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OPERATIONAL AI OPPORTUNITY FORMATION IN SMALL INDUSTRY: A TOE-DOI EXPLANATION

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ABSTRACT
Artificial intelligence (AI) is increasingly accessible to small firms, but prior studies mainly explain readiness, adoption, or downstream value rather than the stage at which AI first becomes visible as an operational opportunity. This study examines that upstream stage in small industrial firms by combining technology-organization-environment (TOE) antecedents with diffusion of innovation (DOI) outcomes. A purposive, census-oriented survey was conducted on the official West Sumatra small-industry frame. The final dataset contains 51 usable responses from 69 registered small industrial firms, equal to 73.91% official-frame coverage, and was analyzed with PLS-SEM in SmartPLS 4. A conservative rerun removed one weak infrastructure indicator while retaining the same inner model. The main supported path is human resources and digital literacy to observability ($\beta = 0.609$, $p = 0.001$, $f^2 = 0.318$), followed by governance, strategy, and budget support to observability ($\beta = 0.447$, $p = 0.030$, $f^2 = 0.179$). Observability reaches $R^2 = 0.496$, whereas infrastructure, data management, competitive pressure, and ecosystem support do not show comparable direct effects. The findings indicate that early AI opportunity becomes visible mainly through interpretive workforce capacity and bounded managerial support.
Keywords : *Operational AI Opportunity, Small Industrial Firms, TOE-DOI, Observability, PLS-SEM*

1. Introduction

Artificial intelligence is becoming increasingly accessible to smaller firms through cloud services, generative interfaces, subscription software, and embedded digital features. Accessibility alone, however, does not make AI operationally meaningful. Before adoption becomes a realistic decision, firms must first judge whether AI fits daily work, can be tested with tolerable risk, and produces benefits visible enough to justify further attention. That early judgment is especially important in small firms because AI is often encountered before formal innovation programs, dedicated data teams, or stable transformation architectures are in place (Badghish & Soomro, 2024; Burggräf et al., 2024; Le Dinh et al., 2025; Schwaeke et al., 2024; Thomas et al., 2025).

Recent literature on AI and digital transformation in SMEs has grown rapidly, yet it tends to concentrate on three adjacent but analytically different stages: readiness, adoption, and downstream value creation. What remains less explicit is the upstream stage that links these streams, namely the point at which AI first becomes visible as a realistic operational opportunity in a constrained firm. That missing stage matters in small industry because AI rarely begins there as a large transformation program. It begins with bounded operational questions about drafting, record handling, coordination, support work, and simple decisions. A firm may therefore possess internet access, devices, and general digital awareness while still failing to see AI as a credible operational option.

This distinction is especially relevant in West Sumatra, where the article addresses a bounded provincial population of officially registered small industrial firms rather than the broader and much more heterogeneous SME universe. The setting is analytically revealing because firms operate under resource scarcity, uneven digital maturity, and strong pressure to justify new tools through immediate operational usefulness rather than through formal innovation portfolios (da Silva et al., 2022; Njah et al., 2026; Sahoo et al., 2024; Volf et al., 2024; Yao et al., 2026). The practical question is therefore not whether AI matters in general, but what makes AI visible enough to count as a plausible operational option in a resource-constrained industrial context.

Based on that gap, the study has two objectives. First, it explains how TOE-based antecedent conditions shape DOI-based judgments of operational AI opportunity in small industrial firms. Second, it identifies which antecedent domains carry the strongest explanatory weight for observability, the DOI outcome that most directly captures whether AI has become operationally visible. The article contributes theoretically by formalizing an upstream perceptual stage between readiness and stabilized adoption, and it contributes practically by clarifying where small industrial firms should focus first when AI is still being evaluated under constrained conditions.

The remainder of the article is organized as follows. The next section reviews the relevant literature and positions TOE, DOI, and RBV-KBV within the study's analytical scope. The subsequent section explains the research methods, including the official population frame, measurement structure, and PLS-SEM estimation logic. The final sections present the results and discussions, followed by the conclusion and suggestions for future work.

2. Literature Review

The article defines operational AI opportunity formation as the stage at which AI becomes visible, trialable, and operationally plausible before stabilized adoption occurs. This stage is analytically different from readiness and from adoption. Readiness-oriented studies explain whether firms possess technological, organizational, and environmental conditions that make adoption conceivable (Badghish & Soomro, 2024; Giang et al., 2025; Jayashree et al., 2022; Sanchez et al., 2025). Adoption-oriented studies explain intention, implementation, or actual use decisions (Kovič et al., 2024; Peretz-Andersson et al., 2024; Schwaeke et al., 2024; Thomas et al., 2025). Value-oriented studies explain resilience, agility, and performance after AI-related initiatives are already underway (Dey et al., 2024; Drydakis, 2022; Mariani & Mancini, 2025; Panigrahi et al., 2023). The missing stage addressed here lies between these streams.

That missing stage is not trivial in small industry. Firms in this context do not usually begin with integrated AI programs. They begin by asking whether AI can handle bounded tasks in a way that is understandable, testable, and visibly useful. Evidence from chatbot, generative-AI, marketing, financial-management, and bounded automation studies suggests that SMEs often start from narrow use cases rather than enterprise-wide redesign (Bapat et al., 2023; Le Dinh et al., 2025; Metzger et al., 2025; Panigrahi et al., 2023; Szenftner et al., 2024). The present article extends that stream by explaining why such bounded possibilities become credible in some firms but remain merely interesting in others.

Technology-organization-environment remains useful for explaining where enabling and constraining conditions originate. In SME and manufacturing settings, TOE-oriented studies repeatedly identify infrastructure, digital maturity, management support, external facilitation, and competitive pressure as relevant determinants of technological change (Giang et al., 2025; Ietto et al., 2024; Jayashree et al., 2022; Njah et al., 2026; Volf et al., 2024; Yao et al., 2026). TOE is therefore appropriate for structuring the antecedent side of the present model.

At the same time, TOE alone is insufficient for the specific question addressed here. A firm may possess basic access conditions, managerial interest, and environmental pressure while still failing to interpret AI as a meaningful operational option. TOE can map readiness and constraint, but it cannot by itself explain whether those conditions are translated into visible, trialable, and work-related opportunity judgments. For that reason, the present article combines TOE with DOI rather than stopping at readiness logic alone.

