-SEM) was used because the model is confirmatory and the data are ordinal [16].

3.1. Population and Sample

The population consists of 495,000 MSMEs registered in DKI Jakarta [17]. A minimum sample of 300 respondents was determined using the RaoSoft sample size calculator (margin of error 5%, power 80%), in accordance with the recommendations of [18]. Sampling technique: stratified proportionate based on region (5 municipalities) and sector (trade, food, creative services). Online (Google Forms) and offline (drop-off) questionnaires were distributed from June to July 2025. A total of 300 valid questionnaires were collected.

3.2. *Operational Definitions and Instruments*

- **AI Usage Intensity** (3 items, $\alpha = 0.81$): frequency, duration, and variety of AI features used per week (5-point Likert scale; 1 = Strongly Disagree, 5 = Strongly Agree; adapted from [4]).
- **Business Performance** (3 items, $\alpha = 0.85$): growth in turnover, profit, and number of customers compared with the previous year (5-point scale; adapted from [19]).
- **Company Size**: micro ($\leq$4 employees), small (5–19 employees), and medium (20–99 employees) based on Law No. 20/2008.
- **Control Variables**: business age (years) and sector (retail, food, creative services).

All constructs were measured using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

3.3. *Validity and Reliability Tests*

- **Convergent validity**: outer loading ≥ 0.60 and significant ($p < 0.001$) [16].
- **Internal reliability**: Cronbach's $\alpha \geq 0.70$ [20].
- **Common method bias**: Harman's single-factor test (42% $<$ 50%) and marker-variable test [21].

3.4. *Data Analysis*

Model testing was performed using Covariance-Based Structural Equation Modeling (CB-SEM) with Maximum Likelihood Estimation (MLE) in JASP 0.18. Missing data were handled using Full-Information Maximum Likelihood (FIML). The goodness-of-fit criteria used were:

- $\chi^2/df < 3.00$
- CFI ≥ 0.95
- RMSEA ≤ 0.08
- SRMR ≤ 0.08 [24, 16]

Mediation testing used bias-corrected bootstrapping with 5,000 replications to estimate confidence intervals following CB-SEM standards [22]. Post-hoc power analysis indicated statistical power > 0.80 for effects of $\beta = 0.15$ (medium effect size).

Design Note This study adopts a cross-sectional design, meaning data were collected at a single point in time. Therefore, results should be interpreted cautiously regarding causality. Cross-sectional designs do not establish temporal precedence among variables, making estimates of mediation or causal relationships potentially biased—especially when the true relationships unfold over time. Previous research shows that cross-sectional mediation tests often produce biased estimates for longitudinal or temporal processes; thus, the nonsignificant effect of AI usage intensity on performance in this study may reflect the temporal limitations of the design, rather than the absence of a true causal mechanism [23].

4. RESULTS

4.1. *Measurement Model Evaluation (Outer Model)*

Before testing the structural relationships, the measurement model was evaluated to ensure construct validity and reliability. Table 1 shows that all indicators have outer loadings ≥ 0.68 and are significant at $p < 0.001$. The AVE values of all constructs are above 0.50, indicating adequate convergent validity (Hair et al., 2019). Internal reliability is also high, with Cronbach's α and Composite Reliability both above the 0.70 threshold [20]. Thus, no indicators were eliminated because all met the validity and reliability requirements.

Table 1. Summary of Construct Validity & Reliability

Construct	Cronbach α	Composite Reliability	AVE	Lowest Loading
Using_AI	0.81	0.87	0.69	0.68
Performance_Business	0.85	0.89	0.73	0.71

Source: JASP 0.18 output (processed by the author, 2025)

4.2. Goodness-of-Fit of the Structural Model

The next step was to evaluate the adequacy of the structural model. The goodness-of-fit test results in Table 2 indicate excellent model fit. The χ^2/df value = 1.13 (< 3.00) indicates a good fit. Furthermore, the CFI = 0.993 and TLI = 0.996 both exceed the ≥ 0.95 criterion, thus meeting the standards for excellent fit [24]. The RMSEA = 0.021 with a 90% CI of 0.000–0.085, and the SRMR = 0.018 (< 0.08), also indicate very adequate model fit [25]. Overall, the combination of various fit indices indicates that the estimated model represents the data very well.

