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Inclusive Competitiveness through AI Use in Informal SMEs: Evidence from an Extended TAM–TOE Model

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Abstract: Informal SMEs are pivotal to inclusive growth, yet capability and infrastructure constraints often limit the effective use of artificial intelligence (AI). This study examines how organizational and technological conditions shape inclusive competitiveness through AI use in Indonesian informal SMEs by extending the Technology Acceptance Model (TAM) with Technology–Organization–Environment (TOE) factors and IS-success attributes. Using a cross-sectional survey of 559 SME owners/managers and partial least squares structural equation modeling (PLS-SEM), we test pathways from organizational competence and readiness, system quality, and service quality to perceived usefulness (PU) and perceived ease of use (PEOU), and ultimately to AI usage. Results show that PU and PEOU strongly predict AI usage, and PEOU also reinforces PU. Organizational readiness and system quality significantly enhance both PU and PEOU, while organizational competence primarily strengthens PU rather than PEOU. Service quality improves PEOU but does not significantly affect PU. Mediation tests confirm that PU and PEOU transmit key organizational and technological effects to AI usage. The findings suggest that policies and managerial interventions targeting readiness-building (skills, resources, governance) and robust system design are essential to translate AI adoption into sustained utilization and more inclusive business competitiveness in the informal economy.

Keywords: Artificial intelligence, Extended TAM–TOE, Inclusive competitiveness, Informal SMEs, PLS-SEM

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INTRODUCTION

Small and medium-sized enterprises (SMEs) remain the backbone of most economies by contributing to innovation, employment, and productivity, yet they often operate with thin resource buffers and limited technological capacity. In this setting, artificial intelligence (AI), including automation, recommendation features, and generative tools, has been promoted as a practical lever to improve operational efficiency, decision-making speed, customer interaction, and overall competitiveness. Recent SME-focused studies consistently emphasize that, despite the promise of AI, many small businesses still struggle to translate AI availability into effective and sustained use because of financial constraints, limited digital skills, uncertainty about returns, and organizational resistance to change (Andayani et al., 2024; Kukreja, 2025; Oldemeyer et al., 2025; Salah & Ayyash, 2024; S. Sharma et al., 2024a; Soomro et al., 2025; Zavodna et al., 2024). These challenges are especially relevant for informal SMEs, namely micro and small enterprises whose operations are often simple, owner-centered, and weakly institutionalized, where learning costs and implementation frictions can quickly outweigh perceived benefits.

In Indonesia, barriers to AI use among SMEs are repeatedly linked to limited technological capability, implementation costs, and uneven digital infrastructure. Prior evidence suggests that many SMEs still rely on traditional methods and have not fully leveraged AI-enabled practices, with owners reporting low confidence in technology skills, concerns about affordability, and uncertainty about AI's fit with business needs (Dinul Khaq et al., 2024; Hermansyah, 2023; Jun Prasetyo & Andrilla, 2025; Khan, 2024; Maghfirah & Eni, 2024; Santosa & Surgawati, 2024). Internal readiness and capacity for change also matter; where time, devices, connectivity, and managerial commitment are insufficient, AI use becomes difficult to integrate into daily routines, and resistance to new technologies may emerge (Bakhary et al., 2024; C. L. Syalum et al., 2025; Murire, 2024). This context raises an inclusion-relevant concern: if AI use is shaped by uneven readiness and system access, the competitiveness benefits of AI may concentrate among better-prepared businesses, widening capability gaps rather than supporting broad-based, inclusive competitiveness.

Research on AI adoption in SMEs has expanded, but three limitations remain salient. First, many studies emphasize acceptance perceptions, such as perceived usefulness and perceived ease of use, without simultaneously modeling organizational constraints that are central in SMEs (Lai et al., 2025; Setyo Widodo et al., 2024). Second, work that draws on information-systems success attributes, for example system and service quality, is often not integrated with acceptance mechanisms when explaining SME AI use (Abdulnabi, 2024; Susan Maestro & Puja Rana, 2024). Third, findings are frequently generalized from larger or more formal organizations, even though SMEs face distinctive constraints in capability, leadership, and infrastructure, and the informal SME setting remains comparatively underexplored (Papathomas et al., 2025; Qu & Kim, 2025). As a result, limited evidence explains how internal organizational factors and technology quality conditions jointly shape perceived usefulness and perceived ease of use, and how these perceptions ultimately translate into AI usage in small businesses (Alofan et al., 2025; D. E. Moreno et al., 2024).