Diffusion of innovation contributes a complementary lens because it focuses on how innovations are perceived. Relative advantage, compatibility, complexity, trialability, and observability are especially useful for studying AI in small industry because these firms frequently rely on practical perception rather than formal investment appraisal. If AI appears too complex, poorly aligned, or difficult to test, it may never become a legitimate candidate for operational use. Conversely, if its benefits can be tried and observed in bounded activities, opportunity formation becomes more plausible (Jayashree et al., 2022; Rogers, 2003; Sanchez et al., 2025; Tornatzky & Fleischer, 1990).

Among the DOI dimensions, observability deserves special attention. In small-industrial firms, visible evidence of usefulness often substitutes for the absence of formal experimentation budgets or dedicated digital project teams. When managers and employees can see clearer documentation, faster drafting, easier information handling, or more useful support outputs, AI becomes credible. Observability is therefore not treated here as merely one more DOI variable. It is the most direct indicator of whether operational AI opportunity has actually formed.

RBV-KBV is retained only as a secondary interpretive bridge rather than as the article's primary tested theory. Prior studies suggest that digital capability, adaptive capability, knowledge-management capacity, and organizational agility influence whether firms convert digital initiatives into meaningful outcomes (Alharthi, 2025; Alshammakhi & Sheikh, 2025; Lu & Shaharudin, 2024; Mariani & Mancini, 2025; Prakasa & Jumani, 2024; Siahaan & Tan, 2022). In the present context, that literature helps explain why human capability, interpretive capacity, and governance support may matter more than simple tool possession during the earliest stage of opportunity formation.

This limited use of RBV-KBV avoids theoretical overload while still clarifying the mechanism behind the expected dominance of human and governance variables. The article therefore uses TOE to structure antecedent conditions, DOI to capture perceived innovation outcomes, and RBV-KBV only to interpret why certain organizational resources may become decisive before broader adoption stabilizes.

Figure 1 summarizes that conceptual integration. The left side groups the TOE antecedents as the source of enabling and constraining conditions, while the right side groups the DOI outcomes as the perceptual dimensions through which operational AI opportunity becomes intelligible to the firm. Observability is visually emphasized because the article treats it as the most consequential early-stage outcome in a bounded small-industry setting.

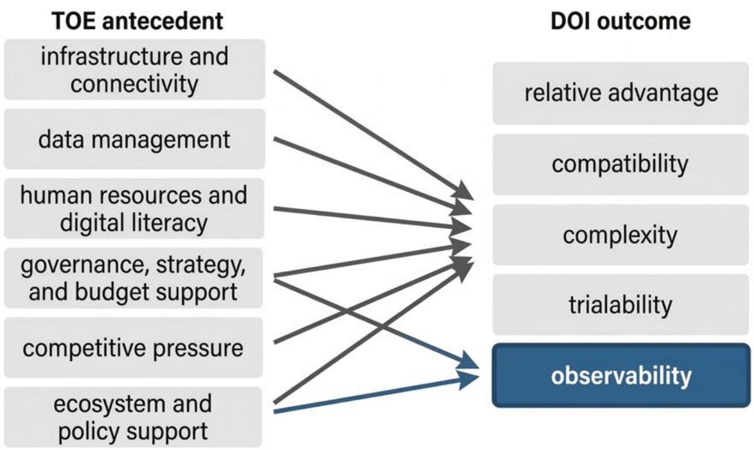

Fig. 1. Conceptual TOE-DOI model of operational AI opportunity formation in small industry.

3. Research Methods

The article seeks to explain an upstream perceptual stage rather than downstream performance, it uses a quantitative survey design and analyzes the data with PLS-SEM in SmartPLS 4. The empirical scope is deliberately limited to the operational AI opportunity model developed in the Introduction. The raw survey workbook contains a structured matrix-format sheet, a response-form sheet, a respondent-profile sheet, and the questionnaire instrument. Only the structured matrix-format dataset functions as the primary analytical source. The response-form dataset was retained only as a historical comparator to confirm that the primary analytical dataset preserved the same substantive response pattern while offering a cleaner basis for repeated estimation and interpretation.

The methodological choice followed a progressive narrowing logic. A literature-only design was not selected because recent review-based studies have already mapped AI adoption and digital transformation in SMEs, but they cannot test whether specific antecedent conditions statistically shape the visibility of operational AI opportunity in one active sample (Islam et al., 2025; Lu & Shaharudin, 2024; Sahoo et al., 2024). A purely qualitative design could have yielded richer narratives, yet it would have made it harder to estimate the full TOE → DOI path structure within one explanatory frame. More prediction-oriented hybrids such as SEM-ANN were also not selected because the purpose here is explanatory rather than predictive (Soomro et al., 2025). The design was therefore narrowed to a quantitative survey analyzed with PLS-SEM, a combination widely used in recent SME and AI-adoption studies when constructs are latent, samples are moderate, and the goal is to explain multivariate relationships rather than maximize prediction accuracy (Giang et al., 2025; Hair et al., 2019; Jayashree et al., 2022; Panigrahi et al., 2023; Sanchez et al., 2025).

Figure 2 makes this narrowing logic explicit. It shows that the selected path is explanatory survey-based PLS-SEM, not review synthesis, purely qualitative inquiry, or prediction-oriented hybrid modeling. The figure also clarifies why the structured matrix-format dataset became the primary analytical source, while the response-form dataset was retained only as a historical comparator.