Table 2. Model Fit Indices

Index	Score	Criteria	Note
χ^2/df	1.13	< 3.00	Good
CFI	0.993	≥ 0.95	Good
TLI	0.996	≥ 0.95	Good
RMSEA	0.021	≤ 0.08	Good
SRMR	0.018	≤ 0.08	Good

Source: JASP 0.18 output (processed by the author, 2025)

4.3. Hypothesis Testing (Path Coefficients)

After confirming the suitability of the model, hypothesis testing was conducted with a focus on path coefficients. The results (Table 3) show that:

- **H1:** The path from AI_Usage $\rightarrow$ Business_Performance produced a coefficient $\beta = 0.085$ with $p = 0.113$. This effect is not significant, so the intensity of AI use has not been shown to improve the business performance of MSMEs in Jakarta directly. This finding is consistent with the study by [13], which emphasizes the importance of complementary assets for AI usage to create value.
- The effect of company size on performance: both small SMEs ($\beta = 0.446$, $p < 0.001$) and medium-sized SMEs ($\beta = 0.548$, $p < 0.001$) have a significant positive effect on business performance, supporting the literature linking firm size to technological capacity [26, 27].
- The effect of firm size on AI usage: Small SMEs show a significant influence on AI usage intensity ($\beta = 0.269$, $p < 0.001$). Conversely, in medium SMEs, the effect is not substantial ($\beta = 0.091$, $p = 0.181$), suggesting that AI usage is not solely influenced by size but also by resource readiness and culture.

Table 3. Summary of Path Coefficients

Path	β	SE	z	p	95% CI	Description
AI_Usage $\rightarrow$ Business_Performance	0.085	0.053	1.60	0.113	[-0.020, 0.189]	Not significant
Small $\rightarrow$ Business_Performance	0.446	0.040	11.15	< 0.001	[0.368, 0.524]	Significant
Medium $\rightarrow$ Business_Performance	0.548	0.034	16.12	< 0.001	[0.481, 0.615]	Significant
Small $\rightarrow$ AI_Usage	0.269	0.066	4.08	< 0.001	[0.140, 0.398]	Significant
Medium $\rightarrow$ AI_Usage	0.091	0.068	1.34	0.181	[-0.042, 0.224]	Not significant

Source: JASP 0.18 output (processed by the author, 2025).

4.4. *Testing for Mediation Effects*

The mediation analysis assessed whether AI use functions as a mediating mechanism between firm size and business performance. Bootstrapping with 5,000 replications (Table 3) indicates that both indirect paths are insignificant ($p > 0.10$). Thus, AI use does not mediate the effect of firm size on performance, supporting the RBV perspective that performance improvements depend on complementary assets rather than technology use intensity alone [6, 7].

Table 4. Summary of Mediation Effects (Bootstrap 5,000 replications)

Mediation Path	β	SE	z	p	95% BC CI	Description
Small → AI_Usage → Business_Performance	0.023	0.016	1.44	0.144	[-0.008, 0.053]	Not significant
Medium → AI_Usage → Business_Performance	0.008	0.008	1.02	0.308	[-0.007, 0.022]	Not significant

Source: JASP 0.18 output (processed by the author, 2025).

4.5. *Coefficient of Determination*

The R^2 value indicates the model's explanatory power. A total of 7.4% of the variance in AI usage intensity is explained by firm size, while 46.9% of the variance in business performance is explained by firm size and AI usage intensity. The R^2 value for business performance is classified as moderate to strong [28], indicating that the model explains nearly half of the variation in business performance among Jakarta MSMEs.