To address this gap, this study advances an extended TAM-TOE model oriented to informal SMEs by integrating three complementary perspectives. The Technology Acceptance Model (TAM) posits that perceived usefulness (PU) and perceived ease of use (PEOU) are primary cognitive drivers of technology usage (Davis, 1989). PU captures the extent to which owners or managers believe AI will enhance business performance, for example efficiency, decision quality, and sales support, whereas PEOU reflects the perceived effort required to learn and operate AI. In informal SMEs, these perceptions are not abstract attitudes; they represent practical judgments about whether the tool pays off in time and effort. TAM also suggests a reinforcing mechanism in which ease of use can shape usefulness perceptions, because tools that feel easier to operate are more likely to be recognized as beneficial within routine work (Anaam et al., 2023; Huang, 2021).

The Technology-Organization-Environment (TOE) lens complements TAM by emphasizing that usage is conditioned by organizational and technological contexts. On the organizational side, this study focuses on competence and readiness because internal support is repeatedly identified as critical for successful technology uptake in SMEs (Herdinata et al., 2019;

Hidayati et al., 2019; Shahadat et al., 2023). Organizational competence, including digital skills, technical knowledge, and the ability to learn and use tools, helps owners or managers understand AI functions and connect them to business needs, thereby strengthening perceived benefits and reducing perceived effort (González-Varona et al., 2021; Jatimoyo et al., 2021; Na et al., 2023). Organizational readiness, including resources, devices, internet access, time allocation, and managerial commitment, creates enabling conditions that make AI experimentation and learning feasible, and it can strengthen both PEOU and PU by reducing implementation frictions and increasing confidence in value capture (Adiguzel et al., 2024; Anh et al., 2024; Cimbaljević et al., 2023; Jöhnk et al., 2021). From an informal SME perspective, readiness is particularly decisive because business routines are tightly coupled to the owner or manager's time, attention, and basic infrastructure.

On the technological side, we draw on the DeLone and McLean IS Success Model, which highlights system quality and service quality as key predictors of information system success and continued use (Delone & McLean, 2003). For AI use in SMEs, system quality, for example reliability, accessibility, speed, and fit with simple operations, affects whether AI tools feel workable in daily processes, while service quality, for example accessible support, understandable instructions, and problem resolution, affects whether users feel guided and confident in learning and operating AI (Assaf Arief et al., 2023; Su et al., 2022). These quality conditions can shape both PEOU and PU because a stable system reduces effort and uncertainty, while supportive services help users overcome barriers and recognize practical value (Ahmad et al., 2020; Daoud, 2023). We emphasize system and service quality as actionable quality dimensions in the SME context, while treating information quality more cautiously because SMEs often rely on AI outputs that are not fully tailored to firm-specific data, and developing high-reliability, firm-specific AI can be costly (Cottier et al., 2025; Kidd & Birhane, 2023; Liang et al., 2022; M. Dolata & K. Crowston, 2024).

Synthesizing these perspectives, the proposed extended TAM-TOE model links organizational competence and readiness, system quality, and service quality to PU and PEOU, and then to AI usage. This approach aligns with the study's emphasis on inclusive competitiveness through AI use in informal SMEs: competitiveness gains are expected not merely from awareness or intention, but from sustained, routine utilization that enables faster learning, improved decisions, and better customer engagement. The model also anticipates indirect pathways, where organizational and technological conditions influence AI usage primarily through their effects on PU and PEOU, consistent with the argument that cognitive evaluations translate structural conditions into behavior.

Accordingly, this research aims to explain AI usage in Indonesian informal SMEs by testing an extended TAM-TOE model that integrates organizational competence and readiness with IS-success quality attributes. By doing so, the study contributes to the SME AI literature in three ways: it extends evidence to an informal-economy setting where constraints are pronounced; it offers a more holistic explanation of AI usage by combining acceptance mechanisms with organizational and system quality drivers; and it provides practical guidance on which levers, readiness-building, competence development, system reliability, and support quality, are most relevant for making AI use feasible and beneficial for a broader base of small businesses.

