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Exploring artificial intelligence adoption challenges: bridging the technology gap for marketing advancements

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ABSTRACT

Artificial intelligence (AI) holds immense potential to enhance marketing strategies for micro, small, and medium enterprises (MSMEs). However, significant barriers, including financial constraints, limited digital literacy, and inadequate government support, hinder its widespread adoption. This study compares AI adoption challenges across two Indonesian MSME ecosystems; tourism-oriented Bali and agrarian Garut using the diffusion of innovation (DOI) lens and complementary model—technology organization environment (TOE), technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT). The findings reveal that MSMEs in Bali exhibit characteristics of "early adopters" and "early majority," driven by the demands of the tourism sector. In contrast, MSMEs in Garut align more with "late majority" and "laggard" profiles, constrained by infrastructural and resource limitations. By mapping these regional disparities onto the DOI curve, this study provides actionable insights for policymakers. It advocates for the development of ecosystem-aware, tailored strategies to bridge the digital divide and foster inclusive digital transformation, enabling MSMEs across diverse regions to leverage AI for a sustainable competitive advantage.

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1. INTRODUCTION

In the digital age, artificial intelligence (AI) has emerged as a transformative force across industries, particularly in marketing [1]. AI-driven tools such as predictive analytics, customer segmentation, and personalized content recommendations enable businesses to engage customers more effectively, optimize marketing strategies, and enhance brand loyalty [2]–[4]. AI has emerged as a profoundly transformative force, reshaping business strategies [3] and creating new frontiers for competitive advantage [5]. For marketing, this transformation is particularly scute. AI-powered tools, from predictive analytics to machine learning algorithms, enable businesses to process and interpret vast datasets [6] yielding deep insights into consumer behavior, market trends, and operational efficiencies [7]. This capability allows for the development of hyper-personalized marketing campaigns, dynamic pricing models, and automated customer service solutions that enhance customer engagement and drive loyalty [8]. The strategic implementation of AI is no longer a futuristic concept but a present-day imperative for firms seeking to optimize their marketing return on investment (ROI) and maintain relevance in saturated markets [9]. Recent studies confirm that effective digital marketing strategies, increasingly powered by AI, are critical for attracting and retaining customers, thereby directly contributing to revenue growth and business sustainability in diverse economic contexts, including those in Indonesia [5], [10].

Despite the clear strategic benefits, the adoption of AI is not uniform across the business landscape. A significant digital divide persists between large, well-resourced enterprises and micro, small, and medium enterprises (MSMEs) [11]. While multinational corporations actively harness AI to fortify their market positions, MSMEs—which form the backbone of most global economies—often lag, particularly in developing nations [12], [13]. This disparity is driven by a confluence of well-documented barriers. MSMEs frequently grapple with severe financial constraints that render the high initial cost of AI technologies prohibitive. Furthermore, they often suffer from limited digital literacy among both owners and employees, inadequate digital infrastructure, and a lack of access to the specialized skills required to implement and manage AI systems effectively [14]. This adoption gap poses a significant threat to the long-term competitiveness and survival of MSMEs in an increasingly AI-driven world [12].

While the general barriers to technology adoption among MSMEs are well-established in the literature [12], [13], there is a notable gap in understanding how these factors manifest and interact within different regional economic ecosystems [15]. Existing research often treats MSMEs as a monolithic group, overlooking the profound influence of local context on their innovative capacity [16]. This study aims to address this gap by providing a distinct theoretical contribution. It applies and extends Rogers *et al.* [17] seminal diffusion of innovation (DOI) framework to empirically analyze and compare the factors shaping AI marketing adoption [6], [17] in two diametrically contrasting Indonesian contexts: a vibrant, tourism-driven economy (Bali) and a traditional, agrarian-based economy (Garut). According to the DOI theory, MSME adoption of AI technology is influenced by factors such as complexity, compatibility, and observability [16], [18]. By examining these divergent cases through the lens of DOI theory, this study offers a nuanced, context-sensitive understanding of how regional economic structures, institutional support systems, and local culture mediate the process of technology diffusion. This moves beyond a simple contextual contribution to demonstrate the analytical power of the DOI framework in explaining regional disparities in technological advancement [14], [19]. On their research added that businesses with greater technological readiness are more inclined to adopt AI, suggesting that well-targeted educational and financial initiatives could drive adoption in regions like Garut. Additionally, the research in [11], [20], [21] highlight the importance of institutional and governmental support for AI adoption. To achieve this objective, this study is guided by the following research questions: i) How do challenges related to digital literacy, government support, and financial constraints in AI marketing adoption differ between MSMEs in Bali (tourism-based) and Garut (agrarian-based)? and ii) How do these factors position the MSMEs in each region along the adopter categories of the DOI curve?