5. DISCUSSION

5.1. *Main Interpretation: The AI Adoption Paradox in Jakarta MSMEs*

The test results show that H1 is rejected: the intensity of AI use does not have a significant effect on the business performance of Jakarta MSMEs ($\beta = 0.085; p = 0.113$). It should be noted that these findings must be interpreted cautiously, as the study's cross-sectional design captures conditions at a single point in time; delayed benefits of AI (lagged effects) may not be detected in an immediate survey [23]. Additionally, performance measurements based on self-reports are susceptible to standard method variance and social desirability, which may influence the estimation of relationships [21, 29]. Therefore, it is recommended that these findings be confirmed through longitudinal studies with objective performance indicators or multi-informant designs before concluding that AI usage intensity does not impact SME performance. This finding confirms the adoption paradox phenomenon: the adoption of advanced technology does not automatically translate into improved performance without the support of complementary resources [6, 7]. Duan, Edwards, & Dwivedi (2019) emphasize that actual AI use only improves decision quality when organizations have data governance and analytical skills. In the context of Jakarta's micro-SMEs, challenges such as limited infrastructure and digital human resources continue to constrain the effective use of digital technologies. As noted by [30, 34], deficiencies in connectivity, digital literacy, and organizational readiness may hinder translating technology use into measurable business performance. From the Task-Technology Fit perspective [8], intensive AI usage without adequate fit risks becoming a routine operational activity, "button pushing" without a feedback loop that leads to process improvement. The R^2 value of AI_Usage = 0.074 reinforces the impression that company size explains only a slight portion of the variation in usage intensity; other factors, such as organizational capabilities, digital culture, and ecosystem networks, are more likely to be decisive [32, 26]. Additionally, it's important to emphasize that "AI" is not a single entity—different categories of AI tools can have varying impacts on business outcomes and operate through distinct mechanisms. Practically, at least three categories are relevant in the context of SMEs: (1) Generative AI (e.g., ChatGPT) primarily enhances content production, customer service, and communication capacity—its direct impact on short-term financial metrics is often limited because it requires process integration and marketing strategies; (2) Predictive analytics (e.g., ad optimization systems/Meta Ads, customer recommendations) can reduce customer acquisition costs and improve marketing efficiency, potentially leading to quicker financial effects; and (3) Process automation (e.g., inventory bots, operational automation) tends to result in operational efficiency improvements and cost reductions that are relatively directly reflected in profitability. Combining all these types into a single aggregate construct of ”AI usage intensity” risks obscuring the heterogeneity of effects—the positive impact of one kind can neutralize the non-significance of another, making the aggregate effect appear weak or nonexistent. Therefore, future studies should measure and analyze AI categories separately (e.g., sub-scales by function) or conduct robustness tests based on tool type to reveal more specific impacts [13, 3]. Thus, policy recommendations and SME support programs should clarify the target technology (AI type) and prepare appropriate complementary packages, as training for predictive analytics differs from mentoring in adopting generative tools or process automation.) Furthermore, the study by [33] shows that dynamic capabilities are a key mediator: without these capabilities, AI usage intensity is difficult to convert into sustainable performance. The current findings reinforce this literature: AI adoption needs to be viewed as part of an organizational capability system, not as a single input that guarantees results.

5.2. The Role of Firm Size as a Direct Contingency

Analysis shows that firm size directly influences performance but does not moderate the relationship between AI usage $\rightarrow$ performance (moderation is not significant in your data). In other words, the size effect emerges as a main effect. For small SMEs, a positive effect on AI usage was found (mediation $\beta = 0.023$; $p = 0.144$), but the mediating path of AI usage $\rightarrow$ performance was not significant (mediation $\beta = 0.023$; $p = 0.144$). This indicates that small SMEs tend to adopt easily accessible AI solutions (cloud apps, chatbots), but limitations in capital, human resources, and capabilities make such adoption less impactful on actual performance. [7, 3] An additional explanation is that medium-sized companies often face different strategic choices. They may focus more on integrating complex ERP/legacy systems, outsourcing digital functions to third parties, or investing in distribution networks, which ultimately have a greater impact on performance than the intensity of using specific AI tools. Differences in sector composition among medium-sized companies can also lead to heterogeneous AI adoption patterns; therefore, separate sector analyses or qualitative case studies would help clarify these findings. For medium-sized SMEs, AI usage is not significantly correlated ($\beta = 0.091$; $p = 0.181$), but medium-sized SMEs have a substantial direct effect on performance ($\beta = 0.548$; $p < 0.001$)). Interpretation: Medium-sized SMEs have alternative resources, operational scale, marketing networks, and organizational structures that contribute more to performance than the intensity of AI usage alone. This aligns with the findings of [31], which emphasize the roles of entrepreneurial capabilities and organizational context in the digital transformation process of SMEs, rather than the intensity of technology use itself. In summary, the data shows that: (a) adoption/usage intensity is not sufficient to drive performance without complementary capabilities; (b) company size affects performance through a direct channel (resource/access), not through moderation of AI usage in this sample.