METHOD

This study employed a quantitative approach with a cross-sectional survey design to examine AI usage in SMEs, following established guidance for survey-based behavioral research and PLS-SEM applications (Creswell, 2014; Hair et al., 2019). A stratified purposive sampling strategy was applied to capture SME owners and managers from diverse regions in Indonesia, including urban and rural areas across major islands (Java, Sumatra, Kalimantan, Papua, Sulawesi, NTB, NTT, and Bali). Eligible participants met two criteria: they were actively managing or owning an SME and had prior exposure to AI technologies or digital platforms in business operations. Data were collected between March and July using an online questionnaire distributed via WhatsApp, Instagram, Facebook, and email, and participants provided informed consent before responding. The final sample consisted of 559 SME owners and managers. Sample size adequacy followed the 10-times rule consideration based on the initial measurement pool, targeting a minimum threshold of approximately 500 responses, and the achieved sample exceeded this requirement.

The questionnaire contained two parts: demographic and business profile items (region, gender, age, education, years in business, business type, number of workers, and prior use of digital technology and AI) and measurement items for the study constructs. The instrument was developed from an integrative framework combining TAM, TOE, and the DeLone and McLean IS Success Model, and all constructs were specified reflectively (Mode A) and measured using a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). A total of 42 items were initially developed, with six indicators per construct for Perceived Ease of Use (PEOU), Perceived Usefulness (PU), AI Adoption Usage (AUA), Organizational Competence (OC), Organizational Readiness (OR), Service Quality (SEQ), and System Quality (SYQ). Content validity was assessed by two business management experts and two digital technology experts, and seven items judged irrelevant were removed prior to model estimation. Operational definitions followed the construct logic embedded in the model: OC reflects digital capability and learning ability to leverage AI, OR captures preparedness resources and commitment to implement AI-supported routines, SEQ reflects perceived accessibility and clarity of support and guidance, SYQ reflects the reliability and functional fit of the system with SME operations, PEOU captures perceived learning and operating effort, PU captures perceived performance benefits, and AUA captures the realized utilization of AI in business activities.

Data analysis used Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.1.0.3. The analysis proceeded in two stages, namely evaluation of the measurement model followed by evaluation of the structural model. Common method bias was assessed using Harman's single-factor test and inner-model Variance Inflation Factor (VIF), with VIF values evaluated against the 3.3 threshold. For the measurement model, indicator reliability was examined using outer loadings and low-loading indicators were removed as part of construct purification. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (rho_A and rho_C), convergent validity using AVE and loading criteria, and discriminant validity using the Fornell-Larcker criterion. For the structural model, explanatory power was evaluated via R^2, effect sizes via f^2, and predictive relevance via Q^2 using PLSpredict. Hypotheses and mediation effects were tested using bootstrapping with 10,000 subsamples at the 5 percent significance level.

RESULTS AND DISCUSSION

Research Results

The survey yielded 559 valid responses from SME owners and managers across Indonesia. Respondents were predominantly female (67.1%) and largely aged 20 to 25 years (77.5%). Most held a bachelor's degree (69.4%), and the businesses were generally young (less than 1 year:

42.9%; 1 to 3 years: 41.3%). The most common business types were culinary (30.2%), general trade (29.9%), and handicrafts (24.0%). Digital technology use was nearly universal (99.6%), and 95.9% reported current AI usage such as chatbots and automated recommendations, while 98.9% expressed interest in AI adoption.

The model was estimated using PLS-SEM in SmartPLS 4.1.0.3 through a two-stage procedure, namely assessment of the measurement model followed by assessment of the structural model. Common method bias was examined using inner-model VIF with the 3.3 threshold, and all VIF values were below 3.3, indicating that common method bias was unlikely to distort the estimates. The reflective measurement model was then purified by removing indicators with loadings below 0.5. After purification, reliability and convergent validity met recommended thresholds, and discriminant validity was supported using the Fornell-Larcker criterion.