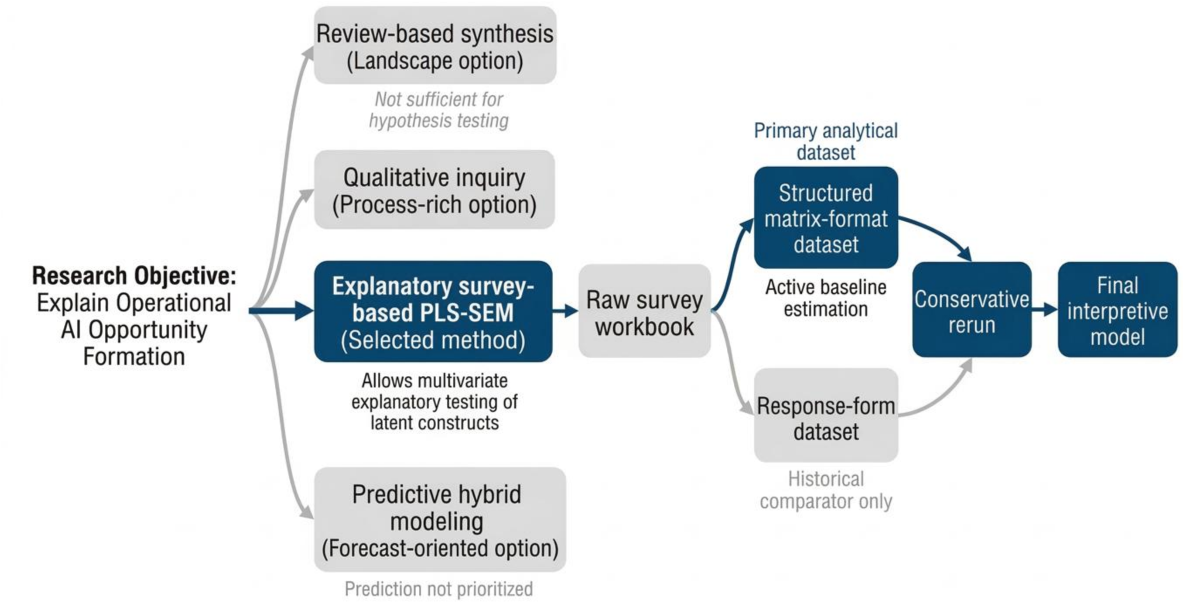

Fig. 2. Research design, method-selection, and dataset-selection logic.

The population frame was anchored in the official 2023 West Sumatra industrial registry from Dinas Perindustrian Sumatera Barat. That registry records 69 small industrial firms, 56,343 micro industrial units, and 10 medium industrial units. This article uses only the 69 small industrial firms as the relevant population frame because the study is explicitly restricted to small industry. The micro and medium counts are reported only to show that the small-industry stratum is numerically narrow from the outset rather than being a large universe from which only a thin slice was captured.

The final analytical sample contains 51 usable responses from small industrial firms in West Sumatra. Relative to the official provincial frame of 69 small industrial firms, this corresponds to 73.91% coverage of the official small-industry population frame. Because auditable logs of refusals and unreachable firms were not preserved, the article reports official-frame coverage rather than a contact-based participation metric. This distinction is important for the argument of the paper. The study does not claim universal statistical generalizability to all SMEs. It claims high coverage of a bounded, officially identified provincial population, which is the relevant evidentiary basis for the upstream explanatory question posed in the Introduction.

The survey approach can therefore be described as a purposive, targeted, census-oriented survey of the official small-industry frame. The sample remains appropriate for the study's purpose because it captures firms that are large enough to face operational coordination issues but still constrained enough that AI must justify itself through visible usefulness rather than through formal innovation programs. Most firms fall into modest workforce bands, most have been operating for more than 10 years, and the sample is predominantly rooted in manufacturing and processing activities. In other words, the article does not infer from a thin convenience slice of a large population; it examines a high share of the bounded small-industry population in which the upstream AI-opportunity question is substantively meaningful. Table 1 summarizes the sample context.

Table 1 - Sample context

Sample characteristic	Result
Official small-industry population frame	69 firms
Usable responses	51 firms
Official-frame coverage	73.91%
Geographic concentration	Kota Padang (17), Kab. Lima Puluh Kota (13), Kota Pariaman (7), Kota Payakumbuh (6), Kab. Padang Pariaman (3), Kab. Tanah Datar (3), Kab. Solok (2)
Gender of respondents	36 male, 15 female
Business age	28 firms older than 10 years, 12 firms 6-10 years, 9 firms 2-5 years, 1 firm under 2 years, 1 missing
Employee band	23 firms with 5-19 employees, 16 firms with 20-49 employees, 12 firms with more than 50 employees
Industrial orientation	50 manufacturing/processing firms and 1 industrial support/logistics firm

The model translates the article's conceptual argument into a full TOE → DOI structure. The TOE side contains six antecedent domains: infrastructure and connectivity, data management, human resources and digital literacy, governance, strategy, and budget support, competitive pressure, and ecosystem and policy support. The DOI side contains five perceived-outcome dimensions: relative advantage, compatibility, complexity, trialability, and observability. Structurally, each TOE construct points to each DOI construct, producing 30 structural paths. All constructs are modeled as reflective. Compatibility remains a single-item construct by design.

Because the study investigates an upstream explanatory stage rather than a narrow single-path adoption-intention model, the TOE constructs are translated into grouped research propositions. Each proposition expands to five structural paths, one to each DOI outcome, producing the full 30-path model. This specification allows the article to test whether explanatory weight concentrates around observability, as argued in the Introduction, or instead diffuses evenly across all DOI outcomes. Table 2. Grouped research propositions.

Table 2 - Research propositions.

Proposition	TOE antecedent set	DOI targets	Rationale
P1	Infrastructure and connectivity	Relative advantage, compatibility, complexity, trialability, observability	Basic access conditions can enable or constrain whether AI is practically reachable in daily work.

Proposition	TOE antecedent set	DOI targets	Rationale
P2	Data management	Relative advantage, compatibility, complexity, trialability, observability	Data routines influence whether AI outputs can be connected to usable operational information.
P3	Human resources and digital literacy	Relative advantage, compatibility, complexity, trialability, observability	Interpretive workforce capacity shapes whether AI outputs are intelligible and actionable in bounded tasks.
P4	Governance, strategy, and budget support	Relative advantage, compatibility, complexity, trialability, observability	Managerial authorization and minimal resource allocation determine whether AI can be tried and evaluated credibly.
P5	Competitive pressure	Relative advantage, compatibility, complexity, trialability, observability	Market and competitive pressures can intensify the search for workable AI-enabled operational responses.
P6	Ecosystem and policy support	Relative advantage, compatibility, complexity, trialability, observability	External support can lower uncertainty and make new digital practices appear more feasible.

To present the TOE-DOI structure as an explicit mathematical model, the latent variables are written in compact vector form. For firm i, let the exogenous latent vector be:

$$\boldsymbol{\xi}_i = [x_{1i}, x_{2i}, x_{3i}, x_{4i}, x_{5i}, x_{6i}]^\top \tag{1}$$

and let the endogenous latent vector be:

$$\boldsymbol{\eta}_i = [y_{1i}, y_{2i}, y_{3i}, y_{4i}, y_{5i}]^\top \tag{2}$$

with the variable mapping $x_1 = IK$, $x_2 = MD$, $x_3 = SDM$, $x_4 = TSA$, $x_5 = KP$, $x_6 = EK$, and $y_1 = RA$, $y_2 = COM$, $y_3 = CX$, $y_4 = TR$, $y_5 = OB$. The structural model is then written as:

$$\boldsymbol{\eta}_i = \Gamma \boldsymbol{\xi}_i + \boldsymbol{\zeta}_i \tag{3}$$

where $\Gamma = [\gamma_{kj}]$ is the 5×6 matrix of structural coefficients, with $k = 1,2,\dots,5$ and $j = 1,2,\dots,6$.

