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REVIEW ARTICLE

Drivers, Barriers and Business Outcomes of Artificial Intelligence Adoption in SMEs
A Systematic Literature Review and Contextual Framework for Bangladesh

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ABSTRACT

Artificial intelligence (AI) is increasingly presented as a route through which small and medium-sized enterprises (SMEs) can overcome information, capability and scale disadvantages. Yet adoption remains uneven, especially in emerging economies where finance, skills, infrastructure and institutional assurance are constrained. This systematic literature review investigates four questions: which technological, organisational and environmental conditions drive AI adoption; which barriers interrupt implementation; which business outcomes are reported; and how the international evidence can be translated into an actionable framework for Bangladesh. Following PRISMA 2020 principles, sixteen structured OpenAlex search routes retrieved 800 records. After removing 320 duplicates, 480 unique records were screened. A relevance pre-screen excluded 309 records; 171 database reports and 14 supplementary reports were assessed. Forty primary empirical studies were included, while eight reviews or conceptual sources were retained separately for theoretical triangulation. Study coding was organised through the Technology–Organization–Environment (TOE) framework and interpreted with resource-based and dynamic-capability perspectives. Human capital and employee skills were the most frequent driver (21 studies), followed by top-management support (12), ecosystem support (11), relative advantage (9) and digital/data readiness (9). The strongest explicit barriers concerned privacy, security, ethics and distrust (7), high cost and limited finance (6), institutional or regulatory gaps (5), and implementation complexity (4). Reported outcomes clustered around workforce learning (14), decision quality and agility (8), operational productivity (8), competitive advantage (8), revenue performance (7) and sustainability (6). However, nineteen studies relied on SEM or PLS-SEM, most evidence was cross-sectional, and only two primary studies directly examined Bangladesh. The paper therefore proposes a capability-gated pathway—diagnose, pilot, integrate, govern and scale—supported by Bangla-ready tools, shared training, affordable finance, vendor assurance and proportionate governance. The review concludes that AI produces business value not as a stand-alone purchase but when complementary skills, data routines, leadership and institutional supports are deliberately assembled.

1. Introduction

Artificial intelligence has moved from a specialist technology into a general-purpose managerial resource. Prediction, language generation, recommendation, image recognition and workflow automation can now be obtained through cloud services and increasingly through ordinary software. This shift is particularly important for small and medium-sized enterprises because their competitiveness often depends upon speed, customer closeness and flexible decision-making. The same firms, nevertheless, work with thinner financial margins, fewer technical specialists and less formal data governance than large corporations. As a result, the apparent accessibility of AI does not automatically become organisational adoption, and adoption does not automatically create performance.

Bangladesh makes this problem practically significant. The country has a very large base of micro and small enterprises, expanding digital services, a growing technology workforce and substantial use of mobile platforms. At the same time, access to finance, reliable connectivity, managerial capability, cybersecurity assurance and regulatory clarity remain uneven. A recent World Bank country analysis reports more than six million individual entrepreneurs and micro or cottage enterprises, nearly 80,000 SMEs, and a sector in which 93.6% of the formal SME population is small. MSMEs contribute around one quarter of GDP and employment, while more than half of surveyed SMEs identified limited finance as the main constraint to technology adoption (World Bank, 2026). These conditions make Bangladesh neither a passive recipient of foreign solutions nor an uncomplicated high-growth AI market. It is a context where usefulness, affordability, language and trust must come together.

Two Bangladesh-specific primary studies illuminate the local problem but do not yet constitute a mature evidence base. Polas et al. (2022) linked AI, blockchain and risk-taking orientations to performance-related behaviour among Bangladesh-based SMEs. More recently, Islam et al. (2026) used interviews with fourteen SME representatives in Dhaka to identify slow internet, limited skills, inadequate infrastructure, high cost, weak government support, political instability and the absence of a clear legal framework as obstacles to agentic AI. Taken together, they show both entrepreneurial interest and institutional fragility. They also reveal the need to connect international evidence to local sequencing rather than transferring a generic adoption checklist.

Accordingly, this review asks four research questions. RQ1: What technological, organisational and environmental factors drive AI adoption in SMEs? RQ2: What barriers constrain implementation and sustained use? RQ3: What business outcomes are associated with adoption? RQ4: How can the international evidence be translated into a contextual framework for Bangladesh? The contribution is threefold. First, the paper assembles and verifies a recent empirical dataset rather than relying on a narrative sample. Second, it joins TOE categorisation with capability-based interpretation so that adoption conditions and value-creation mechanisms are not treated as the same thing. Third, it offers a staged framework, with measurable gates, for SME managers, financial institutions, vendors and policymakers in Bangladesh.

2. Conceptual Background

2.1 AI adoption as an organisational change process

AI adoption is sometimes represented as a binary decision: an enterprise adopts or does not adopt. In practice, adoption includes recognition, experimentation, data preparation, employee acceptance, integration, monitoring and repeated redesign. A firm may subscribe to a generative AI service but fail to connect it to a workflow; another may embed machine learning in demand planning without calling the activity "AI." Therefore, this review treats adoption as purposeful organisational use rather than awareness or procurement alone. This distinction matters because the resources that trigger a pilot differ from those that sustain operational value. Perceived usefulness may begin experimentation, while data quality, process ownership and employee learning determine whether a pilot survives.

2.2 TOE, resources and dynamic capabilities

The Technology–Organization–Environment framework provides the main coding structure. The technological context concerns relative advantage, compatibility, complexity, data and infrastructure. The organisational context concerns leadership, resources, skills, culture, coordination and readiness. The environmental context concerns competitors, customers, vendors, government, finance and regulation. TOE is suitable because SME adoption is not only an individual acceptance decision; it is a firm-level response shaped by internal and external conditions. Several included studies explicitly use TOE, including work in Saudi Arabia, Jordan, Pakistan, Europe and emerging-market settings (Badghish & Soomro, 2024; Abaddi, 2024; Arroyabe et al., 2024; Haq et al., 2026).

TOE explains the field of pressures but is less precise about how resources turn into performance. The resource-based view and knowledge-based view suggest that an AI tool becomes valuable when combined with scarce complementary assets, such as domain knowledge, clean data, customer relationships or process expertise. Dynamic-capability reasoning adds sensing, seizing and transforming: managers recognise an AI opportunity, mobilise a bounded experiment, and then redesign routines when evidence supports scaling. Resource orchestration similarly highlights how leadership bundles technology, knowledge and human skills. These perspectives explain why identical software can generate different outcomes across firms (Dey et al., 2023; Peretz-Andersson et al., 2024; D'Amico et al., 2026).

The integrated model used in this review separates three analytical moments. TOE conditions influence adoption readiness and implementation. Complementary capabilities mediate whether usage becomes embedded. Outcomes then depend upon fit, governance and learning over time. Environmental support can compensate for SME resource scarcity through shared infrastructure, trusted vendors, finance or training, whereas weak institutions can magnify uncertainty. This layered interpretation is particularly relevant to Bangladesh, where an enterprise may be entrepreneurially willing but structurally unable to assemble data, talent, finance and assurance on its own.

