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Sensing without Seizing: The Institutional Barriers to AI Adoption in Indonesian MSMEs

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ABSTRACT

Despite strong policy support, the adoption of Artificial Intelligence (AI) among Indonesian Micro, Small, and Medium Enterprises (MSMEs) remains critically low, creating a notable "digital paradox." This study investigates the "gap between sensing and seizing," defined as the disparity between awareness of AI opportunities and deployment capability. Integrating Dynamic Capabilities Theory and Institutional Theory, we examine how internal organizational capabilities intersect with contextual barriers. Utilizing an interpretivist approach based on the Gioia Methodology, data were analyzed from 28 MSMEs in the Special Region of Yogyakarta through indepth interviews, focus group discussions, and document analysis. The analysis reveals that while sensing capability is widespread, it relies heavily on informal peer networks and is constrained by a cognitive mismatch regarding the relevance of AI for small businesses. Seizing capability is hampered less by financial constraints than by weak absorptive capacity and challenges in assessing return on investment. Transforming capabilities among early adopters are incremental and highly dependent on external ecosystem support. The study concludes that this adoption gap reflects institutional voids, specifically infrastructure inequality and regulatory uncertainty, rather than a lack of entrepreneurial will. These findings refine the theoretical understanding of technology adoption in developing economies and offer strategic guidance for policymakers and technology providers.

Keywords: *Dynamic Capabilities; AI Adoption; MSMEs; Institutional Voids; Gap between Sensing and Seizing; Indonesia.*

INTRODUCTION

The acceleration of digital transformation in the era following COVID-19 has fundamentally reconfigured the competitive landscape for Micro, Small, and Medium Enterprises (MSMEs) globally (Drydakis, 2022; Lu et al., 2022). Once considered a technological novelty, Artificial Intelligence (AI) has emerged as a strategic imperative by offering automation, personalization, and the capacity for evidence-based decisions essential for organizational sustainability (Kumar et al., 2024). In Indonesia, where MSMEs contribute 61.07% to the GDP and absorb 97% of the national workforce (BPS, 2024), the successful integration of AI represents more than an operational upgrade. It is a critical determinant of national economic resilience and sustained competitiveness in the global marketplace.

However, a significant paradox characterizes the Indonesian MSME context. While basic digital adoption shows promise, evidenced by 39% of MSMEs entering the digital ecosystem and widespread QRIS adoption reaching 93.16% of merchants, adoption of advanced technologies such as AI remains critically low. Less than 10% of MSMEs have integrated AI into their core operations (Kominfo, 2024), despite empirical evidence suggesting that AI and IoT integration can enhance production efficiency by 30% (Nana et al., 2025). This striking disparity between the high availability of digital tools and the low depth of their strategic utilization represents the central puzzle motivating this investigation.

This discrepancy reveals a critical phenomenon termed the "gap between sensing and seizing." It refers to a condition where MSMEs exhibit strong sensing capabilities regarding AI opportunities but systematically fail to develop the seizing capabilities necessary for investment and deployment. Theoretically, Dynamic Capabilities Theory (DCT) posits that technology adoption requires the integration of sensing, seizing, and transforming capabilities (Teece, 2007), a framework validated in European and Pakistani contexts (Ardito et al., 2024; Soomro et al., 2025). Yet, in developing economies, this mechanism is frequently stifled by complex institutional barriers. Indonesian MSMEs exhibit significant ambivalence. While acknowledging the value of AI, they are constrained by perceived costs, technical complexity, and ethical concerns regarding automation (Azizah et al., 2020; Chiu et al., 2021).

Existing literature has predominantly focused on internal organizational factors, often neglecting critical contextual impediments. These include the digital divide, exemplified by infrastructural disparities between urban Yogyakarta and rural areas like Gunungkidul (Sutirman et al., 2025), regulatory lags regarding data privacy and cybersecurity (Kurniawan et al., 2024), limited absorptive capacity to assimilate new technologies (Cohen & Levinthal, 1990), and institutional resistance to workforce restructuring (Petersson et al., 2022).