To answer these questions, this article is structured as follows. The subsequent section provides a comprehensive literature review of the DOI theory, the strategic application of AI in marketing, and digital innovation management. Section 3 details the comparative case study methodology employed for this research. Section 4 presents the empirical results and provides an in-depth discussion, interpreting the findings through the DOI framework and exploring their implications. The discussion concludes with an acknowledgment of the study's limitations, suggestions for future research, and a final summary of its contributions. Our contribution is twofold. First, we offer an ecosystem-aware DOI positioning that contrasts regional MSME profiles rather than treating MSMEs as a single category. Second, we integrate technology organization environment (TOE) and unified theory of acceptance and use of technology (UTAUT) to explain why positions differ; linking infrastructure and organizational readiness (TOE) with perceived usefulness/effort and social influence (UTAUT).

2. LITERATURE REVIEW

2.1. The diffusion of innovation theory: core concepts and adopter categories

DOI explains where adopters sit along an innovation curve; technology acceptance model (TAM)/UTAUT explain why users adopt (perceived usefulness/effort, social influence, facilitating conditions); TOE explains what firm-level and environmental enablers constrain adoption. The DOI theory, developed by Rogers [22], is one of the most established and widely cited theories for understanding how new ideas, practices, and technologies spread within a social system. The theory posits that the diffusion process is influenced by four key elements: the innovation itself, the communication channels through which information about it is transmitted, the time it takes for adoption to occur, and the nature of the social system in which the diffusion takes place [22], [23].

A central component of the theory is the set of five perceived attributes of an innovation that influence an individual's or organization's decision to adopt it. These are [22], [24]: i) relative advantage: the degree to which an innovation is perceived as being better than the idea it supersedes; ii) compatibility: the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters; iii) complexity: the degree to which an innovation is perceived as difficult to understand and use. Simpler innovations are adopted more rapidly; iv) trialability: the degree to which an innovation may be experimented with on a limited basis. Innovations that can be tried out are generally adopted more quickly; and v) observability: the degree to which the results of an innovation are visible to others. The easier it is for individuals to see the results of an innovation, the more likely they are to adopt it.

Based on an individual's or organization's propensity to adopt innovations, Rogers classifies members of a social system into five adopter categories, which typically follow a normal distribution curve over time. These categories, summarized in Table 1, provide a powerful framework for segmenting a population and understanding the dynamics of technology adoption. We apply DOI to locate regional adoption positions and use TOE/UTAUT to interpret the organizational and behavioral mechanisms behind those differences. This theoretical framework is particularly relevant for this study, as it provides the analytical lens to not only identify barriers to AI adoption but also to classify and compare the developmental stages of MSMEs in different economic contexts.

Table 1. Core concepts of DOI theory

Adopter category	Key characteristics	Approx. % of population
Innovators	Venturesome, risk-takers, high social status, access to financial resources. Willing to adopt technologies that may fail.	2.5
Early adopters	Respected opinion leaders, high social status, well-educated, more judicious in adoption choices than innovators.	13.5
Early majority	Deliberate, adopt new ideas just before the average member. Have contact with early adopters but rarely hold leadership positions.	34
Late majority	Skeptical, adopt an innovation only after a majority of society has done so. Motivated by peer pressure and economic necessity.	34
Laggards	Traditional, last to adopt an innovation. Averse to change, focused on past traditions, and have the lowest social and financial status.	16

2.2. Artificial intelligence in marketing: a strategic linkage

The integration of AI into marketing is not merely an incremental improvement but a paradigm shift that redefines strategic capabilities [3]. AI technologies empower marketers to move beyond traditional, broad-stroke campaigns toward highly precise, data-driven strategies [25]. Key applications that establish this strategic linkage include customer segmentation, personalization, and churn prediction [8], [26].