3. Materials and Methods

3.1 Review design and eligibility

The review followed PRISMA 2020 principles for transparent identification, screening, eligibility assessment and reporting (Page et al., 2021). The protocol was specified around the four research questions, a 2018–2026 publication window, English-language scholarly records, and an SME-level unit of analysis. Primary inclusion required empirical evidence on an AI-related adoption condition, implementation barrier or business outcome. Studies could be quantitative, qualitative, mixed-method or secondary-data designs. Reviews and conceptual contributions were not counted as primary studies, but eight were retained as background sources to triangulate theory and terminology.

The operational definition of SMEs followed each source because legal thresholds vary by country. Studies were excluded when they focused only on large enterprises, individual consumer acceptance, purely technical algorithm development, medical diagnosis without an SME context, education without enterprise adoption, or general digital transformation in which AI was incidental. Conference-like or repository records without adequate bibliographic identity were also excluded when verification could not establish a reliable scholarly source. No restriction was imposed on sector or national income group because transferability to Bangladesh required comparison across both emerging and developed contexts.

Table 1.
Review protocol and eligibility criteria

Element	Operational decision	Rationale
Review period	2018–2026; search completed 28 July 2026	Captures the contemporary SME AI literature and current generative/agentic developments.
Population	Micro, small and medium-sized enterprises; mixed samples only when SME evidence was explicit	Maintains firm-level relevance while respecting country-specific SME definitions.
Phenomenon	AI adoption, readiness, implementation, barriers, capabilities or business outcomes	Links adoption conditions with value realisation.
Evidence	Empirical journal articles and verified scholarly reports; reviews separated as background	Avoids double counting review findings as primary observations.
Language	English	Search and coding resources were available in English.
Exclusions	Large-firm-only, consumer-only, technical-only, education/medical without SME context, weak identity or no relevant evidence	Protects topical and methodological alignment.

3.2 Search strategy and dataset construction

Sixteen structured searches were run in OpenAlex using combinations of “artificial intelligence,” “AI,” “machine learning,” “generative AI,” “agentic AI,” “SME,” “small and medium enterprise,” “MSME,” adoption, readiness, barriers, drivers, performance and business outcomes. Each route retrieved up to fifty records, producing 800 raw records. DOI and normalised-title matching removed 320 duplicates, leaving 480 unique records for title and abstract screening. Because a single route cap can omit relevant papers and indexed abstracts vary in completeness, fourteen supplementary reports were added through citation and publisher-page searching. The supplementary records were subjected to the same verification and eligibility rules.

3.3 Screening, verification, quality and extraction

After the 309-record relevance pre-screen exclusion, 171 database reports and fourteen supplementary reports were assessed, giving 185 reports in the verification pool. Bibliographic identity was checked through DOI resolution, Crossref and OpenAlex metadata, and publisher information where available. One hundred and thirty-seven reports were excluded after verification or quality screening. Forty primary empirical studies were included and eight background reviews or conceptual sources were placed in a separate synthesis layer. The resulting counts are reported in Figure 1 and in the companion workbook.

Each primary study was coded across bibliographic, contextual, theoretical, methodological and substantive fields. Extraction captured country, sector, AI category, research method, sample, theory, dominant TOE dimension, drivers, barriers, outcomes, key findings, Bangladesh transferability and limitations. A twelve-point quality rubric scored bibliographic identity, topical alignment, method clarity, data/context clarity, findings clarity and source quality. Included studies scored between nine and twelve. A “manual full-text check” flag was retained where the accessible abstract did not support complete method or sample extraction; therefore, silence in an abstract was not coded as evidence that a barrier or outcome was absent.

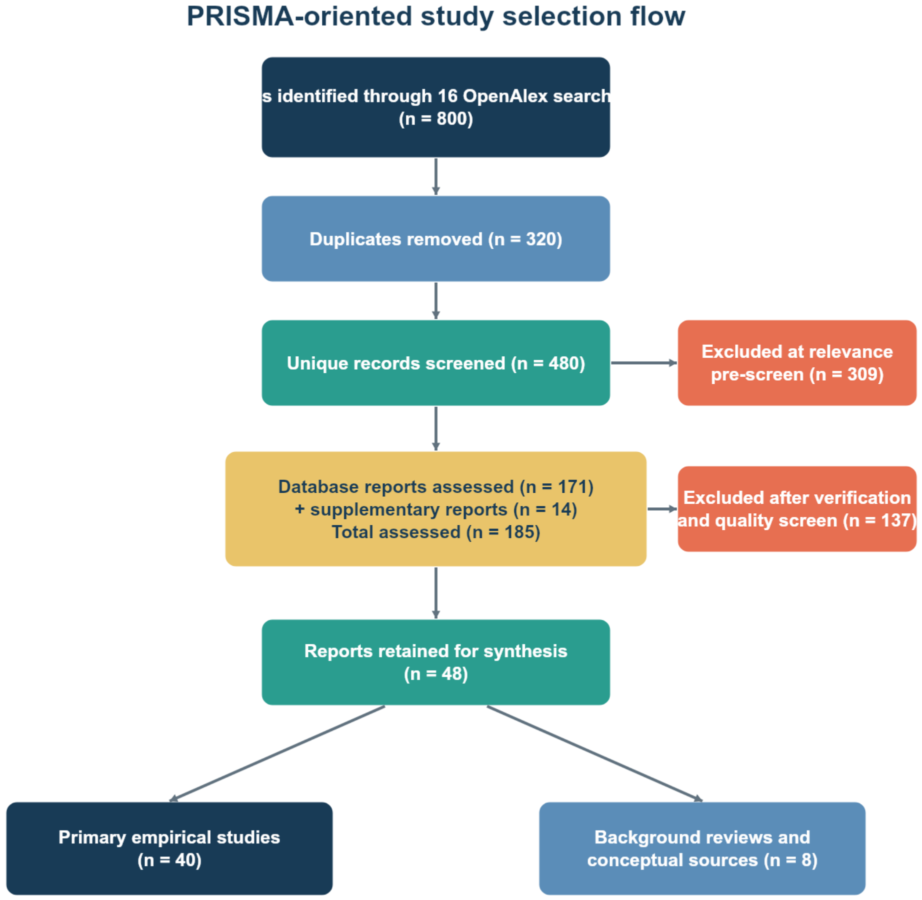

Figure 1. PRISMA-oriented identification, screening and inclusion flow.

3.4 Synthesis

A framework synthesis was used because the evidence is heterogeneous in technology, country, sector and design. Drivers and barriers were first coded inductively from explicit study content and then organised under TOE. Business outcomes were grouped into workforce/learning, decision quality, operational productivity, competitive position, finance/revenue, sustainability, resilience, innovation and customer/marketing performance. Theme frequencies identify how often a topic was explicit in a study; they are not pooled effect sizes, and multi-coding means totals can exceed forty.