Because observability is the focal early-stage outcome in this article, the structural equation is written explicitly as:

$$y_{5i} = \alpha_5 + \gamma_{51}x_{1i} + \gamma_{52}x_{2i} + \gamma_{53}x_{3i} + \gamma_{54}x_{4i} + \gamma_{55}x_{5i} + \gamma_{56}x_{6i} + \zeta_{5i} \tag{4}$$

Equation (4) is the direct mathematical expression of the article's central question: to what extent do infrastructure, data routines, people, governance, competitive pressure, and ecosystem support make AI operationally visible in small industrial firms?
Because the retained constructs are reflective, the measurement model is written as:

$$X_{jri} = \lambda_{jr}\xi_{ji} + \varepsilon_{jri}, \quad j = 1,2,\dots,6 \tag{5}$$

$$Y_{ksi} = \lambda_{ks}\eta_{ki} + \varepsilon_{ksi}, \quad k = 1,2,\ldots,5 \tag{6}$$

where λ denotes the outer loading of an indicator on its latent variable and ε denotes measurement error.

The explanatory power of the focal endogenous construct is evaluated through the coefficient of determination:

$$R^2_{y_5} = 1 - \frac{SSE_{y_5}}{SST_{y_5}} \tag{7}$$

$$SSE_{y_5} = \sum_i (y_{5i} - \hat{y}_{5i})^2 \tag{8}$$

$$SST_{y_5} = \sum_i (y_{5i} - \bar{y}_5)^2 \tag{9}$$

where $\hat{y}_{5i}$ is the model-predicted observability score for firm i and $\bar{y}_5$ is the sample mean of observability.

The local contribution of one antecedent to the focal outcome is assessed by Cohen's effect size:

$$f^2 = \frac{R^2_{in} - R^2_{ex}}{1 - R^2_{in}} \tag{10}$$

where R^2_{in} is the coefficient of determination when the focal predictor remains in the model and R^2_{ex} is the coefficient after that predictor is omitted.

For hypothesis testing in the bootstrap stage, the reported t-statistic follows the standard ratio:

$$t = \frac{\hat{\beta}}{SE(\hat{\beta})} \tag{11}$$

The notation used in Equations (1) to (11) is as follows. Index i denotes firm i in the sample. IK denotes infrastructure and connectivity, MD denotes data management, SDM denotes human resources and digital literacy, TSA denotes governance, strategy, and budget support, KP denotes competitive pressure, EK denotes ecosystem and policy support, RA denotes relative advantage, COM denotes compatibility, CX denotes complexity, TR denotes trialability, and OB denotes observability. Γ is the matrix of structural path coefficients, α_5 is the intercept of the observability equation, γ_{kj} is the path coefficient from antecedent j to endogenous construct k, $\boldsymbol{\zeta}$ is the structural disturbance term, λ is the outer loading, ε is measurement error, SSE is the residual sum of squares, and SST is the total sum of squares.

Estimation began with an active baseline run and then proceeded to a final conservative interpretive run. The conservative rerun retained the same structural model but removed one weak indicator, IK1. The decision rule was intentionally minimal: remove one clearly weak indicator, preserve the inner model, and avoid repeated cosmetic trimming. This restrained refinement is important because the article's substantive claim depends on a stable explanatory structure, not on aggressive post hoc optimization.

PLS-SEM evaluation followed the standard sequence of assessing the measurement model first and the structural model second (Hair et al., 2019). The final SmartPLS 4 run used 5,000 bootstrap subsamples. The archived outputs retain outer loadings, reliability and validity metrics, HTMT values, path coefficients, p-values, confidence intervals, effect sizes, R^2 values, and estimated SRMR. However, the archived project outputs do not retain formal Q^2 or collinearity VIF diagnostics. The article therefore does not claim those statistics and instead treats their absence as a reporting boundary. The same caution applies to common method bias. Because the design is single-informant, cross-sectional, and self-report based, common method risk cannot be assumed away and is acknowledged explicitly as a study limitation. Results are reported in the same order as this methodological logic: sample context first, measurement adequacy second, and structural explanation third.

4. Results and Discussions

This section follows the methodological sequence established above. It first describes the empirical context of the firms included in the official-frame coverage, then evaluates whether the measurement model is adequate for cautious interpretation, and finally reports where the structural explanatory weight actually concentrates across the DOI outcomes.

The respondent profile reinforces that the article is not analyzing speculative AI interest in a generic SME population. It examines early AI opportunity judgments in a high-coverage provincial frame of small industrial firms. The usable responses cover nearly three quarters of the officially recorded small-industry population, and the firms are distributed across seven districts or cities rather than concentrated in a single locality. The empirical issue is therefore not low frame coverage, but the genuinely small size of the provincial small-industry population itself.

The profile also fits the article's upstream focus. Most firms have operated for more than a decade and most remain in the lower small-industry workforce bands, indicating established routines but limited slack. In such a setting, AI is unlikely to be judged first through abstract strategic rhetoric; it is more likely to be judged through visible usefulness in bounded operational work. The sample is also overwhelmingly industrial in character: 50 of 51 firms are in manufacturing or processing, while only one operates in industrial support or logistics. The findings are therefore interpreted as evidence about small industrial firms rather than about SMEs in general.

Because structural interpretation depends on the adequacy of the retained indicators, the measurement model was assessed before the inner model was interpreted. The main measurement issue in the baseline run was the weak loading of IK1. It was therefore removed in the conservative rerun, leaving infrastructure and connectivity represented by IK2 only. After that refinement, no retained indicator loading remained below 0.60, and the minimum retained loading increased to 0.803. This indicates a cleaner measurement structure without any broader re-specification of the inner model.

Table 3 summarizes the final measurement results. Multi-item constructs generally show acceptable to strong reliability and convergent validity. Composite reliability values are above 0.80 for all multi-item constructs, and average variance extracted values remain above 0.50. Single-item constructs are reported transparently but are not evaluated through internal-consistency metrics.

Table 3 - Final measurement-model summary.