i) Customer segmentation [27]: AI algorithms can analyze vast and complex datasets, including demographics, purchase history, and online behavior. This analysis identifies distinct customer segments with a level of granularity previously unattainable. Unsupervised learning techniques can uncover latent patterns and clusters in consumer data, allowing businesses to tailor marketing messages and product offerings to highly specific groups.
ii) Personalization at scale [26]: AI is the engine behind hyper-personalization, which is crucial for customer engagement and loyalty in the digital age [25]. By leveraging machine learning, businesses can deliver real-time, individualized content, product recommendations, and offers across multiple touchpoints [28]. Systems like Amazon's recommendation engine and Netflix's content suggestion algorithm are prime examples of AI-driven personalization that significantly impact revenue and customer retention [29].
iii) Predictive analytics and churn prediction: predictive models powered by AI enable businesses to forecast future customer behavior, including the likelihood of churn (i.e., customers ceasing their relationship with a company) [26]. By identifying customers at risk of leaving, companies can proactively intervene with targeted retention campaigns, special offers, or improved customer service, thereby reducing attrition and preserving revenue streams [27].

Collectively, these AI applications transform marketing from reactive to proactive function, enabling businesses to anticipate customer needs, optimize resource allocation, and build a sustainable competitive advantage.

2.3. Digital innovation management and micro, small, and medium enterprises transformation

The adoption of AI by MSMEs should not be viewed as an isolated technological upgrade but as part of a broader and more complex process of digital innovation management. As Nambisan *et al.* [30] argue, the pervasive digitization of the economy has fundamentally upended traditional theories of innovation management. Digital innovation is defined as "the creation of (and consequent change in) market offerings, business processes, or models that result from the use of digital technology".

This perspective challenges several key assumptions. First, innovation is no longer a well-bounded phenomenon focused on a fixed product; digital technologies make products and services more fluid, dynamic, and interconnected [31]. Second, the agency of innovation is no longer centralized within the firm but becomes distributed across a network of actors, including customers, partners, and external developers (i.e., open innovation) [32]. For an MSME, therefore, adopting AI is not simply about acquiring a new tool. It necessitates a fundamental re-evaluation and potential reconfiguration of its entire business model, its value proposition, its customer relationships, and its internal capabilities [9]. This process is a socio-technical one, where technology, people, processes, and strategy must co-evolve. This insight elevates the research problem from a simple question of "barriers to adoption" to a more profound exploration of "challenges in digital transformation," providing a richer theoretical context for analyzing the struggles of MSMEs in Bali and Garut.

2.4. Complementary adoption models (TOE, TAM) and DOI's unique role

Beyond DOI, prior work highlights complementary lenses, the TOE framework (technology readiness, organizational resources, and environmental pressure), the TAM (perceived usefulness/ease of use). In our context, DOI remains central because it explains where firms sit along the adopter categories and why diffusion stalls (e.g., low observability in Garut, high compatibility in Bali's tourism). We therefore integrate TOE/TAM constructs into the codebook (e.g., facilitating conditions, government; effort expectancy and perceived complexity) while using DOI to map regional positions on the adoption curve. This integrated framing sharpens explanations for ecosystem-specific gaps and policy levers. Recent AI in marketing tools extend the literature: generative AI for copy/images, customer relationship management (CRM) automation and chatbots for service, and prediction engines for targeting and churn. These tools raise capability requirements (skills, data) and governance issues (privacy and vendor lock-in), making TOE/UTAUT variables salient alongside DOI categories.

3. METHOD

3.1. Research design

This study adopted a qualitative case study design to investigate the challenges and opportunities surrounding AI adoption for marketing within MSMEs. According to Yin [33], a case study is an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident. Using DOI theory as a guiding framework [20], the study aims to understand how MSMEs in distinct regions progress through stages of technology adoption and the factors influencing their readiness for AI. A qualitative approach was chosen to capture in-depth, context-specific insights from key informants [10], [34]. This design aligns with existing literature emphasizing the value of qualitative inquiry in exploring nuanced, region-specific challenges of technology adoption [10]. Given the complex socio-economic and infrastructural factors at play, a case study design provides the flexibility to examine these dimensions in detail, offering actionable insights relevant to policymakers and MSME stakeholders [35].