Interpretation followed a structured transferability test for Bangladesh: similarity of resource constraints, digital infrastructure, institutional conditions, workforce capabilities and market structure. Findings from emerging economies were not assumed to be automatically local, while developed-economy evidence was not dismissed. Instead, each mechanism was considered for the conditions it requires. This distinction supports contextual inference without pretending that the review contains a nationally representative causal estimate for Bangladesh.

4. Results

4.1 Evidence profile

The 40 primary studies were published between 2021 and 2026, with a sharp increase after 2022. Fourteen appeared in 2024, nine in 2025 and six in 2026. Twenty-three studies were situated in emerging or developing economies other than Bangladesh, twelve in developed or transition economies, three were multi-country or did not disclose the country clearly in the accessible abstract, and two directly examined Bangladesh. The geographic profile gives the review reasonable exposure to resource-constrained contexts, although the direct local evidence remains thin.

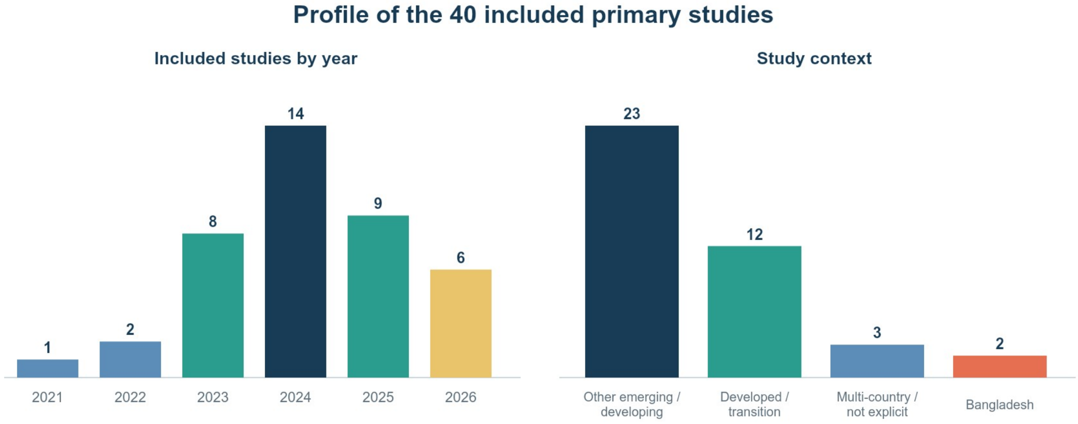

Figure 2. Publication trend and geographic context of the included studies.

Table 2.
Profile of the primary evidence base

Dimension	Distribution	Interpretive implication
Publication year	2021: 1; 2022: 2; 2023: 8; 2024: 14; 2025: 9; 2026: 6	The literature is recent and fast moving.
Context	Other emerging/developing: 23; developed/transition: 12; multi/not explicit: 3; Bangladesh: 2	Transferability is possible but must be conditional.
Dominant TOE dimension	Technology: 17; organisation: 14; environment: 9	Technology initiates attention; organisational and environmental complements shape use.
Leading method	SEM/PLS-SEM: 19; survey: 5; survey/regression: 4; qualitative interviews: 3	Association evidence is stronger than longitudinal causal evidence.
Quality score	Range 9–12 out of 12	Included records met bibliographic, topical and reporting thresholds.

4.2 RQ1: Drivers of AI adoption

Employee skills and human capital were the most frequent drivers, appearing in twenty-one studies. The construct included technical knowledge, employee adaptability, training, domain competence and the ability to work across human–technology boundaries. This finding is consistent across different applications. Dey et al. (2023) show how leadership creates a data-driven culture and strengthens employee competencies around AI-enabled supply chains. Peretz-Andersson et al. (2024) similarly interpret implementation as resource orchestration rather than simple technology acquisition. Skills therefore operate as both an adoption antecedent and a value-conversion capability.

Government, vendor and ecosystem support appeared in eleven studies. SMEs commonly access AI through external providers because they cannot maintain specialist teams or infrastructure internally. Vendors, universities, industry associations, financial institutions and public agencies can reduce search costs, provide training, certify practices and spread fixed costs. In emerging economies these supports partly substitute for scarce internal resources. However, external dependence introduces vendor lock-in, uncertain data jurisdiction and quality problems. Ecosystem support should therefore be assessed for reliability and accountability, not merely availability.

Relative advantage and perceived usefulness appeared in nine studies, and digital/data readiness also appeared in nine. Relative advantage is especially important at the initiation stage: a manager needs to see how AI can reduce errors, accelerate a task, improve customer response or support a decision. Readiness matters later because a useful idea cannot be integrated when records are fragmented or staff cannot access consistent data. Arroyabe et al. (2024), using a large European SME sample, show that digital capabilities and innovation conditions are materially connected with adoption. D'Amico et al. (2026) similarly foreground knowledge resources. The implication is sequential: visible usefulness creates attention; readiness sustains execution.

Competitive and customer pressure appeared in seven studies, while organisational readiness/change capacity appeared in six. Pressure can accelerate experimentation, particularly in marketing, e-commerce and customer service, but it can also produce imitation without fit. Firms that respond only because competitors advertise AI may select a prominent tool rather than a valuable use case. Organisational readiness makes environmental pressure productive by translating it into priorities, roles and learning routines. Compatibility, ease of use, trust, responsible governance and investment were less frequent but remain important gating conditions.

Table 3.
Drivers of SME AI adoption through the TOE and capability lenses

Driver	TOE location	Studies	Interpretation for Bangladesh
Employee skills and human capital	Organisation	21	Use shared, task-based training; combine AI literacy with sector knowledge and verification.
Top-management and leadership support	Organisation	12	Owner-managers should sponsor a bounded use case, name a process owner and protect learning time.
Government/vendor/ ecosystem support	Environment	11	Build trusted advisory, finance, vendor-assurance and university/industry support channels.
Relative advantage/perceived usefulness	Technology	9	Start with observable time, quality or customer-response problems rather than technology novelty.
Digital, data and technology readiness	Technology/ organisation	9	Standardise records, access controls and workflow before automation.
Competitive/customer pressure	Environment	7	Treat pressure as a signal, not a business case; require local process fit.

4.3 RQ2: Barriers to implementation and sustained use

Privacy, security, ethics and distrust formed the most frequent explicit barrier cluster, appearing in seven studies. AI can expose customer, employee, supplier and proprietary data through poorly governed prompts, external APIs or inappropriate training use. Cybersecurity concerns are especially serious for SMEs that lack dedicated security personnel. Rawindaran et al. (2021) demonstrate that even cybersecurity-oriented machine learning adoption requires organisational and environmental preparedness. Risk is therefore double-sided: AI may improve detection, but the method of deploying it can create a new attack and compliance surface.