Grounded in a preliminary exploratory study conducted from August to October 2025, this research addresses four critical gaps in the extant literature. First, a persistent bias toward developed economies (e.g., Ardito et al., 2024) overlooks how institutional contexts in developing countries shape AI adoption. Second, there is a scarcity of qualitative insights into the nuanced sensemaking processes and dilemmas underlying adoption decisions. Third, limited theoretical integration exists between internal dynamic capabilities and external institutional pressures. Fourth, limited research examines marketing enabled by artificial intelligence in settings with limited resources. Collectively, these gaps underscore the need for an empirically grounded inquiry that is sensitive to context in explaining technology adoption dynamics in developing economies.

This study addresses these gaps by investigating the gap between sensing and seizing through an integrated lens of Dynamic Capabilities Theory and Institutional Theory within the Indonesian MSME context. A qualitative interpretivist design enables the research to uncover hidden narratives explaining low AI adoption rates while providing theoretical advancement and practical guidance for policymakers and practitioners in emerging economies.

METHODS

This study adopts an interpretivist qualitative design to examine the complex mechanisms underlying technology adoption decisions. Rather than pursuing variance models common in quantitative research, this approach prioritizes the exploration of subjective meanings and the lived experiences of MSME practitioners (Creswell & Poth, 2016). The research design integrates two complementary analytical approaches. First, a generic qualitative inquiry framework (Caelli et al., 2003) ensures systematic data collection and thematic exploration. Second, the Gioia Methodology (Gioia et al., 2013) facilitates rigorous progression from first order codes derived from participants to second order theoretical themes. This dual approach ensures both inductive fidelity to participant voices and deductive alignment with theoretical frameworks.

The research was conducted within the Special Region of Yogyakarta (DIY), a location strategically chosen for its relevance to the study's objectives. First, preliminary data from FEB UNY (2025) indicates a significant digital divide between urban and rural areas within the province, offering a rich context for analyzing adoption disparities across infrastructure gradients. Second, DIY represents a complete spectrum of digital readiness, ranging from the advanced infrastructure of Yogyakarta City to the developing ecosystems of Gunungkidul and Kulon Progo. Third, the regional MSME landscape is characterized by high sectoral and scale heterogeneity, providing a microcosm representative of the broader Indonesian national context. Collectively, these characteristics establish DIY as an ideal setting for investigating the gap between sensing and seizing.

The target population comprised MSMEs operational for a minimum of two years, adhering to the classification criteria of Law No. 20/2008. To ensure maximum variation, the study employed a combination of purposive and snowball sampling techniques (Palinkas et al., 2015). Participation was restricted to business owners or senior managers with direct authority over technological investment decisions. Inclusion criteria required participants to articulate their business experiences in detail and commit to comprehensive interviews lasting 60 to 90 minutes. This purposeful selection ensured participants possessed the requisite organizational knowledge and decision making authority to address the research questions. Conversely, MSMEs fully acquired by large corporations or possessing complex shareholding structures were excluded to maintain focus on independent MSME dynamics. The final sample size was determined by data saturation. The study initially targeted 24 to 30 participants for indepth interviews (IDI) and 3 to 4 focus group discussions (FGD), with data collection ceasing upon reaching informational redundancy where no new themes emerged.

Data were collected through robust methodological triangulation employing three complementary methods. First, indepth interviews were conducted using a semi structured guide derived from Dynamic Capabilities Theory (DCT) and Institutional Theory. These interviews explored domains such as sensing, seizing, and transforming capabilities, alongside institutional barriers, stakeholder perceptions, and ethical considerations. Each interview, lasting 60 to 90 minutes, was digitally recorded and transcribed verbatim. Second, to supplement and validate individual narratives, three focus group discussion (FGD) sessions were conducted. The first FGD explored initial themes from preliminary analysis, the second served as a member checking mechanism to verify interpretive accuracy, and the third focused on synthesizing findings to capture collective consensus. Third, document analysis was performed on strategic artifacts, such as business plans, standard operating procedures (SOPs), and digital marketing materials, to verify participant claims and provide objective context. This multi method approach strengthened the validity of findings through source triangulation.