Construct	Retained items	Loading range	α	ρA	CR	AVE	Note
Infrastructure and connectivity	1	1.000-1.000	n/a	n/a	n/a	n/a	Single-item after IK1 removal
Data management	2	0.950-0.965	0.911	0.931	0.957	0.917	Strong convergent quality
Human resources and digital literacy	2	0.827-0.832	0.547	0.547	0.815	0.688	Acceptable for a short two-item block
Governance, strategy, and budget support	2	0.842-0.888	0.666	0.677	0.856	0.749	Acceptable
Competitive pressure	2	0.803-0.926	0.682	0.780	0.857	0.751	Acceptable
Ecosystem and policy support	2	0.972-0.978	0.948	0.958	0.975	0.951	Very strong convergent quality

Relative advantage	2	0.889-0.902	0.752	0.754	0.890	0.801	Strong convergent quality
Compatibility	1	1.000-1.000	n/a	n/a	n/a	n/a	Single-item by design
Complexity	2	0.931-0.956	0.879	0.910	0.942	0.891	Strong convergent quality
Trialability	2	0.831-0.876	0.630	0.638	0.843	0.729	Acceptable
Observability	2	0.949-0.955	0.896	0.899	0.951	0.906	Strong convergent quality

Discriminant validity is improved but not pristine. Three HTMT pairs remain above the conservative 0.90 heuristic: MD-IK = 0.914, SDM-KP = 0.967, and SDM-MD = 0.955. These residual concerns suggest that some constructs remain empirically close in this bounded context. The measurement results are therefore adequate for cautious interpretation, but they also set the boundary for the structural claims that follow.

Table 4 reports the supported, marginal, and theory-relevant nonsignificant paths. Among the 30 structural paths estimated, two are supported at $p < 0.05$, two are marginal, and the remaining 26 are nonsignificant. The supported effects concentrate on observability rather than spreading evenly across the DOI outcomes, which directly addresses the article's central question about what makes AI visible first in small-industry settings.

For compact reporting, the structural abbreviations are as follows: IK = infrastructure and connectivity, MD = data management, SDM = human resources and digital literacy, TSA = governance, strategy, and budget support, KP = competitive pressure, EK = ecosystem and policy support, CX = complexity, and OB = observability.

Table 4 - Key structural paths in the final model.

Path	β	t	p	95% CI	f²	Decision
IK → OB	-0.089	0.337	0.736	[-0.634, 0.406]	0.003	Not supported
MD → OB	-0.153	0.470	0.639	[-0.697, 0.553]	0.008	Not supported
SDM → CX	0.316	1.738	0.082	[0.000, 0.713]	0.072	Marginal
SDM → OB	0.609	3.323	0.001	[0.203, 0.927]	0.318	Supported
TSA → OB	0.447	2.176	0.030	[0.012, 0.813]	0.179	Supported
KP → CX	0.317	1.854	0.064	[-0.022, 0.664]	0.095	Marginal
KP → OB	-0.131	0.953	0.341	[-0.414, 0.120]	0.019	Not supported
EK → OB	0.050	0.269	0.788	[-0.303, 0.425]	0.002	Not supported

The explanatory power of the endogenous DOI constructs is moderate. R^2 reaches 0.496 for observability, 0.401 for complexity, 0.365 for trialability, 0.354 for relative advantage, and 0.299 for compatibility. The estimated SRMR is 0.102, which suggests an interpretable but not pristine model fit. Taken together, the structural results show a clear pattern: the earliest explanatory weight concentrates around observability and is driven mainly by human resources and digital literacy together with governance support.

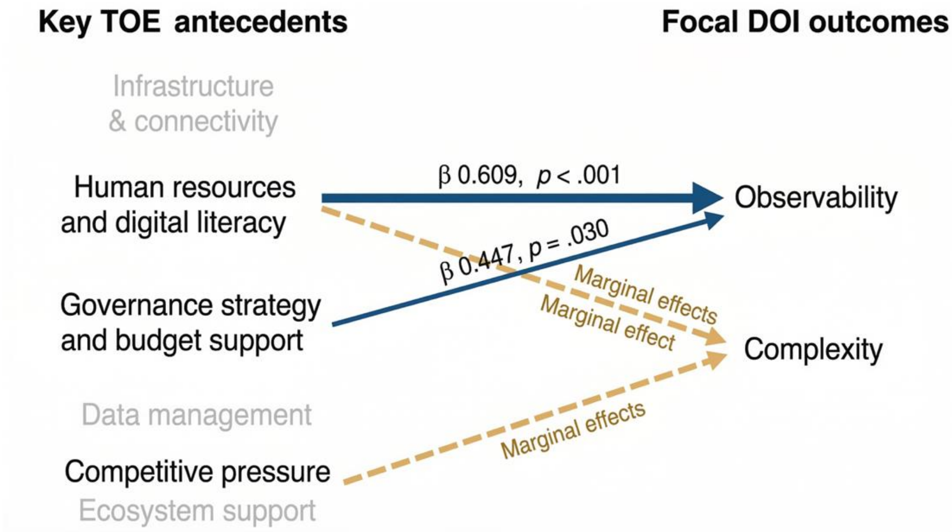

Fig. 3. Summary of the final PLS-SEM findings for operational AI opportunity formation.

Figure 3 condenses that empirical pattern into a simplified interpretive map. The figure emphasizes the two supported paths toward observability and distinguishes them visually from the marginal paths toward complexity. It also keeps infrastructure, data management, and ecosystem support present as background constructs, but de-emphasized, to reflect the fact that they remain part of the model without emerging as strong direct triggers of early opportunity visibility.

The discussion returns to the gap established in the Introduction and interprets the structural pattern reported in the results. The central empirical result is not simply that two paths are significant. It is that explanatory weight is concentrated around observability rather than being distributed evenly across all DOI outcomes. This concentration suggests that the earliest stage of AI formation in small industry is primarily a visibility problem: firms must first see AI as intelligible, testable, and operationally plausible before broader adoption logics become dominant.

The first implication is that operational AI opportunity in small industrial firms is not primarily a tool-access issue. It is an interpretive-capacity issue. The strongest path in the model is SDM → OB, which suggests that AI becomes visible when personnel can understand outputs, connect them with work tasks, and judge whether the tool is useful in concrete routines. That pattern is consistent with studies emphasizing employee competence, organizational learning, and resource orchestration in AI or digital transformation (Alharthi, 2025; Alshammakhi & Sheikh, 2025; Dey et al., 2024; Drydakis, 2022; Mariani & Mancini, 2025; Peretz-Andersson et al., 2024). The present article extends that literature by locating the effect earlier than stabilized adoption or performance. The issue is not yet whether AI improves resilience, agility, or downstream value. The issue is whether AI becomes visible as a plausible operational option in the first place.