High cost and limited finance appeared in six studies. Costs include subscriptions, connectivity, data preparation, integration, training, monitoring and the managerial time absorbed by experimentation. The sticker price of a generative AI tool can be low while the total implementation cost is not. This issue is central for Bangladesh, where limited finance is already a leading constraint on broader technology adoption (World Bank, 2026). Financing schemes should consequently be linked to defined use cases, capability milestones and performance evidence rather than encouraging indiscriminate software purchasing.

Regulatory and institutional gaps appeared in five studies, while implementation complexity and uncertainty appeared in four. Uncertainty concerns not only law but also the reliability of outputs, liability for decisions, the future direction of vendors and the durability of benefits. Ganguly et al. (2025) show that barriers in Indian MSMEs are interlinked rather than independent; financial, capability and organisational constraints reinforce one another. Ledesma Chaves et al. (2026) similarly foreground risk factors. A policy that addresses only awareness, or only credit, is therefore unlikely to shift adoption when assurance, data and skills remain unresolved.

The two Bangladesh studies make these interacting constraints concrete. Islam et al. (2026) identify slow internet, inadequate infrastructure, limited knowledge, weak government support, political instability, high costs and an absent legal framework through interviews with fourteen firms in Dhaka. Polas et al. (2022) show that technology-oriented entrepreneurial behaviour exists, but their study does not remove the underlying institutional constraints. Bangladesh's draft National AI Policy 2026–2030 recognises the need for responsible and inclusive AI, data protection, accountability, cybersecurity and local-language inclusion (ICT Division, 2026). The practical gap is implementation: SMEs need simple rules and accessible support, not only national aspirations.

Table 4.
Barrier-response matrix

Barrier	Evidence signal	Managerial response	Ecosystem/policy response
Privacy, security, ethics and distrust	7 studies	Classify data; prohibit sensitive prompts; require human review; log consequential use.	Issue SME-ready guidance, baseline controls and vendor assurance.
High cost and limited finance	6 studies	Estimate total implementation cost and stage investment against measured value.	Offer milestone-based vouchers, credit guarantees and shared services.
Regulatory/institutional gaps	5 studies	Document decisions and assign accountability even before regulation matures.	Clarify data, consumer, labour and sector obligations through practical notices.
Complexity/uncertainty	4 studies	Use a narrow workflow, sandbox, fallback process and stop criteria.	Provide testbeds, neutral advisory services and reusable procurement templates.
Skills/readiness/ resistance	3 studies each	Train around real tasks; involve employees early; redesign work, not only software.	Support sector-specific curricula and trainer networks in Bangla and English.
Infrastructure/digital maturity	2 explicit studies	Prefer resilient, low-bandwidth services and offline fallbacks.	Improve connectivity and shared cloud/data infrastructure outside major hubs.

4.4 RQ3: Business outcomes of AI adoption

Workforce and learning outcomes were the most commonly reported cluster, appearing in fourteen studies. The category includes employee adaptability, augmented capability, knowledge sharing, accounting automation and workforce-management effectiveness. AI value is thus not limited to labour substitution. In many SMEs the more plausible mechanism is augmentation: employees retrieve information faster, draft routine content, identify anomalies and focus attention on exceptions. Kumar et al. (2022) connect AI-powered workforce management with revenue growth, while Dey et al. (2023) place employee competence inside a resilience mechanism. These findings also imply a distributional question: benefits depend on whether employees receive training and meaningful role redesign.

Decision quality and agility appeared in eight studies, and operational efficiency/productivity also appeared in eight. AI can compress the time required for forecasting, classification, scheduling, reporting or customer-response tasks. In supply chains, Dey et al. (2023) and Roux et al. (2023) relate AI to agility, risk management and resilience-supporting routines. In accounting and marketing settings, automation can improve consistency and free managerial attention. Yet speed can amplify errors when data are poor or outputs are accepted without review. Decision improvement therefore requires an evidence trail, responsibility and a process for contesting or correcting AI-supported recommendations.

Competitive advantage and market position appeared in eight studies. Financial performance or revenue growth appeared in seven. Abrokwah-Larbi and Awuku-Larbi (2023) report performance benefits from AI in marketing among Ghanaian SMEs, while Ardito et al. (2024) use European data to examine revenue growth and complementarities with IoT and big-data analytics. Kopka et al. (2023) connect AI integration in knowledge bases with SME catch-up and growth. These findings reinforce the complementarity argument: returns are more credible when AI is joined with existing digital assets, market knowledge and absorptive capacity.

Sustainability and low-carbon performance appeared in six studies, resilience and risk reduction in four, and innovation/business-model renewal in three. Farmanesh et al. (2025) associate AI and green innovation with competitive advantage, while Shaik et al. (2023) examine AI-driven business-model innovation for carbon-neutral business. Saleem et al. (2024) connect AI, frugal innovation and internationalisation readiness. These outcomes are strategically attractive to Bangladesh SMEs participating in export supply chains, but the evidence should not be read as proof that AI is intrinsically green. Model use consumes energy and can encourage unnecessary automation; environmental benefit depends upon the process changed and the net resource effect.

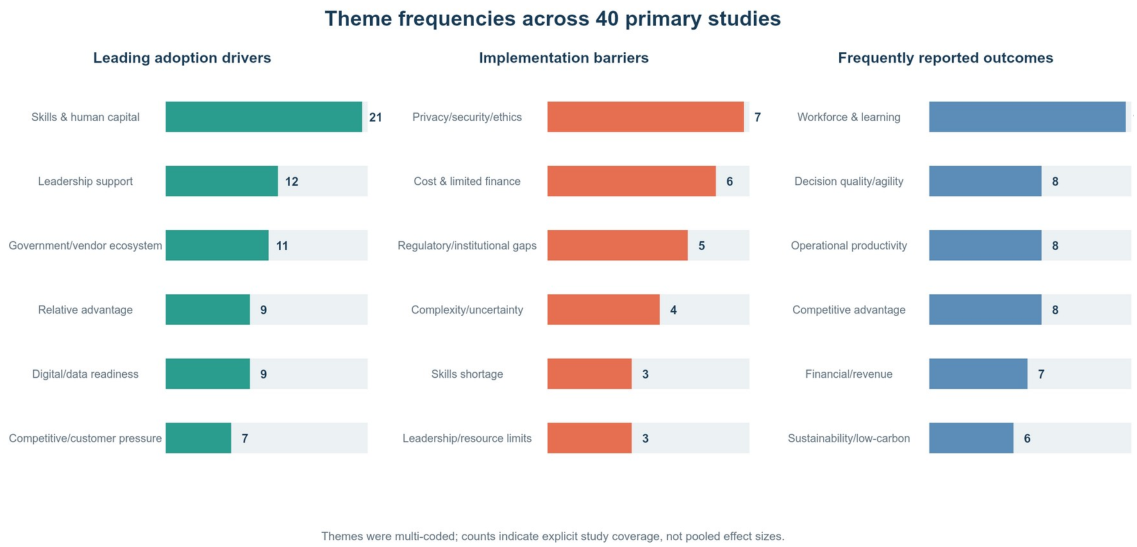

Figure 3. Leading drivers, barriers and outcome themes. Counts are multi-coded study frequencies.