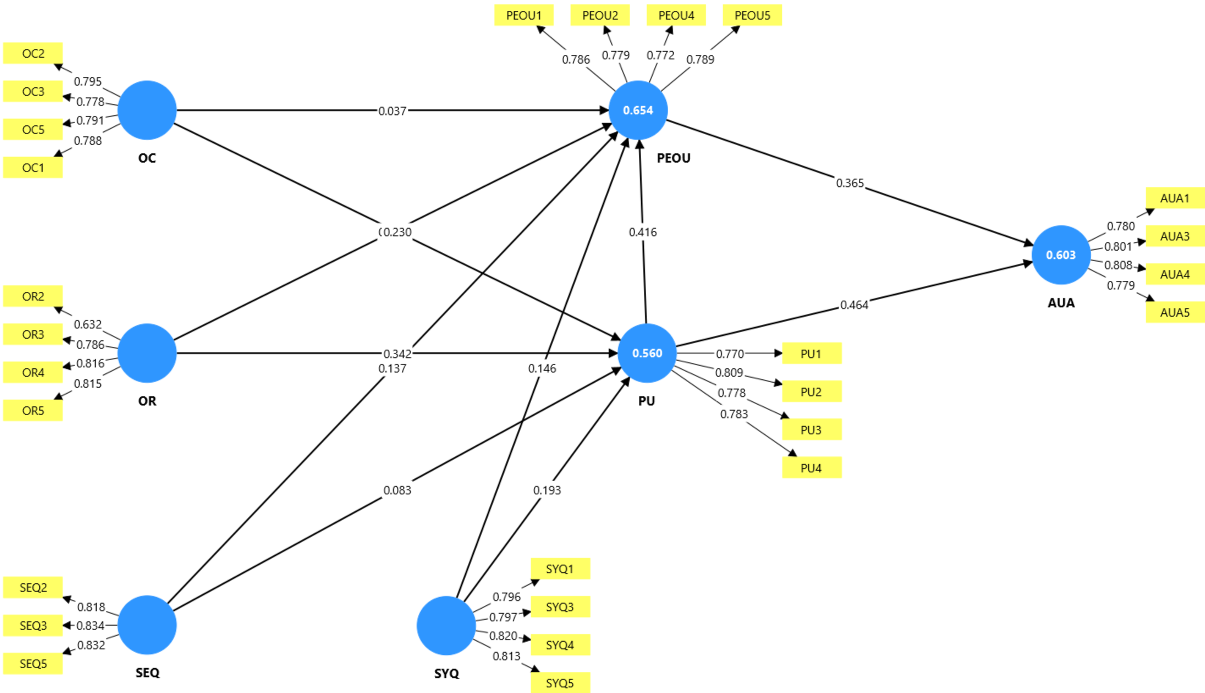

Figure 1. Complete analysis of the proposed model using the consistent PLS algorithm

The structural model demonstrated substantial explanatory power for AI Adoption Usage (AUA) with R2 = 0.603. Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) were also well explained, with R2 = 0.654 for PEOU and R2 = 0.560 for PU. Predictive relevance was strong, as indicated by Q2 values of 0.516 (AUA), 0.526 (PEOU), and 0.505 (PU). Effect size results further suggest that PU and PEOU provide the most meaningful contributions to AUA, while organizational readiness contributes more strongly to PU than to PEOU, and system and service quality primarily operate through perceptual channels.