The analysis integrated Reflexive Thematic Analysis (Braun & Clarke, 2022) with the structural rigor of the Gioia Methodology (Gioia et al., 2013). This hybrid approach combined the flexibility of reflexive thematic analysis with the systematic rigor of Gioia's conceptualization pathway from first order concepts to second order themes, ensuring both inductive openness and theoretical alignment. The process commenced with an extensive familiarization phase, wherein all transcripts and documents were read iteratively to develop deep familiarity with the dataset. Initial observations and analytic memos were systematically documented to establish a foundation for subsequent stages.

Following familiarization, rigorous line by line open coding was conducted to capture participants' own language and meanings with fidelity. Codes such as "expensive training costs" and "we don't have the right skills" were preserved verbatim to maintain the authenticity of participant perspectives. Building upon these initial codes, analysis advanced to the development of first order concepts, grouping individual codes to reflect lived experiences. Subsequently, these concepts were abstracted into second order themes through the interpretive lenses of DCT and Institutional Theory. For instance, codes like "training costs" and "technical skill gaps" were aggregated under the second order theme "Absorptive Capacity Limitations," establishing a transparent linkage between empirical observations and theoretical constructs. Finally, these themes were synthesized into aggregate theoretical dimensions, specifically the three dynamic capabilities (sensing, seizing, transforming) and the three institutional pillars (regulatory, normative, cognitive), ensuring coherent integration of findings with the analytical framework.

Rigorous validation mechanisms were embedded throughout the process. Member checking with eight purposively selected participants verified that analytical interpretations aligned with their experiences. Concurrently, inter coder reliability checks on 20% of the dataset yielded a Cohen's kappa coefficient of 0.82, exceeding the conventional threshold of 0.75 and demonstrating robust reliability. Data saturation was confirmed when analysis of the final two interviews yielded no substantively new themes.

Research quality adhered to Lincoln and Guba's (1985) criteria. Credibility was achieved through prolonged engagement (August to October 2025), triangulation, and member checking. Transferability was ensured by providing a thick description of the context and participants. Dependability and confirmability were established through a detailed audit trail and reflexive journaling. Ethically, the study complied with the Declaration of Helsinki, obtaining informed consent from all participants and ensuring anonymity through codes (e.g., "Urban Ecommerce 02"). The protocol underwent rigorous review by the relevant institutional ethics committee prior to data collection.

RESULTS AND DISCUSSION

Participant Profile and Data Collection Context

The study engaged 28 participants (18 business owners, 10 senior managers; mean age 42 years, mean tenure 7.2 years) representing MSMEs across Yogyakarta, purposively selected to reflect diverse sectoral and operational backgrounds.

Table 1. Participant Demographics and Organizational Characteristics (N=28)

Characteristic	Category	Frequency	Percentage
Position	Business Owners	18	64.3%
	Senior Managers	10	35.7%
Business Sector	Ecommerce	8	28.6%
	Traditional Manufacturing	6	21.4%
	Food & Beverage	7	25.0%
	Digital Services	7	25.0%
Enterprise Scale	Small Enterprise (IDR 50-500M)	20	71.4%
	Micro/Medium Enterprise	8	28.6%
Geographic Location	Urban Centres	12	42.9%
	Semi Urban Areas	10	35.7%

	Rural Locations	6	21.4%
Digital Maturity Level	Advanced Digitalized	9	32.1%
	Moderately Digitalized	12	42.9%
	Low Digitalized	7	25.0%
Prior AI Experience	No Prior Experience	17	60.7%
	Minimal Awareness	7	25.0%
	Moderate Experience	4	14.3%

Source : Analysis of Interview and Demographic Data (2025)

The sample composition reflects strategic distribution across multiple analytical dimensions. The cohort captured sectoral heterogeneity (ecommerce 28.6%, traditional manufacturing 21.4%, food and beverage 25.0%, digital services 25.0%), geographic gradient (urban 42.9%, semi urban 35.7%, rural 21.4%), and digital maturity variation (advanced 32.1%, moderate 42.9%, low 25.0%). Notably, 60.7% of participants reported no prior AI experience, establishing a representative sample of low adoption MSMEs typical of developing economies.

Data saturation was reached at the 24th interview. Three focus group discussions involving 24 participants (85.7%) further triangulated findings, with purposive sampling maintaining proportional representation across analytical dimensions.