Table 5.
Reported outcomes and evidence cautions

Outcome cluster	Studies	Value mechanism	Evidence caution
Workforce and learning	14	Augmentation, knowledge access, adaptability, automation	Job quality and distribution of benefits are seldom measured longitudinally.
Decision quality and agility	8	Faster analysis, prediction and exception handling	Poor data or over-trust can accelerate mistakes.
Operational productivity	8	Reduced handling time, errors and coordination delay	Many measures are manager perceptions rather than process logs.
Competitive advantage	8	Differentiation, responsiveness and knowledge leverage	Selection effects may favour already capable firms.
Financial/revenue	7	Sales conversion, capacity and complementary digital assets	Causal and audited financial evidence remains limited.
Sustainability/resilience	6 / 4	Resource optimisation, risk sensing and response agility	Net environmental effect and crisis performance require longer observation.

4.5 RQ4: A contextual framework for Bangladesh

The synthesis indicates that Bangladesh should not pursue SME AI adoption as a one-time technology-diffusion campaign. A more credible strategy is capability gated: enterprises progress when a business problem, minimum data readiness, employee capability and proportionate safeguards are demonstrable. Five stages are proposed. Diagnose establishes the process baseline and identifies a problem worth solving. Pilot tests a narrow, reversible use case. Integrate connects the tool to roles, data and workflow. Govern formalises oversight and protection. Scale expands only after operational and financial evidence is visible.

Stage one, diagnose, should begin with a task rather than an AI category. Candidate processes may include product-description drafting, bilingual customer support, inventory exception detection, invoice extraction, quality inspection or demand planning. Managers should record the present time, error rate, delay, cost and customer effect. They should identify what data are used, whose data they are, whether they can be transferred to a vendor, and who is accountable for the final decision. A use case should stop if it cannot define a responsible owner or measurable baseline.

Stage two, pilot, should be small enough to reverse. The firm can test a cloud service or vendor solution on non-sensitive or de-identified data, with employees checking every consequential output. The pilot needs a comparison period and a simple scorecard: time saved, errors introduced or avoided, employee use, customer response, direct cost and security incidents. A pilot is not successful because a demonstration looks impressive. It is successful when the process performs better under realistic operating conditions and staff understand the limitations.

Stage three, integrate, changes the organisation around a validated use case. Data definitions are standardised, access is controlled, prompts or models are versioned where relevant, staff receive role-specific training, and a fallback method is retained. Integration also requires deciding which capability stays inside the firm. SMEs may outsource infrastructure but should preserve process knowledge, vendor-evaluation ability and control over critical records. Bangla language quality, local terminology and mixed Bangla-English workflows need deliberate testing because apparent fluency does not guarantee accurate domain output.

Stage four, govern, applies proportionate controls. Low-consequence drafting can use light review, while decisions affecting employment, finance, safety, health or consumer rights require stronger evidence, human authority and traceability. Vendor contracts should address data retention, model training, breach notification, service continuity and deletion. The absence of a final comprehensive AI law is not a reason to postpone accountability. Bangladesh's draft policy already signals responsible, inclusive and locally relevant development; firms can prepare through basic privacy, cybersecurity, human-review and incident-management practices (ICT Division, 2026).

Stage five, scale, expands a system after evidence survives repeated cycles. Scaling may involve new branches, products or workflows, but it should also trigger renewed risk assessment. Financial institutions can support this stage with milestone-based instruments rather than unsecured technology consumption. SME Foundation, industry associations, universities and technology providers can create shared training, testbeds, sector data templates and trusted vendor lists. Such ecosystem arrangements lower fixed costs while retaining enterprise responsibility.

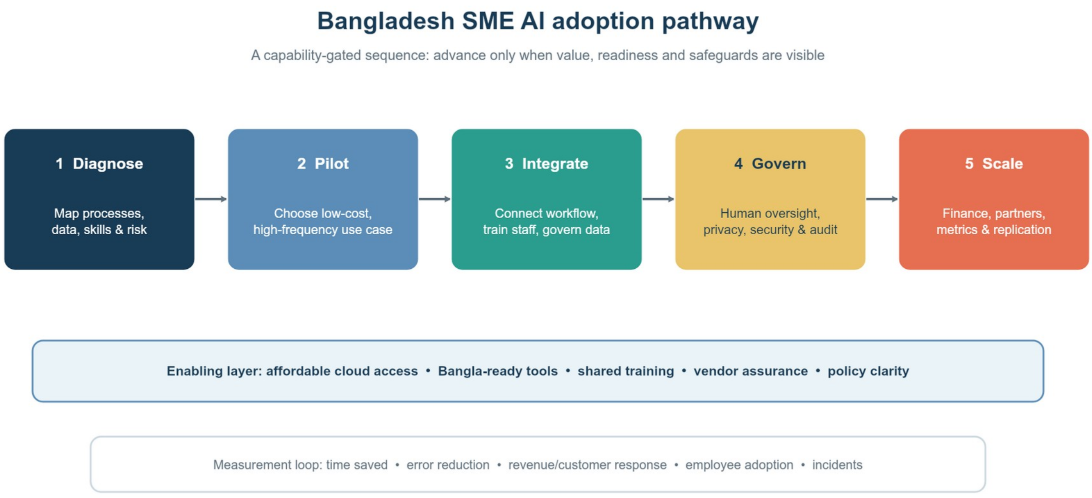

Figure 4. Capability-gated AI adoption pathway for Bangladesh SMEs.

Table 6.
Bangladesh implementation action matrix

Actor	Priority actions (0–18 months)	Medium-term actions (18–48 months)	Suggested indicators
SME owner-managers	Select one measurable use case; assign owner; classify data; train users; retain fallback.	Integrate successful pilots, negotiate data terms, develop internal evaluation capability.	Cycle time, error rate, margin/revenue effect, staff adoption, incidents.
Government/ SME agencies	Publish plain-language guidance; fund diagnostic clinics and sector pilots; map connectivity and skill gaps.	Create regulatory sandboxes, shared testbeds, procurement standards and regional support hubs.	Verified pilots, survival after 12 months, regional participation, compliance maturity.
Banks and financiers	Use small milestone-based vouchers or loans tied to diagnostics and evidence.	Develop cash-flow products for proven digital investment and co-financing with vendors.	Repayment, productivity gain, additionality and inclusion outside Dhaka.
Vendors/ platforms	Disclose data use and retention; offer Bangla testing, low-bandwidth modes and transparent pricing.	Provide audit logs, portability, partner training and sector integrations.	Uptime, complaint resolution, portability, verified language/task performance.