3.2. Case selection and informants

A purposive sampling technique was employed to select the two cases, Garut and Bali, and the informants within them. The cases were chosen for their contrasting economic structures: Garut represents a traditional, agrarian-based economy, while Bali represents a modern, tourism-driven service economy. This contrast provides a natural experiment for examining how local context influences technology adoption.

Within each case, informants were selected based on their direct involvement and knowledge of MSME development and digital transformation. This included government officials from relevant agencies (e.g., the cooperative and UMKM service division) and MSME owners from key local industries (e.g., creative industries and culinary businesses in Garut; tourism and non-tourism sectors in Bali). This purposive strategy ensured that the data collected would provide diverse and expert perspectives, reflect different levels of digital readiness and capture the multifaceted nature of the adoption challenge, consistent with the study's exploratory goals. We interviewed 10 informants across two regions; 8 MSME owners (tourism and non-tourism in Bali; culinary, creative, and tech-novice in Garut) and 2 government officials (Denpasar City and Garut Regency Cooperative/UMKM agencies). Purposive sampling targeted information-rich cases directly involved in MSME digitization. Roles, sectors, and region were recorded as case attributes in NVivo.

3.3. Data collection: the semi-structured interview

The primary method of data collection was semi-structured interviews and contemporaneous field notes conducted with the selected informants in both Garut and Bali. The guide covered three main areas: i) digital literacy and awareness of AI, ii) perceived government and infrastructural support, and iii) financial barriers and opportunities for technology investment. Interviews typically lasted between 45 and 60 minutes, and with permission, were audio-recorded and transcribed verbatim to ensure data accuracy. This was supplemented by observational data from community service events in Garut. Where full audio was not feasible, we reconstructed short transcript excerpts from field notes immediately after the visit and flagged them as reconstructed in NVivo. Government briefings were documented as field notes with verbatim fragments where available.

3.4. Data analysis: a six-phase thematic approach

The transcribed interview data and observation notes were analyzed using thematic analysis to systematically identify, analyze, and report patterns (themes) relevant to the research questions. To enhance the rigor of this process, the analysis was supported by the use of NVivo qualitative data analysis software [36]. The analytical approach was guided by the seminal phase framework developed by Braun and Clarke [37]. We combined deductive and inductive coding in NVivo to support a transparent, replicable thematic analysis. The codebook was seeded from DOI and complementary adoption constructs (TOE, TAM, and UTAUT) and then refined inductively from the corpus: i) codebook and structure: parent themes comprised: AI_Literacy_and_Awareness, Financial_Constraints, GovSupport_and_Infrastructure. Child nodes included perceived_complexity, program_limitations, infrastructure/connectivity, and high_costs_and_ROI. This structure connected micro-level constraints to ecosystem differences; ii) coding steps and stability: coding proceeded in two cycles. Because the study used a single-coder design, we conducted a stability check by re-coding a 20% subset at a separate time point. Decisions were consistent with no new major nodes emerged, only minor label refinements. An audit trail and analytic memos captured all decision points; iii) saturation and rigor: saturation was assessed during the final two interviews: new node emergence ≤5% and no new properties for dominant themes; a decision memo was archived; and iv) reporting artifacts: to quantify and compare theme prevalence, we exported data from NVivo, including coding summaries (files coded, references, and coverage %), a matrix coding table (themes×region), and quotes. These outputs are presented in the results section (NVivo summary tables and the DOI curve figure) and described in the results narrative.

3.5. Ethical considerations

Ethical standards were rigorously upheld throughout the research process. Ethical approval was secured prior to data collection, and all informants provided informed consent after being briefed on the study's objectives and confidentiality assurances. Interviews were anonymized to protect informant identities, and informants were granted the right to withdraw at any stage. Sensitive information, such as challenges related to funding and specific government support gaps, was managed with discretion, safeguarding data integrity and maintaining confidentiality.

4. RESULTS AND DISCUSSION

4.1. Results: key findings from the comparative cases

Three cross-cutting themes structure the findings: AI literacy and awareness, financial constraints, and government support and infrastructure are the key themes. We first summarize regional patterns in Table 2. We then contextualize them with representative quotes and NVivo metrics (files coded, references, and percentage coverage), followed by a Bali–Garut matrix comparison.