Gap between Sensing and Seizing: Thematic Findings

Thematic analysis reveals that the adoption blockage does not stem from lack of awareness but from the systematic failure to convert sensing into strategic action. Sensing capability is widespread among Indonesian MSMEs, yet remains constrained by cognitive mismatches and weak institutional support, preventing the development of seizing capability.

Theme 1. Sensing Capability as High Awareness, Limited Strategic Perception

Sensing Occurs Primarily Through Informal Peer Networks

AI awareness among MSMEs is mediated primarily by informal peer networks rather than formal institutional channels, indicating a structural void in the advisory ecosystem. As Table 2 shows, 57% of participants (n=16) identified peer referrals as their primary AI knowledge source, significantly surpassing government initiatives (21%) and training programs (7%). This pattern, illustrated by participant Urban Ecommerce 02 ("I first learned about AI from a friend in a similar business"), reveals that while sensing is high, its quality remains limited. Dependence on anecdotal information rather than structured curricula creates heterogeneity in how MSMEs interpret AI relevance and perpetuates incomplete information through echo chambers (Rogers, 2003).

Table 2. Sources of AI Awareness and Sensing Capabilities among MSMEs (n=28)

Source of Awareness	Frequency (%)	Strategic Implication
Peer Networks	57% (n=16)	Primary informal knowledge conduit; high influence but limited depth
Government Initiatives	21% (n=6)	Formal awareness channel; viewed as legitimate but less engaging than peer validation.
Formal Training Programs	7% (n=2)	Structured learning; limited impact due to accessibility barriers and perceived complexity.

Other / Self Discovery	15% (n=4)	Sporadic individual research via digital channels.

Source : Authors' analysis (2025)

Cognitive Mismatch: Awareness without Perceived Relevance

Despite widespread awareness, a critical cognitive mismatch persists between general AI knowledge and perceived business relevance. A substantial majority (71%, n=20) describe AI as designed "for large companies" or "for tech specialists." As one rural food and beverage owner stated, "I thought AI meant robots. I didn't see how it could apply to selling food in a small shop" (Rural F&B 05). This reflects inaccurate cognitive schemas regarding AI suitability for small scale operations. Significantly, when researchers explained tangible applications such as chatbots, perceived relevance increased markedly, indicating the barrier is rooted in knowledge perception gaps rather than fundamental technological resistance.

This "cognitive and institutional ceiling" reveals that sensing reaches a saturation point but cannot translate into strategic action due to inaccurate mental models. This extends institutional theory by demonstrating that cognitive pillars can create adoption barriers independent of regulatory or normative constraints. The implication is critical: awareness campaigns alone are insufficient; targeted knowledge translation demonstrating context specific applications is essential.

Sensemaking Relies on Cognitive Heuristics

When evaluating AI adoption, participants relied on cognitive heuristics rather than systematic analysis. Less experienced MSMEs adopted imitation heuristics ("if many use it, it must be valuable"), while more experienced ones attempted structured reasoning but faced opacity of AI technologies. As one participant noted, "With so many variables unknown, we couldn't reach a confident number" (Urban Ecommerce 04). This aligns with bounded rationality theory (Simon, 1957), revealing that decision making under uncertainty is adaptive but problematic when heuristics themselves are based on incomplete information. This creates a reinforcing cycle where cognitive shortcuts perpetuate low adoption rates despite favorable economic conditions.

Theme 2. Seizing Capability: The Critical Blockage

Absorptive Capacity Limitations Create Financial Uncertainty

While cost is universally cited as a barrier, the deeper constraint lies in uncertainty regarding financial returns. Although 86% of participants expressed willingness to invest if returns were guaranteed, only 11% (n=3) possessed sufficient technical capability to calculate ROI. As one manufacturing owner stated, "We have the money to invest. What we don't have is clarity about what we're investing in" (Urban Manufacturing 01). This reveals what we term a "valuation trap": the inability to quantify value creates investment paralysis regardless of available capital.

This finding extends Peretz-Andersson et al. (2024) by demonstrating that weak absorptive capacity amplifies perceived financial risk, preventing owners from distinguishing between speculative hype and feasible applications. Consequently, AI investments are postponed even when capital is available, reinforcing conservative bias toward familiar low complexity solutions and widening the sensing and seizing gap.