Actor	Priority actions (0–18 months)	Medium-term actions (18–48 months)	Suggested indicators
Universities/ associations	Deliver task-based AI and verification training; support neutral vendor comparison.	Build sector-specific datasets, applied labs and train-the-trainer networks.	Learner completion, enterprise application, women/youth inclusion, applied projects.

5. Discussion

5.1 Theoretical interpretation

The review supports TOE as a useful map but shows that its dimensions are not independent boxes. Skills affect whether technological complexity is manageable; leadership affects whether external support is absorbed; regulation affects vendor trust and the cost of experimentation. The Bangladesh interview evidence is especially relational: weak infrastructure, skills, finance and law reinforce one another (Islam et al., 2026). Future theorising should therefore model configurations and sequences, not only the separate net effects of TOE variables. The included fsQCA and ANN studies begin this movement, but process and longitudinal designs are still required.

The capability interpretation adds a distinction between adoption capital and value-conversion capital. Adoption capital includes awareness, perceived advantage, minimum finance and vendor access. Value-conversion capital includes domain knowledge, process discipline, data stewardship, employee learning and governance. A firm can possess enough adoption capital to buy a tool but insufficient value-conversion capital to produce reliable returns. This distinction helps explain why surveys may find strong intention while implementation remains shallow. It also shifts policy from maximising the number of “AI adopters” toward building enterprises able to learn and govern.

The outcome evidence suggests complementarity rather than replacement. Revenue and productivity effects are often linked to other digital capabilities, employee competence, IoT, big-data analytics or organisational change (Ardito et al., 2024; Arroyabe et al., 2024; Dey et al., 2023). Theoretically, AI should be treated as a component in a socio-technical bundle. This finding also addresses the deterministic language sometimes used around AI. The technology offers capabilities; the organisation determines the use, and the institutional environment changes the cost and legitimacy of that use.

5.2 Managerial and policy implications

For managers, the most important implication is to narrow the first question. “How can we adopt AI?” is too broad. “Can we reduce invoice-processing time without exposing customer data?” is answerable. A narrow question supports a baseline, an owner, a controlled test and an exit rule. Managers should also distinguish vendor fluency from reliability. Generative systems can produce polished Bangla or English while giving incorrect facts, calculations or legal interpretations. Human review must therefore be assigned to a knowledgeable role rather than left as a general expectation.

For policymakers, the evidence argues for joined-up intervention. Training without finance can produce awareness but no implementation. Finance without advisory support can fund unsuitable products. Regulation without plain-language translation can increase fear, while promotion without safeguards can damage trust. An SME-focused implementation package should connect diagnostics, skills, finance, vendor assurance, cybersecurity and measurement. Regional delivery is important because technology ecosystems are concentrated in Dhaka, whereas enterprise needs are geographically dispersed.

For vendors, trust is a market capability. Clear pricing, accessible contract terms, data-retention disclosure, export and deletion functions, low-bandwidth options, incident support and evidence of Bangla task performance can differentiate responsible suppliers. Vendors should avoid presenting broad benchmark scores as proof of fitness for a specific SME workflow. Local validation with representative terminology, documents and users is more informative.

5.3 Research agenda

The first research priority is longitudinal, firm-level evidence. Studies should observe the journey from decision to pilot, integration, abandonment or scale and use operational measures before and after implementation. Where randomisation is infeasible, matched comparisons, phased rollouts, difference-in-differences or detailed process tracing can improve causal inference. Revenue should be separated from margin, and time saving from actual labour productivity. Failed and abandoned pilots should be reported, because survivorship bias otherwise inflates expectations.

Second, Bangladesh research needs broader geographic and sector coverage. Dhaka-based interviews provide valuable early insight, but manufacturing clusters, agro-processing, retail, logistics, light engineering, women-owned enterprises and rural service firms may face different connectivity, labour and language conditions. Comparative work should examine whether the proposed stages and gates vary by firm size and digital maturity. It should also study informal and micro enterprises, which are economically important but often absent from indexed management research.

Third, responsible AI outcomes need stronger measurement. Privacy incidents, cybersecurity exposure, bias, employee autonomy, work intensity, deskilling, consumer understanding and environmental costs should sit alongside productivity and revenue. Agentic AI makes this especially urgent because a system may act across tools rather than only generate content. Research should document what decisions remain human, how exceptions are escalated, and whether workers can contest an output.

5.4 Limitations

This review has five principal limitations. First, the search relied on OpenAlex and supplementary citation/publisher searching; Scopus and Web of Science were not directly searched. Second, English-language inclusion may omit locally published evidence. Third, coding often depended on abstracts, and inaccessible full text reduced detail for some samples, methods and limitations. Fourth, thematic frequencies indicate visibility in the literature, not effect magnitude or importance. Fifth, publication through 2026 includes recent records whose final issue assignment or citation impact may still change.

The review also inherits limitations of the field. Many studies are cross-sectional and use self-reported perceptions, common-method survey designs and convenience samples. Technologies, contexts and outcome measures are heterogeneous, making meta-analysis inappropriate for the present dataset. Two Bangladesh-specific studies cannot support national generalisation. The contextual framework is therefore a theory-informed implementation proposition that should be tested and revised, not a validated national causal model.

6. Conclusion

AI adoption in SMEs is driven less by technology availability than by the ability to assemble a complementary system. Across forty primary studies, employee capability, leadership, ecosystem support, perceived usefulness and digital readiness repeatedly shaped adoption. Privacy and security concerns, finance, institutional gaps and complexity constrained implementation. Reported outcomes were broad—learning, agility, productivity, competitiveness, revenue, sustainability and resilience—but the underlying evidence remains more associative than causal.

For Bangladesh, the practical lesson is disciplined ambition. SMEs should not wait for perfect conditions, yet they should not scale an unmeasured demonstration. A staged diagnose–pilot–integrate–govern–scale pathway allows experimentation while protecting scarce resources and trust. Public agencies, financiers, vendors, universities and associations should reduce the fixed costs of skills, assurance and infrastructure, with particular attention to Bangla-ready services and firms outside Dhaka. If capability and accountability grow together, AI can become a productive enterprise resource. If they separate, adoption may remain superficial, risky and unequal.

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Appendix A. Included Primary Study Register

The appendix is excluded from the target manuscript word count. Full 43-field coding, search routes, screening decisions, verification notes and quality scores are supplied in the companion Excel workbook.