Table 2. Technological literacy and marketing awareness of AI in MSMEs

Region	Digital literacy for AI in marketing	Awareness of AI benefits in marketing	Specific challenges encountered
Garut	Low; most MSMEs rely on basic digital tools like WhatsApp and Facebook for marketing.	Minimal; AI is often viewed as irrelevant or inaccessible, especially for traditional sectors.	High complexity of AI tools, lack of resources to learn new technologies.
Bali	Moderate; MSMEs, particularly in tourism, exhibit familiarity with digital marketing tools	Growing; tourism-based MSMEs see AI's role in customer engagement but lack access to advanced tools.	Difficulty scaling from basic digital tools to advanced AI-driven applications.

To ground the table in informants' voices, the excerpts illustrate how MSMEs and officials described each theme, quotes were retrieved from NVivo node references.

> Bali MSME owner (tourism)*: "We answer the same questions again and again. If a bot can handle it quickly, that helps."*
> Bali government official: *"Training is moving from generic social-media tips to hands-on content workflows."*
> Garut MSME owner (tech-novice): *"The tools look complicated; WhatsApp is enough for our customers."*
> Garut MSME owner (culinary): *"I follow online tutorials, but I still need step-by-step onboarding."*

Table 3's institutional context aligns with how officials and MSMEs describe support and constraints.

> Bali Government official: *"Programs must be vendor-neutral and avoid lock-in."*
> Bali MSME owner: *"Workshops are useful, but follow-up mentoring is limited."*

Garut MSME owner: *"Connectivity drops on busy market days; online orders become risky."*
Financial constraints in AI marketing adoption are summarized in Table 4.

Table 3. Government support and infrastructure for AI-driven marketing

Region	Government initiatives in AI for marketing	Infrastructure for AI in marketing	Key limitations in government support
Garut	Minimal AI-specific programs; general digital marketing training but lacks continuity	Limited access to high-speed internet and digital resources.	Training lacks follow-up support: most government programs are reactive rather than proactive.
Bali	Targeted digital marketing training programs for tourism sectors; collaborations with banks	Varies by sector; tourism sector has better infrastructure access than non-tourism.	Programs are sector-specific; few initiatives for MSMEs outside tourism.

Table 4. Financial constraints in AI marketing adoption

Region	Financial aid availability for marketing AI	Financial challenges for MSMEs in AI marketing	Example cases of financial constraints
Garut	Limited; general funds are available but not allocated specifically for digital or AI investments	High costs are prohibitive; MSMEs unable to justify AI expenses in traditional budgets	MSMEs perceive AI as a luxury, with limited justification for investment.
Bali	Some low-interest loans available for tourism-focused MSMEs; limited support for non-tourism	AI tools are costly; non-tourism MSMEs lack financial support	Poison Street Coffee received training but lacks funds for AI tools.

Cost sensitivity and perceived complexity are decisive in both regions, but they bind more tightly in Garut. MSMEs describe thin margins, subscription anxiety, and fear of disrupting existing workflows. Bali MSMEs are more open to low-risk pilots provided there is clear early ROI and minimal configuration burden.

Garut MSME owner (culinary): *"We can't justify the cost until we see results nearby."*
Garut MSME owner (tech novice): *"Small margins—subscriptions worry us."*
Bali MSME owner (retail): *"Low-risk pilots are fine, but we need quick ROI signals."*
Bali MSME owner (tourism): *"I'd adopt if configuration is simple and won't break our booking flow."*

To make the thematic claims transparent, we report NVivo metrics per theme and region. Table 5 summarizes the number of references, files coded, and coverage (%) for each theme in Bali and Garut. Table 6 then presents a compact theme×region matrix of reference counts for quick comparison. The R1 metrics indicate denser discussion of AI literacy and government support/infrastructure in Bali, while financial constraints are discussed at comparable levels across regions; files-coded counts confirm patterns are not driven by document length.