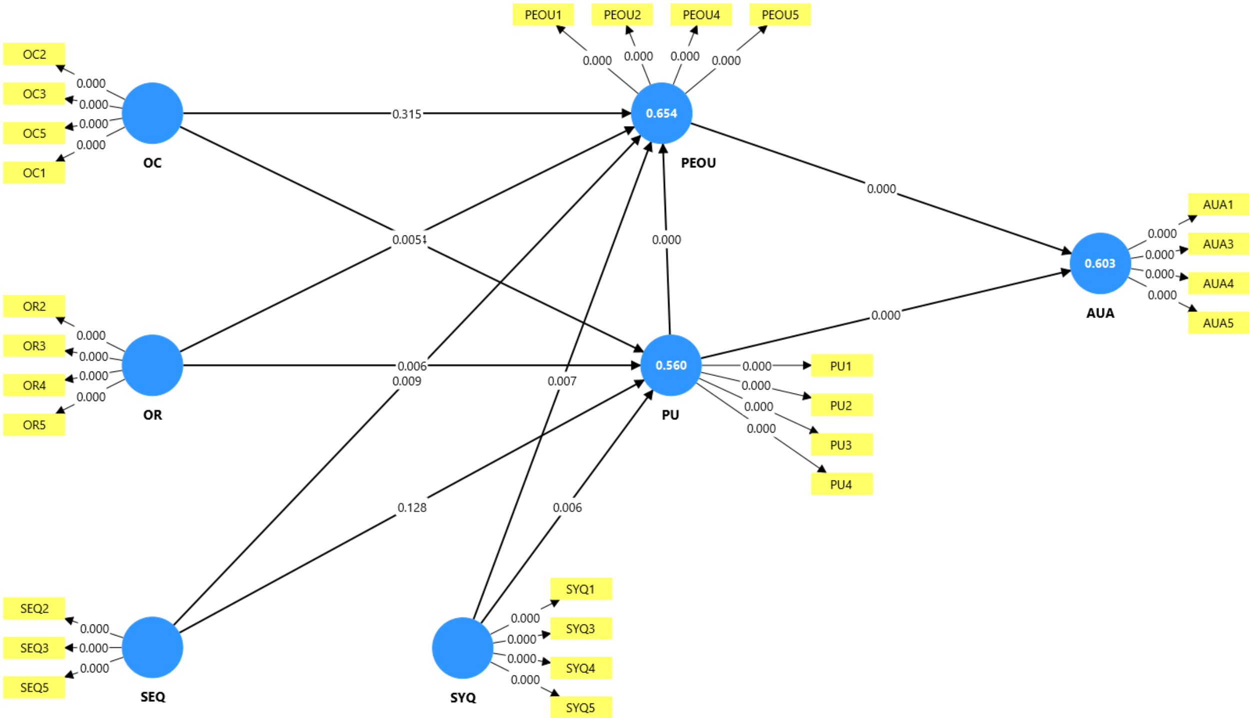

Figure 1. The structural model

Hypotheses were tested using bootstrapping with 10,000 subsamples at the 5% significance level. Table 1 presents a compact summary of the direct and indirect effects, including standardized path coefficients and significance decisions.

Table 1. Summary of Hypothesis Testing

Type	Path	Beta	p-value	Decision
Direct	OC → PEOU	0.037	0.315	Not supported
Direct	OC → PU	0.230	0.004	Supported
Direct	OR → PEOU	0.193	0.005	Supported
Direct	OR → PU	0.342	0.006	Supported
Direct	SEQ → PEOU	0.137	0.009	Supported
Direct	SEQ → PU	0.083	0.128	Not supported
Direct	SYQ → PEOU	0.146	0.007	Supported
Direct	SYQ → PU	0.193	0.006	Supported
Direct	PU → PEOU	0.416	< 0.001	Supported
Direct	PEOU → AUA	0.365	< 0.001	Supported
Direct	PU → AUA	0.464	< 0.001	Supported
Indirect	OC → PEOU → AUA	0.013	0.320	Not supported
Indirect	OR → PEOU → AUA	0.070	0.009	Supported
Indirect	OC → PU → AUA	0.107	0.006	Supported
Indirect	OR → PU → AUA	0.159	0.008	Supported
Indirect	SEQ → PEOU → AUA	0.050	0.012	Supported

Type	Path	Beta	p-value	Decision
Indirect	SEQ → PU → AUA	0.038	0.131	Not supported
Indirect	SYQ → PEOU → AUA	0.053	0.011	Supported
Indirect	SYQ → PU → AUA	0.090	0.007	Supported
Indirect	PU → PEOU → AUA	0.152	< 0.001	Supported

Table 1 indicates that PU and PEOU are the strongest direct drivers of AI Adoption Usage. PU shows the largest effect on AUA (beta = 0.464, $p < 0.001$), followed by PEOU (beta = 0.365, $p < 0.001$). In addition, PU significantly strengthens PEOU (beta = 0.416, $p < 0.001$), suggesting that when SME owners or managers perceive AI as beneficial for performance, they also tend to perceive it as easier to use, which in turn supports higher AI usage.

The upstream determinants show a clear pattern across organizational and technological conditions. Organizational readiness significantly improves both PEOU (beta = 0.193, p = 0.005) and PU (beta = 0.342, p = 0.006), indicating that preparedness in resources and commitment is associated with lower perceived effort and higher perceived benefit. System quality also significantly enhances both PEOU (beta = 0.146, p = 0.007) and PU (beta = 0.193, p = 0.006), implying that reliable and fit-for-purpose systems help informal SMEs recognize value and reduce friction in use. Organizational competence strengthens PU (beta = 0.230, p = 0.004) but does not significantly affect PEOU (beta = 0.037, p = 0.315), which suggests that capability is more closely linked to recognizing AI's usefulness than to reducing perceived effort. Service quality significantly improves PEOU (beta = 0.137, p = 0.009) but does not significantly influence PU (beta = 0.083, p = 0.128), implying that support and guidance help reduce perceived difficulty but do not automatically translate into higher benefit perceptions.