The second implication is that governance matters because small industrial firms need bounded authorization before they need broad transformation. The supported path from governance, strategy, and budget support to observability indicates that AI becomes credible when managers create a legitimate space for limited experimentation. This interpretation aligns partly with adoption studies that emphasize leadership, top-management support, and organizational readiness (Badghish & Soomro, 2024; Jung et al., 2023; Peñarroya-Farell et al., 2025; Thomas et al., 2025; Wang et al., 2022). Yet it also refines them. In the present model, governance does not appear as a broad strategic-performance mechanism. It appears as a minimalist enabling structure that lets firms test AI without pretending that they already possess a full transformation architecture. Read together, SDM → OB and TSA → OB indicate that early AI visibility depends on a combination of interpretive capability and managerial permission.

The non-significant findings also matter theoretically. Several studies report that technological readiness, digital infrastructure, ecosystem support, and Industry 4.0 maturity matter for adoption or transformation in SMEs and manufacturing firms (Chen et al., 2022; Giang et al., 2025; Ietto et al., 2024; Kovič et al., 2024; Kumar et al., 2023; Njah et al., 2026; Volf et al., 2024). In the present study, however, infrastructure, data management, and ecosystem support do not strongly predict observability. This does not mean these factors are irrelevant. It suggests that they function more as background enablers than as immediate triggers of early opportunity visibility. In a bounded small-industry setting, access conditions may already be sufficient for basic experimentation, but the decisive difference lies in whether someone can interpret outputs and whether management permits structured trials.

This sequencing argument also helps explain why a separate upstream stage deserves analytical attention. Prior TOE-DOI applications typically use DOI attributes to enrich adoption explanations (Jayashree et al., 2022; Sanchez et al., 2025). This article shows that the same pairing can also explain an earlier stage: a perceptual stage between readiness and stabilized adoption. The contribution is therefore not a new grand theory, but a sharper empirical specification of a missing phase. Evidence from chatbot, generative-AI, marketing, financial-management, and bounded automation studies already suggests that SMEs often begin with narrow tasks rather than enterprise-wide redesign (Bapat et al., 2023; Le Dinh et al., 2025; Metzger et al., 2025; Panigrahi et al., 2023; Szenftner et al., 2024). The present article adds that those bounded tasks become meaningful only when they are rendered visible and interpretable at the operational level. That is why observability, rather than relative advantage alone, becomes the pivotal DOI outcome in this model.

Figure 4 clarifies this contribution positioning visually. The figure contrasts the dominant emphases of prior SME AI studies, which often stop at readiness, adoption intention, or downstream value, with the missing intermediate stage addressed by the present article. It then places the article's contribution on the right side by highlighting operational AI opportunity formation, observability, and the dominant role of human and governance variables in the earliest phase of AI visibility.

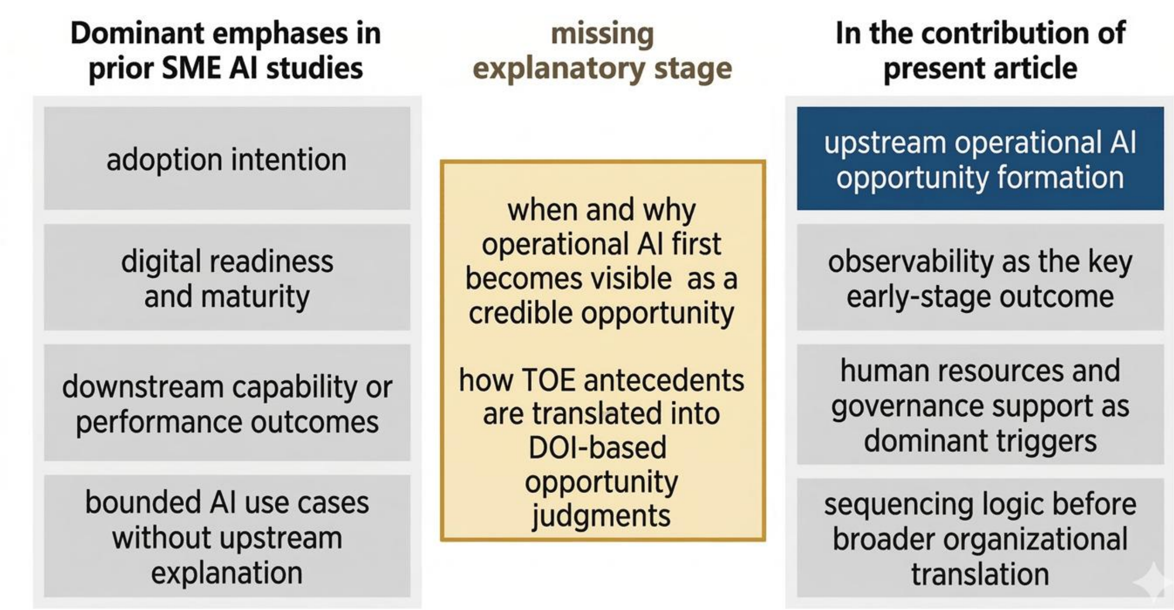

Fig. 4. Comparative positioning of the study's contribution against prior SME AI research streams.

The managerial message is sequential rather than maximalist. Small industrial firms should not assume that the right first move is always more software, more infrastructure, or a formal AI strategy. The results indicate that the more immediate priority is to make AI outputs intelligible and reviewable inside existing routines. This requires personnel who can interpret prompts, outputs, and errors, and managers who can sanction limited trials, allocate modest time, and judge usefulness at the task level. In practical terms, the empirical pattern suggests an early priority order: sensemaking capability first, bounded governance second, broader scaling later.

For firms at the earliest stage, practical starting points are therefore modest but concrete: identify one or two bounded operational tasks, assign a responsible staff member who can compare AI outputs against current work, and create a simple review rule for checking usefulness and error risk. This sequence is more realistic for small industrial firms than large-scale transformation narratives and is consistent with evidence that SME AI use often starts in drafting, support, documentation, communication, or other narrow functional domains before it expands further (Bapat et al., 2023; Le Dinh et al., 2025; Metzger et al., 2025; Panigrahi et al., 2023; Szenftner et al., 2024). The practical implication is therefore directly aligned with the structural pattern of the model: do not expect infrastructure alone to create momentum if the firm still lacks interpretive staff capacity and managerial permission for bounded experimentation.