Table 5. NVivo coding summary by theme and region (references, files coded, coverage %)

Theme	Bali refs	Garut refs	Total refs	Bali_files coded	Garut_files coded	Total_files coded	Bali share (%)	Garut share_(%)
AI_Literacy_and Awareness	13	16	29	5	5	10	44.8	55.2
Financial Constraints	8	8	16	5	5	10	50	50
GovSupport_and_Infrastructure	15	11	26	5	3	8	57.7	42.3

Table 6. Matrix coding (theme×region)

Theme	Region	
	Bali (refs)	Garut (refs)
AI_Literacy_and_Awareness	13	16
Financial_Constraints	8	8
GovSupport_and_Infrastructure	15	11

Matrix counts show AI literacy/awareness is mentioned slightly more in Garut (16 vs. 13), while government support and infrastructure are discussed more in Bali (15 vs. 11); financial constraints appear balanced (8 vs. 8). Together, these metrics support the qualitative patterns described in Tables 2 to 4 and provide a quantitative cross-check of the Bali-Garut contrast. As shown in Figure 1, MSMEs in Bali cluster around the early majority stage, whereas Garut remains at the early adopters/early majority boundary. This visualizes how theme prevalence (Tables 5 and 6) translates into DOI positioning, clarifying why Bali exhibits stronger trial-to-adoption momentum.

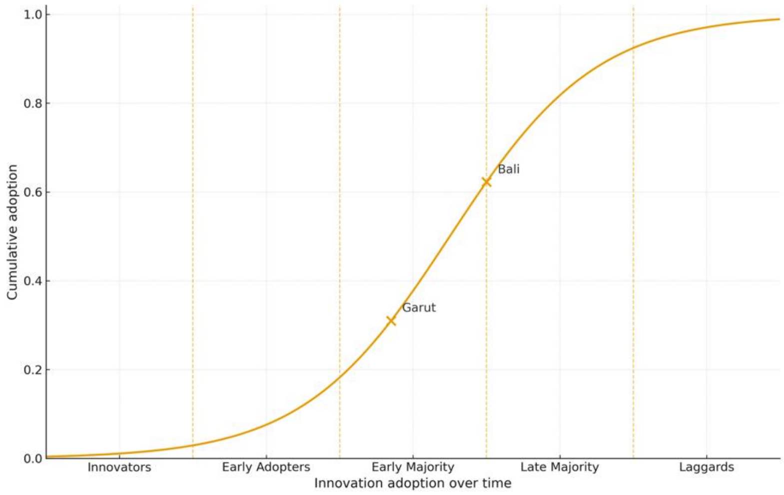

Figure 1. DOI adoption curve with regional placement

4.2. Results: discussion

This section interprets empirical patterns via the DOI lens, situating them against national MSME digitalization indicators. We treat DOI not as a theme but as an interpretive frame that locates each region on the adoption curve. Based on the coded evidence and matrix summaries, Bali clusters in the early majority, while Garut sits near the early adopters/early-majority boundary (Figure 1). Our NVivo metrics, however, reveal the underlying reasons. Bali's higher references to government support/infrastructure alongside AI literacy coincide with easier onboarding plus better connectivity. Garut's references, conversely, cluster on financial constraints coupled with perceived complexity. These distinct factors consequently position the two ecosystems at different points on the DOI curve.

4.2.1. The regional digital divide: positioning MSMEs on the DOI curve

The comparative evidence positions MSMEs in Bali near the early adopter/early majority boundary: owners are willing to trial customer-facing tools when onboarding is simple, workflows are not disrupted, and city programs provide vendor-neutral guidance. In Garut, many MSMEs match late majority tendencies: perceived relative advantage is lower, complexity and subscription risk loom larger, and connectivity gaps make experimentation fragile. These positions are consistent with the NVivo matrices where Bali shows more references linked to government support/infrastructure, while Garut features financial.

4.2.2. Positioning with complementary models (TOE/TAM/UTAUT)

While DOI clarifies where each region sits on the adoption curve, complementary lenses explain why those positions persist. TOE highlights the role of technology and context: Garut owners emphasize tool complexity and vendor lock-in risk, whereas Bali owners stress integration with familiar apps and access to programs. At the individual level, TAM/UTAUT map onto our codes: perceived usefulness is higher in Bali (faster response and richer content), but effort expectancy is a barrier in Garut. Facilitating mentoring conditions, templates, reliable connectivity shift perceived risk and move firms along the DOI curve. Taken together, DOI locates the adoption stage, while TOE/TAM/UTAUT explain the mechanism which linking regional programs, infrastructure, and perceived effort/benefit to observed adoption gaps.