Organizational Readiness: Skills and Malleable Resistance

While 89% of participants reported severe workforce digital literacy limitations, psychological resistance proved more malleable. Job displacement anxiety dropped significantly (46% to 32%) after AI was reframed as task automation rather than worker replacement. As one participant reflected, "I thought AI would replace my workers, but now I understand it can help them work more efficiently without losing their jobs" (Semi Urban Manufacturing 07).

Table 3. Organizational Barriers to Seizing Capability and Intervention Outcomes

Organizational Barrier	Prevalence (n=28)	Nature of Barrier	Intervention & Outcome
Workforce Digital Literacy Gap	High (89%, n=25)	Structural; technical skill deficit	Persisting challenge; raises concerns about system maintenance and sustainability in the long term.
Anxiety about Job Displacement	Moderate (46%, n=13) → Dropped to 32% (n=9)	Psychological; cognitive misconception	Malleable; resistance softened after reframing AI as task automation rather than worker replacement.

Source : Authors' analysis (2025)

This demonstrates that opposition is driven more by cognitive misconceptions than fundamental technological resistance. Reframing and dialogue functioned as inexpensive yet powerful interventions, indicating that normative and cognitive barriers (Scott, 2008) are more malleable than regulatory barriers and addressable through targeted communication without substantial investment. Internal champions and participatory change processes can unlock seizing capability even in firms with modest digital baselines.

Risk Perception Rooted in Knowledge Gaps

Data security emerged as the primary adoption barrier (82%, n=23), yet participants' concerns were typically vague and driven by anxiety rather than informed by technical risk assessment. When researchers explained basic governance and security practices, concerns shifted from abstract fears to concrete inquiries about vendor reliability and implementation capacity. In contrast, ethical concerns regarding algorithmic bias remained marginal (18%), overshadowed by business continuity priorities.

Table 4. Nature of Perceived Risks and Impact of Knowledge Intervention

Perceived Risk Category	Prevalence (n=28)	Initial Nature of Concern	Intervention & Outcome
Data Security	Dominant (82%, n=23)	Vague and abstract; grounded in general anxiety rather than specific threat models.	Shifted to Concrete Inquiry. Concerns moved toward implementation capacity, vendor reliability, and technical mitigations.
Ethical & Algorithmic Bias	Minor (18%, n=5)	Low priority; overshadowed by immediate business continuity concerns.	Remained secondary; viewed as less critical for immediate organizational survival.

Source : Authors' analysis (2025)

This pattern demonstrates that MSME risk perception varies by context and can be modified. In the absence of accessible advisory services, owners tend to overestimate security risks while underestimating feasible mitigations. Theoretically, this extends prospect theory (Kahneman & Tversky, 1979) by showing that loss aversion regarding data security reflects information deficits rather than inherent preferences, and therefore can be addressed through targeted communication using concrete examples.

Theme 3. Transforming Capability: Incremental Adoption Patterns

Coevolution through Incremental Trials

The eight early adopters (29%) demonstrate that transformation occurs through incremental adoption targeting specific tasks rather than sweeping strategic overhaul. As Table 5 shows, these firms followed opportunistic approaches grounded in trial and error, targeting reconfiguration at the process level including data cleaning and workflow redesign, without radically altering core business models. One early adopter illustrated this: "We didn't do a master plan. We tried a simple chatbot solution. Low cost, limited downside. If it worked, we'd expand; if not, we'd learn and try something else" (Urban Ecommerce 04).

This pattern aligns with Teece's (2007) concept of coevolution, whereby capabilities develop gradually through operational pressures rather than through design imposed from above. In resource constrained environments, incremental experimentation reduces both financial risk and cognitive burden, enabling learning through practice. However, without ecosystem support, trial and error learning can become inefficient, resulting in abandoned experiments and sunk costs.