5.3. Theoretical Contribution

This study makes an essential contribution to the development of the Technology Acceptance Model (TAM) in a post-adoption context. For more than three decades, TAM has been widely used to explain the intention to use technology, but relatively few studies have examined the actual use $\rightarrow$ performance pathway [34]. The results of this study show that the intensity of AI use does not have a significant effect on the business performance of MSMEs in Jakarta, thereby strengthening the argument that the TAM model needs to be expanded with an additional theoretical framework. First, these findings support the Resource-Based View (RBV) perspective that technology can generate performance advantages only when complemented by resources such as analytical skills, data governance, and digital infrastructure [6, 13]. In other words, usage intensity alone is insufficient to explain performance without complementary assets. Second, company size was found to directly influence performance, although it did not function as a moderator. This is consistent with the [3] finding that SME digitalization is size-dependent, with small businesses often facing resource constraints (liability of smallness) that limit their use of technology. Third, this study highlights the importance of combining TAM with the RBV lens and size contingency when applied in emerging markets. Thus, the post-adoption model cannot be viewed solely from the perspective of individual behavior; it must also consider organizational context, resource constraints, and environmental conditions [5, 32] Overall, this study enriches the literature by emphasizing that technology adoption should be understood as a process tied to organizational capacity and environment, rather than simply an individual usage decision.

5.4. Policy Implications and Managerial Practices

The results of this study also have important implications for public policy and MSME management. Local government support programs such as the Jakarta AI-SME Voucher 2.0 should not stop at license subsidies; they should be designed as comprehensive resource-enabling packages [7]. First, intensive mentoring for at least three months is needed, focusing on practical application, setting key performance indicators (KPIs), and feedback loop mechanisms. This step helps improve task-technology fit so that AI adoption is not merely routine use but truly supports core business processes [8]. Second, digital infrastructure support needs to be a priority, for example, through cloud credits and subsidies to ensure adequate internet connection speeds. Without a basic data pipeline, AI usage is difficult to integrate into daily business processes [3]. Third, program budget allocation needs to be strategically directed. As research shows that small SMEs tend to be more interested in adopting AI ($\beta = 0.269$) but are constrained by limited resources, at least 60% of the budget should be allocated to this group. Finally, the effectiveness of interventions must be measured through measurable ROI indicators. Mentoring should report weekly business benefits so that MSME managers can see concrete evidence of digital investment. This aligns with the findings of the [3] and [26] that absorptive capacity is a determining factor for AI to truly provide added value.

5.5. Research Limitations

This study has several methodological limitations. **Cross-sectional design.** This research employed a cross-sectional design, meaning that the data collected only represent a single point in time (a snapshot). Such a design is inadequate for testing temporal order or delayed (lagged) effects that often arise in technology adoption processes and the realization of their benefits. Methodological literature indicates that cross-sectional analyses may yield biased estimates when used to assess longitudinal mediation mechanisms; effects that emerge after process adjustments, employee training, or data governance improvements may only become evident after several months and are not captured in a one-time survey. Therefore, the finding that AI intensity does not significantly affect performance should be interpreted as being limited by the temporal design of this study rather than as definitive evidence that no causal relationship exists [23]. **Self-reported performance.** The performance variable in this study was measured using subjective responses from SME owners (self-reported data). Self-reported data are prone to several biases, such as social desirability bias, recall bias, and standard method variance (CMV), which can affect the validity of inferences. Although Harman's single-factor test and the marker-variable technique were applied to detect CMV, methodological studies suggest that these statistical remedies are only partial and cannot eliminate the bias risk inherent in single-source data. Therefore, performance-related findings should ideally be validated using objective data whenever possible [21]. **Aggregate AI construct.** This study measured "AI usage intensity" as an aggregate construct encompassing diverse tools (e.g., chatbots, predictive analytics, inventory bots, etc.). This aggregation risks treating inherently heterogeneous effects as homogeneous: certain AI types may deliver immediate operational benefits (e.g., inventory automation), while others may affect service quality or marketing outcomes that take time to manifest in financial metrics. Hence, interpretations of aggregate effects must be made cautiously, and future research is encouraged to disaggregate AI types (as already discussed in the Discussion section). **Mitigation suggestions for future studies.** To address these limitations, future research should consider several methodological improvements:

- Longitudinal (panel) design with at least two waves (T1–T2) separated by a realistic interval (e.g., 6–12 months), allowing cross-lagged testing and the assessment of AI usage trajectories as well as delayed effects on performance. Such a design strengthens temporal arguments and reduces bias in mediation estimation [35].
- Use of objective performance indicators, such as financial reports, recorded sales data, or administrative records (e.g., tax or certification data), to validate findings from self-report instruments.
- Multi-informant design (e.g., data from owners and operational managers, or triangulation with customer metrics) to minimize single-method effects. Procedural remedies and advanced statistical techniques for

reducing CMV—such as temporal separation of variable collection, anonymity, reverse-coded items, or marker variables can also be applied [21].

- Measurement of complementary resources (e.g., data governance, absorptive capacity, task–technology fit, dynamic capabilities) as mediating or moderating variables. Testing these mechanisms can help "open the black box" between AI usage and performance and explain why usage intensity alone may not suffice [21].

Additionally, this study's sample was limited to three sectors (trade, food, and creative services), restricting generalization to other industries such as manufacturing or agribusiness. Future studies should broaden sectoral coverage to test the consistency of findings across diverse economic contexts. By acknowledging these limitations and recommending methodological enhancements, future research can provide more robust evidence regarding how AI influences SME performance in developing economies.