ID	Author/year	Context	Method	Sector/AI focus	Main coded contribution	DOI
I001	Dey et al. (2023)	Vietnam	Quantitative survey with SEM/PLS-SEM	Manufacturing and supply chain; AI-enabled supply chain	Our results demonstrate that leadership will drive AI adoption by creating a data-driven, digital and conducive culture, and strengthening employee skills and competencies. We reveal the enablers that will help in transforming SMEs to become…	10.1080/00207543.2023.2179859
I002	Badghish et al. (2024)	Saudi Arabia	Quantitative survey with SEM/PLS-SEM	Cross-sector SMEs; AI for sustainability	Data analysis was performed on SmartPLS 3, and the results suggest that dimensions of the TOE framework, such as relative advantage, compatibility, sustainable human capital, market and customer demand, and government support, play a significant…	10.3390/su16051864
I003	Abrokwah-Larbi et al. (2023)	Ghana	Quantitative survey with SEM/PLS-SEM	Cross-sector marketing; AI-enabled marketing	Findings The analyzed data shows that AIM has significant impact on the financial performance, customer performance, internal business process performance and learning and growth performance in the case of SMEs in Ghana. Originality/value The…	10.1108/JEEE-07-2022-0207
I004	Soomro et al. (2025)	Developing-economy SMEs; country not explicit in accessible abstract	Quantitative survey with PLS-SEM and ANN	Cross-sector SMEs; AI for sustainability	The results reveal that all the proposed factors significantly and positively affect AI adoption, with top management support, employee capability, and relative advantage being the most influential predictors. The ANN results confirm the…	10.1038/s41598-025-86464-3
I005	Farmanesh et al. (2025)	Türkiye	Quantitative survey with SEM/PLS-SEM	Construction; AI for sustainability	The findings of this study reveal that FRs significantly impact the SCA among SMEs, while GIS serves as a mediator in the relationship.	10.3390/su17052162
I006	Abaddi (2024)	Jordan	Quantitative survey with SEM/PLS-SEM	Cross-sector SMEs; General organisational AI	Findings The results of the study support seven out of eight hypotheses. However, the innovation culture, employee digital skill level and market competition were found to moderate the relationships between some of the independent variables and…	10.1108/MSAR-10-2023-0049
I007	Haq et al. (2026)	Pakistan	Quantitative survey with SEM/PLS-SEM	Manufacturing; AI-enabled marketing	The results show that AI adoption significantly mediates the relationship between key organizational and environmental factors and SME performance.	10.1016/j.jdec.2025.07.002
I008	Ganguly et al. (2025)	India	Empirical design; details limited in accessible abstract	Industrial automation; General organisational AI	Findings The barriers identified are top management support, change resistance from employees, lack of knowledge about AI in automation, Lack of resources to implement the solution, uncertainty regarding the future of benefits, perception of job…	10.1108/IGDR-05-2024-0070
I009	Sharma et al. (2024)	Developing small-island economy; country not explicit in accessible abstract	Quantitative survey with SEM/PLS-SEM	Customer service/chatbots; AI chatbot	The empirical results reveal that perceived employee capability, perceived availability of financial support, perceived top management support, perceived cost, perceived complexity, and perceived relative advantage are positively associated with…	10.1109/TEM.2022.3203469
I010	Kumar et al. (2022)	India	Quantitative survey with SEM/PLS-SEM	Workforce management; AI-enabled marketing	According to the research findings, all of the offered hypotheses are significant. The findings suggest to MSME decision-makers that AI-powered WFM may help revenue growth, workforce risk reduction, intelligent business and marketing, and…	10.1080/09537287.2022.2131620
I011	Rawashdeh et al. (2023)	Country not explicit in accessible abstract	Quantitative survey	Accounting; AI-enabled accounting	The findings confirmed the relationships between the predictive variables and AI adoption. The results showed that accounting automation partially mediated the relationship between predictive variables and the adoption of AI.	10.5267/j.ijdns.2022.12.010
I012	Peretz-Andersson et al. (2024)	Sweden	Qualitative multiple-case study	Manufacturing; General organisational AI	Our findings indicate that SMEs structure a portfolio based on acquiring and accumulating AI resources.	10.1016/j.ijinfomgt.2024.102781

ID	Author/year	Context	Method	Sector/AI focus	Main coded contribution	DOI
I013	Shaik et al. (2023)	United States	Quantitative survey with SEM/PLS-SEM	Cross-sector sustainable business models; AI for sustainability	The findings of this study affirm the significant positive relationships between AIDBMI and both technological and strategic enablers for CNB.	10.1002/bse.3617
I014	Lada et al. (2023)	Malaysia (Sabah)	Quantitative survey with SEM/PLS-SEM	Cross-sector SMEs; General organisational AI	The results revealed that top management commitment and organisation readiness have a significant relationship with AI adoption. Overall, these findings can guide decision-making and resource allocation, emphasizing the importance of OR and TMC…	10.1016/ j.joitmc.2023.100144
I015	Arroyabe et al. (2024)	European Union	Quantitative survey with PLS-SEM and ANN	Cross-sector SMEs; Machine learning	Our findings highlight the importance of digital capabilities in driving AI adoption, where complementing innovation capabilities exhibit synergistic effects. For practitioners, our results underscore the need for a balanced investment in digital…	10.1016/ j.techsoc.2024.102733
I016	Khan et al. (2024)	Developing-country construction SMEs; country not explicit in accessible abstract	Quantitative survey with SEM/PLS-SEM	Construction; AI for sustainability	Knowledge Management-Based Artificial Intelligence (AI) Adoption in Construction SMEs: The Moderating Role of Knowledge Integration. Small and medium enterprises (SMEs) in the construction sector play a pivotal role in any emerging market economy.	10.1109/ TEM.2024.3403981
I017	Roux et al. (2023)	Vietnam	Quantitative survey	Manufacturing and supply chain; AI for sustainability	A survey of 375 Vietnamese manufacturing SME managers found that organisational change capacity facilitates AI adoption, which in turn supports supply-chain productivity, resilience and low-carbon management through data-driven decision-making.	10.1007/s10479-023-05760-1
I018	Aljarboa (2024)	Saudi Arabia	Quantitative survey with SEM/PLS-SEM	E-commerce; AI-enabled e-commerce	Factors influencing the adoption of artificial intelligence in e-commerce by small and medium-sized enterprises. • Testing the factors influencing the adoption of AI tools in e-commerce for SMEs. • The study model was proposed based on the…	10.1016/ j.jjimei.2024.100285
I019	Saleem et al. (2024)	Oman	Quantitative survey with SEM/PLS-SEM	Cross-sector SMEs; General organisational AI	The results are analyzed using Smart PLS 4.1 software.	10.1016/ j.joitmc.2024.100326
I020	Zavodna et al. (2024)	Czech Republic and Austria	Qualitative interview study	Cross-sector SMEs; General organisational AI	Findings – First, a notable lack of trust emerges as a significant barrier, with stakehold- ers harboring apprehensions regarding AI’s reliability, ethical implications, or potential consequences. Research implications/limitations – The findings…	10.22367/ jem.2024.46.13
I021	Almashawreh et al. (2024)	Jordan	Quantitative survey	Cross-sector SMEs; General organisational AI	Findings reveal the significant impact of employee IT knowledge, IT infrastructure, managerial commitment, training initiatives and well-designed reward systems in shaping SME owners’ or managers’ attitudes to AI. These findings provide valuable…	10.1177/097215092412 50273
I022	Jamil et al. (2025)	Pakistan	Quantitative survey with SEM/PLS-SEM	Cross-sector SMEs; AI for sustainability	The results reveal that both AI adoption and technological readiness significantly enhance employee capacity building, which, in turn, positively impacts sustainable performance. These findings offer actionable insights for managers in optimizing…	10.3390/su17083599
I023	Enshassi et al. (2025)	Malaysia	Quantitative survey with SEM/PLS-SEM	Cross-sector SMEs; AI-enabled marketing	The results show that these factors explain 23 % of the variance in AI adoption intention. These findings provide practical guidance for businesses and policymakers aiming to promote AI adoption in the digital marketing sector.	10.1016/ j.joitmc.2025.100519
I024	Apostoaie et al. (2025)	Romania	Quantitative survey with SEM/PLS-SEM	Cross-sector SMEs; AI-enabled marketing	Our findings highlight the significant role played by leadership, organizational readiness, as well as the “push-and-pull” effect of competitors and customers in encouraging SMEs to adopt AI technologies.	10.3846/ jbem.2025.23650
I025	Santosa et al. (2024)	Indonesia	Empirical design; details limited in accessible abstract	Marketing; AI-enabled marketing	The results emphasize the significance of top management commitment (TMC), employee adaptability (EA), perceived usefulness (PU), and perceived ease of use (PEOU) in encouraging the adoption of AI among micro, small, and medium	10.12962/ j24433527.v17i1.20520