Table 5. Characteristics of Transforming Capability among Early Adopters (n=8)

Dimension of Transformation	Key Pattern	Evidence/Implication
Adoption Strategy	Incremental and opportunistic; trial and error rather than formal road mapping.	Allows MSMEs to manage risk while building familiarity with technology.
Scope of Change	Reconfiguration at the process level; focus on data cleaning and workflow redesign.	Core business models unchanged; consistent with coevolution
External Enablers	High dependency on external ecosystem support.	87.5% of adopters had external partners compared to 5% of nonadopters.
Internal Drivers	Reliance on "digital champions"; typical younger staff or external consultants.	Essential for bridging gap between technical complexity and business application.

Source : Authors' analysis (2025)

The Ecosystem as a Critical Enabler

Transforming capability exhibits strong structural dependence on external support. A stark contrast emerges: 87.5% of early adopters engaged external technical partnerships compared to only 5% of nonadopters. This indicates that transforming capability is not merely an internal organizational attribute but an emergent property of firm level initiative interacting with the ecosystem.

Digital champions, often younger staff or hired consultants, served as catalytic bridges between vendor offerings and business application. As one ecommerce owner noted, "My nephew has studied programming. He helped us understand the chatbot vendor's proposal and helped train the team. Without him, we would have given up" (Urban Ecommerce 04). Nonadopters, by contrast, operated in relative isolation, reflecting broader institutional voids: the scarcity of affordable, MSME focused implementation partners and limited government subsidized technical support.

This finding extends dynamic capabilities theory by demonstrating that in developing economies, capabilities are coproduced through ecosystem interactions rather than developed autonomously within firm boundaries. Policy interventions must therefore strengthen not only firm level capacity but also the intermediary layer of technical partners, consultants, and support organizations that enable technology transfer.

Theme 4. Institutional Barriers Explaining the Gap

The persistence of the sensing and seizinggap despite policy support reflects institutional impediments across Scott's (2008) three pillars: regulatory mechanisms, normative pressures, and cognitive schemas. These collectively constrain the development and deployment of dynamic capabilities among Indonesian MSMEs.

Regulatory Pillar: Infrastructure Inequality and Uncertainty

A marked digital divide across Yogyakarta produces systematic technological readiness inequalities. As Table 6 shows, urban MSMEs benefit from reliable high speed connectivity (20+ Mbps) enabling cloud based AI applications, while rural firms operate with constrained bandwidth (1-5 Mbps), creating structural exclusion independent of firm level capability. This infrastructural asymmetry functions as a "hard constraint" where inability to adopt AI stems from deficient digital utility rather than lack of desire or capability.

Table 6. Institutional Barriers: Infrastructure Inequality and Regulatory Uncertainty

Institutional Dimension	Segment/Metric	Finding/Status	Operational Implication
Digital Infrastructure (The Digital Divide)	Urban MSMEs	*Reliable High Speed (20+ Mbps)*	Enables cloud applications and real time processing
	Rural MSMEs	Constrained (1–5 Mbps)	Severely limits AI platform access; structural exclusion
Regulatory Environment	Knowledge Gap	93% (n=26) Lack Awareness	High uncertainty regarding compliance and legal exposure

Source : Authors' analysis (2025)

Beyond infrastructure, 93% of participants reported no clear knowledge of AI regulations, data privacy standards, or cybersecurity requirements, creating regulatory uncertainty. The absence of accessible guidance on data governance leaves MSMEs unsure about compliance obligations, amplifying perceived risk and discouraging experimentation. This demonstrates that regulatory institutions constrain adoption through omission as well as commission—a form of institutional void where lack of clarity functions as a barrier to action. Governments must provide not only enabling regulations but also accessible guidance systems.

Normative Pillar: Weak Social Pressure and Cultural Tension

Normative pressure for AI adoption remains weak, with only 21% of participants (n=6) citing competitive pressure or industry norms as motivators, reflecting the nascent nature of AI discourse in developing economies. However, cultural tension between "craftsmanship" and "automation" proved addressable. Resistance grounded in fear of losing the "human touch" shifted markedly when AI was reframed as a tool enhancing artisanal precision rather than threatening tradition. Unlike rigid infrastructural gaps, normative barriers are malleable and responsive to strategic messaging and cultural bridging.