The article has several limitations that should be stated explicitly. First, the absolute sample size remains small, even though the study captures 73.91% of the official provincial small-industry frame. The findings are therefore best read as high-coverage evidence for a bounded regional population rather than as a universal SME claim. Second, the design is cross-sectional, single-informant, and self-report based, which leaves common method risk unresolved. Third, residual discriminant-validity concerns remain, especially in the HTMT pairs involving data management, infrastructure, and human resources. Fourth, the model is complex relative to the modest population size, and the archived project outputs do not retain Q^2 or collinearity VIF diagnostics. Finally, because auditable logs of refusals and unreachable firms were not preserved, the article reports official-frame coverage rather than a formal contact-based participation metric.

5. Conclusion

This study explains an upstream stage of AI use that is often assumed but rarely modeled explicitly. Using a TOE-DOI framework and 51 usable responses from a bounded official frame of 69 small industrial firms in West Sumatra, the article shows that operational AI opportunity becomes visible mainly through human resources and digital literacy together with governance, strategy, and budget support. The strongest explanatory weight concentrates on observability, not on infrastructure or ecosystem support. In other words, small industrial firms do not move toward AI simply because the tools are present. They move when employees can interpret outputs and managers make bounded experimentation legitimate.

The article therefore contributes by positioning operational AI opportunity formation as a distinct perceptual stage between readiness and stabilized adoption. This helps explain why firms can appear digitally prepared yet still hesitate when AI must be judged in concrete work settings. Practically, the findings point to a disciplined early sequence: build interpretive capacity, create lightweight governance for bounded trials, and only then pursue broader scaling. The boundary of this claim should also remain clear: the evidence comes from a high-coverage but regionally bounded small-industry population and from a cross-sectional self-report design. As a suggestion for future research, subsequent studies should test the model in multi-region settings, strengthen construct separation, use multi-informant or longitudinal designs, and extend the upstream model into downstream analyses of routinization, capability building, and performance across more specific task categories.

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References

Alharthi, S. (2025). Harnessing knowledge: The robust role of knowledge management practices and business intelligence systems in developing entrepreneurial leadership and organizational sustainability in SMEs. *Sustainability, 17*(14), Article 6264. https://doi.org/10.3390/su17146264

Alshammakhi, Q. M., & Sheikh, R. A. (2025). Driving sustainable entrepreneurship through AI and knowledge management: Evidence from SMEs in emerging economies. *Sustainability, 17*(24), Article 10928. https://doi.org/10.3390/su172410928

Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology-organization-environment framework. *Sustainability, 16*(5), Article 1864. https://doi.org/10.3390/su16051864

Bapat, G., Mahindru, R., Kumar, A., Rroy, A. D., Bhoyar, S., & Vaz, S. (2023). Leveraging ChatGPT for empowering MSMEs: A paradigm shift in problem-solving. *Engineering Proceedings, 59*, Article 197. https://doi.org/10.3390/engproc2023059197

Burggräf, P., Steinberg, F., Sauer, C. R., & Nettesheim, P. (2024). Machine learning implementation in small and medium-sized enterprises: Insights and recommendations from a quantitative study. *Production Engineering, 18*, 751-764. https://doi.org/10.1007/s11740-024-01274-2

Chen, Q., Zhang, W., Jin, N., Wang, X., & Dai, P. (2022). Digital transformation evaluation for small- and medium-sized manufacturing enterprises using the fuzzy synthetic method DEMATEL-ANP. *Sustainability, 14*(20), Article 13038. https://doi.org/10.3390/su142013038

da Silva, N. A., Abreu, J. L., Klingenberg, C., Antunes, J. A. V., & Lacerda, D. P. (2022). Industry 4.0 and micro and small enterprises: Systematic literature review and analysis. *Production & Manufacturing Research, 10*(1), 696-726. https://doi.org/10.1080/21693277.2022.2124466

Dey, P. K., Chowdhury, S., Abadie, A., Yaroson, E., & Sarkar, S. (2024). Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises. *International Journal of Production Research, 62*, 5417-5456. https://doi.org/10.1080/00207543.2023.2179859

Drydakis, N. (2022). Artificial intelligence and reduced SMEs' business risks: A dynamic capabilities analysis during the COVID-19 pandemic. *Information Systems Frontiers, 24*, 1223-1247. https://doi.org/10.1007/s10796-022-10249-6

Giang, N. T. P., Tan, T. D., & Nhung, L. T. H. (2025). Determinants of e-commerce adoption and its effect on marketing performance among Vietnamese SMEs: A PLS-SEM approach using the TOE framework. *Journal of Open Innovation: Technology, Market, and Complexity, 11*(4), Article 100670. https://doi.org/10.1016/j.joitmc.2025.100670

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Haug, A., Wickstrom, K. A., Stentoft, J., & Philipsen, K. (2023). Adoption of additive manufacturing: A survey of the role of knowledge networks and maturity in small and medium-sized Danish production firms. *International Journal of Production Economics, 255*, Article 108714. https://doi.org/10.1016/j.ijpe.2022.108714

Heenkenda, H. M. J. C. B., Xu, F., Kulathunga, K. M. M. C. B., & Senevirathne, W. A. R. (2022). The role of innovation capability in enhancing sustainability in SMEs: An emerging economy perspective. *Sustainability, 14*(17), Article 10832. https://doi.org/10.3390/su141710832

Ietto, B., Ancillai, C., Sabatini, A., Carayannis, E. G., & Gregori, G. L. (2024). The role of external actors in SMEs' human-centered Industry 4.0 adoption: An empirical perspective on Italian competence centers. *IEEE Transactions on Engineering Management, 71*, 1057-1072. https://doi.org/10.1109/TEM.2022.3144881

Islam, A., Islam, M. A., Dal Mas, F., Fijalkowska, J., Rahman, M., & Massaro, M. (2025). Configuring AI-guided sustainable competitive advantage for SMEs through business model innovation: A systematic literature review approach. *Journal of Engineering and Technology Management, 78*, Article 101921. https://doi.org/10.1016/j.jengtecman.2025.101921

Jayashree, S., Reza, M. N. H., Malarvizhi, C. A. N., Gunasekaran, A., & Rauf, M. A. (2022). Testing an adoption model for Industry 4.0 and sustainability: A Malaysian scenario. *Sustainable Production and Consumption, 31*, 313-330. https://doi.org/10.1016/j.spc.2022.02.015

Jung, S., Kim, D., & Shin, N. (2023). Success factors of the adoption of smart factory transformation: An examination of Korean manufacturing SMEs. *IEEE Access, 11*, 2239-2249. https://doi.org/10.1109/ACCESS.2022.3233811