4.2.3. National context and benchmarks

National MSME digital programs report faster progress in tourism-dense urban areas than in agrarian districts. Our cases refine that picture by showing how program design details determine conversion from training to sustained use: Bali respondents point to vendor-neutral guidance and hands-on mentoring, Garut respondents to thin margins, connectivity volatility, and subscription anxiety. The implication is that coverage targets alone are insufficient; implementation frictions decide whether diffusion continues or stalls.

Apoga and Petrovska [10] identified financial barriers as a key impediment to sustainable digital transformation. Our study, however, adds a crucial comparative dimension. In Garut, the lack of dedicated funding for technology makes AI adoption a non-starter for most MSMEs, who perceive it as an unjustifiable luxury. In Bali, the availability of some targeted, low-interest loans for tourism businesses enables a degree of experimentation, characteristic of early adopters. Yet, even here, the lack of funds for non-tourism MSMEs, such as the interviewed coffee shop owner who received training but could not afford the tools, demonstrates that without broader and more inclusive financial policies, diffusion stalls. This highlights that financial access is a critical gatekeeper to progressing through the innovation adoption stages.

4.2.4. Policy implications by region

The results indicate the need for region-specific adoption strategies. Bali (early majority) requires the scaling of simple, interoperable tools with clear governance or guidelines. In contrast, Garut (late majority) necessitates reducing the risk of first-time use. This objective can be achieved through interventions such as coached pilots, micro-grants, and vendor-neutral templates as shown in Table 7. When programs shift from "one-off training" to coached, low-risk trials using interoperable tools, perceived effort drops and DOI movement follows.

Table 7. Region-tailored policy actions derived from the evidence

Focus area	Bali (tourism-dense)	Garut (agrarian)
Onboarding and skills	Short mentored pilots embedded in familiar apps; playbooks for content workflows	Step by step coaching; template-based configuration; peer shadowing
Financing and risk	Low-risk vouchers for add-ons; performance-linked top-ups	Micro-grants for first year licenses; ROI checklists before purchase
Infrastructure and tools	Promote interoperable, vendor-neutral options; data-privacy guardrails	Ensure connectivity at hubs; offline-first tools; simple dashboards
Program design	Convert training to coaching and follow-up; certify mentors	Mobile coaching clinics; cohort support groups; office-hours
Measurement	Track conversion/response-time improvements	Track time saved and error reduction; onboarding completion

4.2.5. Limitations, trustworthiness, and avenues for future research

This study's findings are limited by its context (two regions, MSME focus) and its reliance on different data sources. We employed several measures to ensure trustworthiness. These included maintaining an audit trail, writing analytic memos, searching for negative cases, and triangulation with secondary materials. Given the single-coder design, we also performed a stability check by re-coding 20% of the material, which confirmed coding consistency. Further analysis verified that findings were not skewed by document length. Future work should aim to: i) quantitatively test the identified adoption factors [38]; ii) conduct longitudinal research to track AI adoption over time; iii) investigate the adoption of newer tools like generative AI, focusing on its promises and challenges which are critical for SMEs [39]; and iv) explore the moderating role of entrepreneurial orientation in AI adoption, a relationship that requires empirical testing in the SME context [40].

4.2.6. Replication potential

The diagnostic logic, which proceeds from theme metrics to DOI positioning followed by region-specific levers. This logic is portable to other economies with urban rural or sectoral divides. This framework can be combined with quantitative indicators (e.g., infrastructure scores and adoption rates) in future work.

5. CONCLUSION

This comparative study reveals that the path to AI adoption for MSMEs is not uniform but is profoundly shaped by the regional economic ecosystem. By applying the DOI theory, we have demonstrated that MSMEs in tourism-driven Bali and agrarian-based Garut occupy vastly different positions on the adoption curve, largely due to disparities in digital literacy, the nature of government support, and access to finance. These findings underscore the critical need for policymakers to move beyond generic national programs and develop tailored, context-sensitive strategies. For regions like Garut, the focus must be on building a foundational ecosystem for innovation. For regions like Bali, the goal must be to deepen existing capabilities and ensure inclusive growth.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Author states no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SST], upon reasonable request. Due to confidentiality and privacy constraints, full interview transcripts cannot be shared publicly; however, anonymized materials (codebook, matrix-coding outputs, and exemplar quotes) are provided in the supplementary material and additional non-identifiable artefacts can be shared on request.

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