Cognitive Pillar: Inaccurate Schemas and Mental Models

Inaccurate mental models were pervasive, with 71% of participants (n=20) equating AI exclusively with physical robots, constraining recognition of software based applications like recommendation engines. These cognitive distortions produce divergent outcomes: unrealistic expectations of transformative impact or dismissal of AI as irrelevant to traditional businesses. Significantly, an "Operational Override" pattern emerged where several firms adopted basic AI tools despite limited conceptual understanding because immediate operational pressures (cost reduction, service acceleration) overrode cognitive gaps. This indicates that cognitive institutions strongly influence deliberative planning but may be bypassed under pragmatic operational demands, introducing the concept of "context contingent institutional influence.

Table 7. Summary of Institutional Pillars Affecting AI Adoption

Institutional Pillar	Key Barrier	Natural of Barrier	Strategic Implication
Regulatory	Infrastructure Inequality and Legal Uncertainty	Structural (Hard)	Difficult for individual firms to overcome without external policy intervention.
Normative	Weak Social Pressure; Cultural tension ("Craftsmanship" vs "Automation")	Cultural (Malleable)	Responsive to reframing and strategic communication; easier to address than structural gaps.
Cognitive	Inaccurate Schemas and Mental Models	Cognitive (Context dependent)	Malleable through targeted intervention and knowledge translation

Source : Authors' analysis (2025)

Synthesis: Institutional Voids and Capability Development

The "gap between sensing and seizing" represents a structural fracture where institutional voids prevent widespread awareness from maturing into strategic execution. Sensing capability, while prevalent (71% aware of AI), is constrained by cognitive mismatches and informal diffusion through peer networks (57%), creating echo chambers of incomplete information. Seizing capability reveals a "valuation trap": 86% express investment willingness but only 11% can calculate ROI, creating investment paralysis as decision making reverts to heuristics. Transforming capability demonstrates ecosystem dependence, with 87.5% of early adopters engaging external partners versus 5% of nonadopters, indicating that capabilities are "imported" through boundary spanners rather than developed autonomously.

These capability constraints are reinforced by institutional barriers: regulatory barriers create hard constraints (infrastructure inequality, legal uncertainty), normative barriers reflect nascent AI discourse, and cognitive barriers restrict strategic imagination. This introduces the concept of "institutionally constrained capability development," extending both Dynamic Capabilities Theory and Institutional Theory by demonstrating their interdependence in developing economies. The digital paradox represents a rational response to institutional voids where adoption risks are amplified by regulatory uncertainty and inadequate technical scaffolding.

CONCLUSIONS

This study elucidates the "digital paradox" characterizing Indonesian MSMEs: high digital awareness coexisting with stagnant AI adoption. Integrating Dynamic Capabilities Theory and Institutional Theory, we identify the gap between sensing and seizing as the central mechanism. The findings reveal that this gap reflects not insufficient entrepreneurial will but a structural condition wherein MSMEs possess adequate sensing capabilities yet systematically lack seizing capabilities—absorptive capacity and strategic confidence—necessary to translate awareness into investment. This bottleneck is exacerbated by infrastructural inequality, regulatory uncertainty, and weak normative pressure.

Theoretically, our findings challenge linear adoption models derived from developed economies. In developing economies, sensing capabilities reach a "cognitive and institutional ceiling" where awareness no longer scales into adoption because environmental constraints prevent conversion of opportunity recognition into strategic action. Consequently, AI adoption manifests as incremental optimization targeting specific tasks and contingent upon external ecosystem support and digital champions. Technology adoption emerges as an embedded process shaped by contextual institutional structures rather than as an isolated phenomenon occurring within firm boundaries, thereby refining understanding of how dynamic capabilities develop in institutionally constrained environments.

For sustainable AI adoption among Indonesian MSMEs, three stakeholder groups must act in concert. MSMEs should shift from comprehensive transformation roadmaps toward incremental pilots with low cost that enable organic absorptive capacity building. Policymakers must prioritize structural enablers including technical training tailored to context, regulatory clarity on data governance, and infrastructure investment to reduce the digital divide between urban and rural areas. Technology providers should develop affordable solutions tailored to MSMEs, incorporating ongoing technical support and user education. This integrative approach, combining firm level pragmatism, policy level structural support, and ecosystem level scaffolding, is essential for bridging the sensing and seizinggap.

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