Mediation results further clarify how competitiveness-relevant usage emerges. Several contextual effects are transmitted through PU and PEOU rather than operating directly on AUA. Organizational readiness affects AUA through both PEOU (beta = 0.070, p = 0.009) and PU (beta = 0.159, p = 0.008), indicating that readiness increases AI usage by simultaneously reducing effort perceptions and strengthening benefit perceptions. Organizational competence affects AUA through PU (beta = 0.107, p = 0.006), confirming that capability contributes to usage mainly by increasing perceived usefulness. System quality affects AUA through both PEOU (beta = 0.053, p = 0.011) and PU (beta = 0.090, p = 0.007), while service quality affects AUA through PEOU (beta = 0.050, p = 0.012). Importantly, the unsupported indirect paths mirror the unsupported direct effects, namely OC → PEOU → AUA and SEQ → PU → AUA, reinforcing that competence does not operate through ease-of-use perceptions in this sample and service quality does not operate through usefulness perceptions.

Discussion

This study provides evidence that AI usage among informal SMEs is primarily explained by a value-and-friction logic, where perceived usefulness and perceived ease of use jointly translate organizational and technological conditions into sustained utilization. The structural results show that perceived usefulness and perceived ease of use are the strongest direct predictors of AI Adoption Usage, and perceived usefulness also significantly strengthens perceived ease of use. In an informal SME context where time, attention, and operating slack are limited, these findings imply that AI contributes to inclusive competitiveness only when owners and managers both recognize clear performance payoffs and experience low barriers to routine use.

The centrality of TAM is reinforced in two ways. First, perceived usefulness has the largest effect on AI Adoption Usage, followed by perceived ease of use, confirming that informal SMEs prioritize tangible performance gains such as efficiency, decision support, customer service improvement, and sales support when deciding to keep using AI. Second, perceived usefulness significantly increases perceived ease of use, indicating a "value-first" pathway in which benefit recognition reduces the psychological and cognitive burden of learning. This pattern aligns with recent TAM extensions that argue outcome value can motivate users to overcome learning barriers, especially when technical expertise is limited and adoption decisions are pragmatic rather than technology-driven (Davis, 1989; Anaam et al., 2023; Huang, 2021).

The findings also clarify the distinct roles of organizational competence and organizational readiness. Organizational competence does not significantly influence perceived ease of use, which suggests that having basic digital skills and managerial capability does not automatically make AI feel simpler to operate in informal SMEs. A plausible interpretation is that ease of use is shaped more strongly by interface design, workflow fit, and the inherent usability of AI tools, which are often determined by vendors and platform architectures rather than by internal capability alone. This explanation is consistent with prior work emphasizing that usability and system design choices can dominate user experience in small firms with limited IT support (Ikpe, 2024; K. Crockett et al., 2023a; Meske & Bunde, 2022). In contrast, organizational competence significantly improves perceived usefulness, indicating that capable owners and managers are better at identifying where AI creates value, selecting relevant use cases, and aligning AI features with business goals. This supports the view that competence functions as an absorptive and interpretive capacity, strengthening value recognition even when it does not reduce perceived effort (González-Varona et al., 2021; Troise et al., 2022; Camillo et al., 2025).

Organizational readiness emerges as a stronger and more balanced lever because it significantly increases both perceived ease of use and perceived usefulness. Readiness in this study reflects practical preparedness, including devices, internet sufficiency, willingness to learn, and time allocation, which are critical for informal SMEs whose operations depend heavily on owner-managed routines and basic infrastructure. The mediation results further show that readiness drives AI Adoption Usage through both perceived ease of use and perceived usefulness.

This indicates that preparedness works through two channels simultaneously: lowering friction (AI feels manageable) and strengthening expected payoffs (AI feels worth using). These mechanisms are consistent with prior studies arguing that readiness reduces resistance and supports technology routinization by ensuring minimal technological and cultural conditions for use (Jöhnk et al., 2021; Uren & Edwards, 2023; Palade et al., 2023). For inclusive competitiveness, the implication is that readiness-building is not simply a technical issue, but a core inclusion strategy because it widens the set of informal SMEs that can move from experimentation to sustained AI use.