ID	Author/year	Context	Method	Sector/AI focus	Main coded contribution	DOI
					enterprises…	
I026	Lim et al. (2024)	Malaysia	Quantitative survey/secondary-data regression	Accounting; AI-enabled accounting	The findings indicated that the adoption of AI in accounting among MSMEs is positively influenced by perceived ease of use, management support, organizational readiness, government support, and external pressure. The results and suggestions will…	10.31966/ jabminternational.v32i1. 1456
I027	González et al. (2025)	Ecuador	Quantitative survey with SEM/PLS-SEM	Human talent management; AI-enabled workforce/HR	This study analyzes the adoption of Artificial Intelligence (AI) in Human Talent Management (HTM) among small and medium-sized enterprises (SMEs), using Ecuador as the empirical case and articulating the results with evidence reported for other…	10.4067/S0718-27242025000300088
I028	Polas et al. (2022)	Bangladesh	Quantitative survey with SEM/PLS-SEM	Cross-sector blockchain-enabled operations; General organisational AI	Results show that: (1) knowledge of artificial intelligence has a positive and significant effect on the adoption of blockchain technology; (2) the relevant advantage of artificial intelligence has a positive and significant effect on the…	10.3390/joitmc8030168
I029	Polisetty et al. (2023)	India	Mixed-method study	Cross-sector SMEs; General organisational AI	The findings suggested that all the AI enablers except perceived benefits and role clarity significantly impacted AI readiness. Further, AI ethics, the moderator of the study, was found to be significant between perceived benefits, role clarity,…	10.1080/08874417.2023 .2219668
I030	Rawindaran et al. (2021)	United Kingdom, Spain and Australia	Quantitative survey	Cybersecurity; Machine learning for cybersecurity	Based on the analysis and findings, this study reveals that from the primary data obtained, SMEs have the appropriate cybersecurity packages in place but are not fully aware of their potential.	10.3390/ computers10110150
I031	Haq et al. (2025)	Pakistan	Quantitative survey with SEM/PLS-SEM	Manufacturing; AI-enabled marketing	Their findings show that technological readiness, organizational preparedness, and strong leadership significantly enhance AIA, resulting in notable improvements in both product and process innovation.	10.1016/ j.dsm.2025.04.002
I032	Islam et al. (2026)	Bangladesh	Qualitative interview study	Cross-sector agentic AI; Agentic AI	Findings The analysis identified eight primary barriers: slow internet speeds, limited knowledge and skills, inadequate infrastructure, lack of government support, political instability, high adoption costs and absence of a legal framework. These…	10.1108/VJIKMS-11-2025-0504
I033	D’Amico et al. (2026)	United Kingdom	Quantitative survey/secondary-data regression	Cross-sector SMEs; Machine learning	Our findings demonstrate that investment in internal and external knowledge including spillovers and knowledge collaboration directly affects the propensity of SMBs’ to adopt AI for both robotics and big data analysis.	10.1007/s11187-026-01214-7
I034	Ardito et al. (2024)	European Union	Quantitative secondary-data analysis	Cross-sector SMEs; General organisational AI	Findings Among the key findings, we found that ceteris paribus, the adoption of AI positively affects SMEs’ revenue growth and, in conjunction with IoT and BDA, appears to be even more beneficial. Originality/value Our results suggest that AI…	10.1108/INTR-02-2024-0195
I035	Kopka et al. (2023)	Firm-level international patent and company data	Quantitative survey/secondary-data regression	Cross-sector SMEs; General organisational AI	Evidence is found that smaller firms experience productivity growth from AI when operating at the productivity frontier, indicating the opposite of the leapfrogging hypothesis.	10.1007/s11187-023-00754-6
I036	Burggräf et al. (2024)	Germany	Empirical design; details limited in accessible abstract	Cross-sector machine learning; Machine learning	Machine learning implementation in small and medium-sized enterprises: insights and recommendations from a quantitative study. Abstract Machine learning (ML) offers high potential in manufacturing industry; moreover, for example the effectiveness…	10.1007/s11740-024-01274-2
I037	Nevi et al. (2025)	Italy	Qualitative interview study	Health/pharmacies; General organisational AI	Findings Technology and environmental dimensions, such as individual entrepreneurial orientation, significantly influence AI adoption in micro and small enterprises. Practical implications The findings suggest that enhancing technological…	10.1108/EJIM-07-2024-0770
I038	Andersson (2026)	Sweden	Quantitative survey/secondary-data	Manufacturing; General organisational AI	The results show substantial variation in digitalization maturity across firms and industries. Regression models show that higher digitalization maturity levels are	10.1007/s10257-026-00740-x

ID	Author/year	Context	Method	Sector/AI focus	Main coded contribution	DOI
			regression		associated with increases in revenue per employee, while the effects on profit…	
I039	Tiago et al. (2026)	European Union plus digital-marketing professionals	Quantitative survey	Cross-sector/digital marketing; AI-enabled marketing	Environmental, organizational, and individual determinants of AI adoption: A multilevel knowledge and analysis. This study examined the determinants of artificial intelligence (AI) adoption in small- and medium-sized enterprises (SMEs) through a…	10.1016/ j.jik.2025.100934
I040	Chaves et al. (2026)	Country not explicit in accessible abstract	Quantitative survey with PLS-SEM and fsQCA	Cross-sector SMEs; General organisational AI	Findings The results reveal that distrust is a decisive factor affecting the intention not to adopt AI. This finding highlights the importance of creating strategies that increase trust in automated processes.	10.1108/EJIM-06-2025-0719