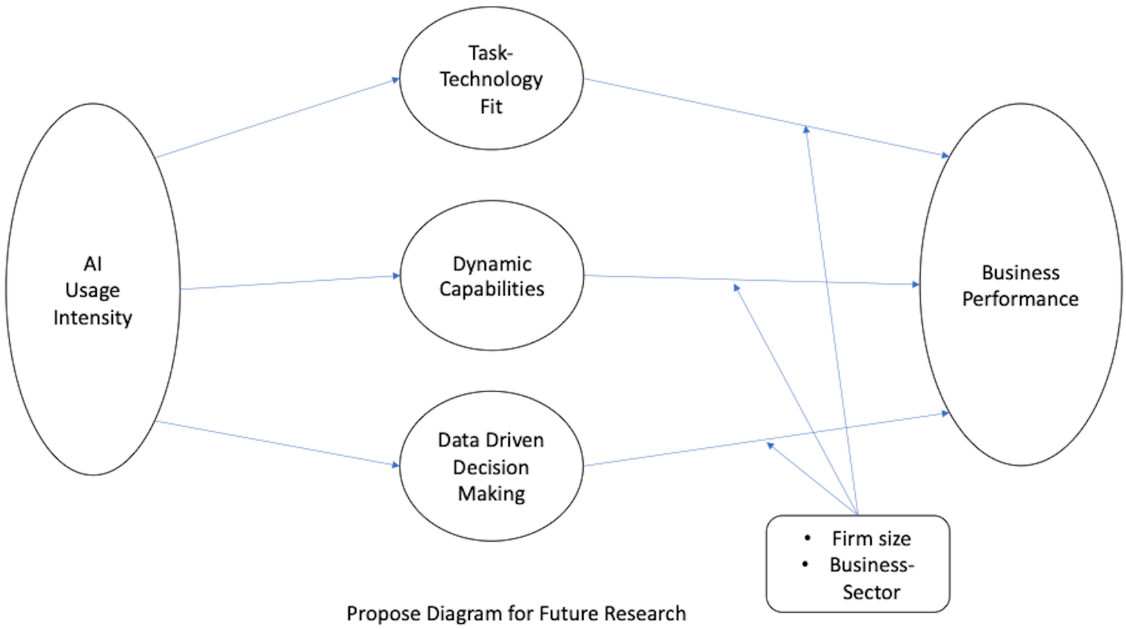

Figure 1. Propose Future Agenda Framework
Source: Authors' Work

5.6. Future Research Agenda

The limitations discussed above provide a basis for a future research agenda. To clarify why AI usage intensity does not always translate into performance gains, future studies should focus on testing mediating mechanisms rather than merely establishing the presence or absence of effects. Without opening the "black box" of mechanisms, interpretations of aggregate results will remain limited. First, Task–Technology Fit (TTF) should be examined as a mediator [36]. The key question is whether the AI tools used truly align with the business tasks they are meant to enhance. If AI is poorly matched to the task, its outputs may be challenging to operationalize into performance improvements. TTF can be measured by assessing the relevance of AI outputs to tasks, ease of integration, and decision-making effectiveness. Second, absorptive capacity represents another important mediating pathway [37]. Firms that can absorb, understand, and apply new knowledge are more likely to translate AI insights into operational or strategic actions. This can be measured through prior technological experience, training frequency, and the ability to convert AI outputs into business practices. Third, dynamic capabilities should be a focal point [38, 39]. An organization's ability to sense opportunities, reallocate resources, and reconfigure processes determines whether AI adoption can be converted into a competitive advantage. Measurement scales should cover sensing, seizing, and reconfiguring dimensions in digital decision-making contexts. To clarify the proposed theoretical model, future research should include a conceptual diagram linking AI Usage Intensity $\rightarrow$ (TTF / Absorptive Capacity / Dynamic Capabilities) $\rightarrow$ Performance, along with direct and moderating paths (e.g., firm size, sector).

Methodologically, longitudinal (panel) designs with at least two waves spaced 6–12 months apart are recommended to capture delayed and causal effects. Mediation tests should employ CB-SEM with bias-corrected bootstrap confidence intervals; for panel designs, cross-lagged models are advised to distinguish directional effects. Moreover, combining self-reported indicators with objective metrics (financial or transactional data) and using multi-informant designs will help mitigate single-method bias. Finally, AI usage disaggregation (e.g., generative, predictive analytics, process automation) is essential, as combining all AI types into one construct can obscure heterogeneous effects. Researchers should test whether each AI category operates through similar or distinct mediators and explore potential reverse causality—where already capable organizations may use AI more intensively. Thus, cross-lagged or experimental/quasi-experimental designs would be particularly valuable for strengthening causal inference. Through this research agenda, future studies will be better equipped to answer not only whether AI matters but also how, when, and for whom AI usage intensity creates business value for SMEs.

6. Conclusion

This study examines the AI adoption paradox among 300 Jakarta SMEs using the TAM model, expanded to include RBV and company size as contingency variables. CB-SEM results show that AI usage intensity does not significantly affect business performance, supporting the view that advanced technology does not automatically generate advantages without complementary resources. Conversely, company size emerges as a stronger direct predictor of performance for both small and medium SMEs, whereas the mediating effect of AI usage proves insignificant. These findings have two main implications. First, this study theoretically expands the post-adoption TAM literature by demonstrating the importance of integrating the RBV perspective and considering organizational contingency factors, such as company size. Thus, this study confirms that usage intensity creates value only when supported by organizational capabilities and supporting resources. Second, practically, the results emphasize the need for comprehensive policy interventions, not just technology license subsidies. Support programs for SMEs should focus on increasing absorptive capacity through training, mentoring, and adequate digital infrastructure, with priority given to small businesses with a strong interest in adoption but constrained by resources. As with other studies, this study has limitations, including its cross-sectional design, reliance on self-reported performance indicators, and limited sector coverage. Therefore, future research is recommended to adopt a longitudinal design, use objective performance data, and employ a mixed-methods approach to explore the mechanisms by which AI use is translated into business value. Overall, the main conclusion of this study is that AI adoption will be effective only if accompanied by dynamic capabilities, digital infrastructure, and comprehensive public policies. Without these, the intensity of technology use tends to be insufficient to generate sustainable competitive advantages for MSMEs in developing markets.

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