The technological context also shows an important asymmetry between service quality and system quality. Service quality significantly improves perceived ease of use but does not significantly improve perceived usefulness. This pattern suggests that support, guidance, and accessible help reduce perceived effort and anxiety in learning AI, yet they do not automatically convince informal SMEs that AI generates measurable business gains. This is consistent with evidence that support services can increase comfort and usability perceptions, while usefulness judgments are often anchored to perceived performance outcomes rather than to service interactions (Ahmad et al., 2020; Pouti & Taghavifard, 2024). In contrast, system quality significantly improves both perceived ease of use and perceived usefulness. A reliable, accessible, fast, and operation-fit system reduces friction while simultaneously reinforcing beliefs that AI can improve performance, which aligns with research emphasizing system dependability and performance as dual drivers of perceived value and usability (Song & Sohn, 2022; Z. I. Saleh et al., 2020).

The mediation findings sharpen these interpretations. Service quality and system quality both increase AI Adoption Usage through perceived ease of use, indicating that better support and system performance translate into higher usage when they make AI feel easier to operate. However, only system quality has a significant indirect effect through perceived usefulness, while the service quality to usefulness mediation is not supported. This implies that usefulness judgments are primarily performance-based, rooted in whether the AI tool works well and fits the business workflow, rather than in the availability of assistance. For informal SMEs, this is a meaningful boundary condition: service quality can accelerate learning and reduce adoption friction, but system quality is the more decisive lever for convincing users that AI is strategically worthwhile. This helps explain why system quality consistently emerges as the stronger technological determinant in integrated TAM and IS-success approaches for emerging technologies in SMEs (Delone & McLean, 2003; Su et al., 2022; Daoud, 2023).

From a practical perspective, the results imply that inclusive competitiveness through AI use requires coordinated intervention across readiness-building and system design. First, readiness-building initiatives should focus on low-cost access to devices and connectivity, structured learning time, and managerial commitment to routine integration, because readiness raises both ease and usefulness perceptions and produces significant indirect effects on usage. Second, AI providers targeting informal SMEs should prioritize system reliability, speed, accessibility, and workflow fit because system quality improves both TAM mechanisms and transmits benefits through usefulness as well as ease of use. Third, support services should be designed as friction reducers, for example through simple onboarding, local-language instructions, and responsive troubleshooting, because service quality improves ease of use and indirectly encourages usage through that channel. The overall implication is that inclusion-oriented AI diffusion should not rely solely on training or awareness campaigns; it must also ensure that informal SMEs receive systems that work reliably in low-resource environments.

Finally, the respondent profile indicates that most participants already report current AI use, which suggests the model captures drivers of AI usage and continuation rather than initial adoption intent. This strengthens the relevance of the findings for inclusive competitiveness because sustained utilization is the stage at which benefits can accumulate into productivity, service improvements, and market access. At the same time, it highlights an important direction for future research, namely testing whether the same drivers hold for non-users and for earlier adoption stages, and whether external factors such as policy incentives or vendor ecosystem support add explanatory power beyond internal readiness and quality conditions.

CONCLUSIONS

This study examined how organizational and technological conditions shape AI usage among informal SMEs through an extended TAM-TOE perspective. The results show that perceived usefulness and perceived ease of use are the strongest direct drivers of AI Adoption Usage, and perceived usefulness also increases perceived ease of use. These findings indicate that

AI contributes to inclusive competitiveness when informal SME owners and managers both recognize clear performance benefits and experience low friction in learning and routine use.

The upstream determinants highlight actionable levers. Organizational readiness and system quality significantly strengthen both perceived usefulness and perceived ease of use, confirming that preparedness and reliable, fit-for-purpose systems jointly reduce barriers and reinforce value recognition. Organizational competence primarily increases perceived usefulness but does not significantly reduce perceived ease of use, suggesting that capability helps SMEs identify AI's business value more than it makes AI feel simpler to operate. Service quality improves perceived ease of use but does not significantly influence perceived usefulness, implying that guidance and support primarily function as friction reducers rather than as sources of benefit perception.

Mediation results further show that many organizational and technological effects on AI Adoption Usage operate through perceived usefulness and perceived ease of use. Therefore, inclusion-oriented AI strategies for informal SMEs should prioritize readiness-building (skills development, resource access, and commitment to learning time) together with system reliability and workflow fit, while maintaining practical support services that lower learning and operational effort.

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