Kovič, K., Tominc, P., Prester, J., & Palčič, I. (2024). Artificial intelligence software adoption in manufacturing companies. *Applied Sciences, 14*(16), Article 6959. https://doi.org/10.3390/app14166959

Kumar, S., Raut, R. D., Aktas, E., Narkhede, B. E., & Gedam, V. V. (2023). Barriers to adoption of Industry 4.0 and sustainability: A case study with SMEs. *International Journal of Computer Integrated Manufacturing*. https://doi.org/10.1080/0951192X.2022.2128217

Le Dinh, T., Vu, M.-C., & Tran, G. T. C. (2025). Artificial intelligence in SMEs: Enhancing business functions through technologies and applications. *Information, 16*(5), Article 415. https://doi.org/10.3390/info16050415

Lu, H., & Shaharudin, M. S. (2024). Role of digital transformation for sustainable competitive advantage of SMEs: A systematic literature review. *Cogent Business & Management, 11*(1), Article 2419489. https://doi.org/10.1080/23311975.2024.2419489

Mariani, C., & Mancini, M. (2025). Harnessing AI for value: Examining the impact of AI capabilities and the mediating role of organizational agility on project value proposition. *International Journal of Managing Projects in Business, 18*(8), 112-143. https://doi.org/10.1108/IJMPB-03-2025-0068

Metzger, M., O'Reilly, S., & Mac an Bhaird, C. (2025). Generative artificial intelligence augmenting SME financial management. *Technovation, 147*, Article 103313. https://doi.org/10.1016/j.technovation.2025.103313

Njah, S., Danjou, C., Armellini, F., Beaudry, C., & Mosconi, E. (2026). A digital maturity model for assessing SMEs in the manufacturing sector. *Digital Engineering, 9*, Article 100084. https://doi.org/10.1016/j.dte.2025.100084

Panigrahi, R. R., Shrivastava, A. K., Qureshi, K. M., Mewada, B. G., Alghamdi, S. Y., Almakayeel, N., Almuflih, A. S., & Qureshi, M. R. N. (2023). AI chatbot adoption in SMEs for sustainable manufacturing supply chain performance: A mediational research in an emerging country. *Sustainability, 15*(18), Article 13743. https://doi.org/10.3390/su151813743

Peñarroya-Farell, M., Vaziri, M., Soto Rivera, S. K., & Miralles, F. (2025). A complex leadership perspective on generative AI adoption in SMEs: The interplay of TAM, TMT, and RBV. *Administrative Sciences, 15*(12), Article 494. https://doi.org/10.3390/admsci15120494

Peretz-Andersson, E., Tabares, S., Mikalef, P., & Parida, V. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. *International Journal of Information Management, 77*, Article 102781. https://doi.org/10.1016/j.ijinfomgt.2024.102781

Prakasa, Y., & Jumani, Z. A. (2024). Linking digital capability to small business performance: The mediating role of digital business transformation. *Cogent Business & Management, 11*(1), Article 2342486. https://doi.org/10.1080/23311975.2024.2342486

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Saeedikiya, M., Salunke, S., & Kowalkiewicz, M. (2024). Toward a dynamic capability perspective of digital transformation in SMEs: A study of the mobility sector. *Journal of Cleaner Production, 439*, Article 140718. https://doi.org/10.1016/j.jclepro.2024.140718

Sanchez, E., Calderon, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE-DOI framework, primary methodology and challenges. *Applied Sciences, 15*(12), Article 6465. https://doi.org/10.3390/app15126465

Schwaeke, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. (2024). The new normal: The status quo of AI adoption in SMEs. *Journal of Small Business Management, 63*(3), 1297-1331. https://doi.org/10.1080/00472778.2024.2379999

Sahoo, S. K., Goswami, S. S., Sarkar, S., & Mitra, S. (2024). A review of digital transformation and Industry 4.0 in supply chain management for small and medium-sized enterprises. *Science and Technology for Energy Transition, 79*, 58-70. https://doi.org/10.2516/stet/2024003

Shore, A., Tiwari, M., Tandon, P., & Foropon, C. (2025). Building entrepreneurial resilience during crisis using generative AI: An empirical study on SMEs. *Technovation, 145*, Article 103063. https://doi.org/10.1016/j.technovation.2024.103063

Siahaan, D. T., & Tan, C. S. L. (2022). What drives the adaptive capability of Indonesian SMEs during the COVID-19 pandemic: The interplay between perceived institutional environment, entrepreneurial orientation, and digital capability. *Asian Journal of Business Research, 12*(2), 8-27. https://doi.org/10.14707/ajbr.220125

Soomro, R. B., Al-Rahmi, W. M., Dahri, N. A., Almuqren, L., Al-mogren, A. S., & Aldaijy, A. (2025). A SEM-ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs. *Scientific Reports, 15*, Article 5438. https://doi.org/10.1038/s41598-025-86464-3

Szenftner, A., Stumpp, S., & Knopf, T. (2024). Exploring the potential of AI to increase productivity in small marketing teams. In *Proceedings of the 19th European Conference on Innovation and Entrepreneurship (ECIE)* (pp. 970-977). https://doi.org/10.34190/ecie.19.1.2850

Thomas, G., Albishri, N. A., Islam, J. U., & Tanveer, M. (2025). Exploring the determinants of artificial intelligence adoption intention in the SMEs of United Arab Emirates. *SAGE Open, 15*(4), Article 21582440251395561. https://doi.org/10.1177/21582440251395561

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Volf, L., Dohnal, G., Beránek, L., & Kyncl, J. (2024). Navigating the fourth industrial revolution: SBRI - a comprehensive digital maturity assessment tool and road to Industry 4.0 for small manufacturing enterprises. *Manufacturing Technology, 24*(4), 668-680. https://doi.org/10.21062/mft.2024.074

Wang, J., Lu, Y., Fan, S., Hu, P., & Wang, B. (2022). How to survive in the age of artificial intelligence? Exploring the intelligent transformations of SMEs in central China. *International Journal of Emerging Markets*. https://doi.org/10.1108/IJOEM-06-2021-0985

Yao, M. X., Wang, D., & Freeman, S. (2026). Digital barriers and capabilities in aspirant emerging-market SMEs: A resource-adaptive dynamic capabilities model of transformation phases. *Technovation, 152*, Article 103506. https://doi.org/10.1016/j.technovation.2026.103506