American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Artificial Intelligence Readiness Among Small and Medium-Sized Enterprises

Dr. Daniel K. Morgan

Associate Professor, University College London (UCL), United Kingdom

Abstract

Artificial intelligence is becoming increasingly accessible to small and medium-sized enterprises through cloud services, generative AI applications, embedded analytics, automation platforms, and subscription-based business software. Accessibility, however, does not necessarily imply organizational readiness. SMEs frequently operate with limited financial reserves, small specialist teams, fragmented data systems, informal governance arrangements, and substantial dependence on external technology providers. Consequently, the ability to experiment with an AI tool may develop considerably faster than the organizational capability required to integrate AI responsibly into core business processes. This study examines artificial intelligence readiness among SMEs through a multidimensional framework incorporating digital infrastructure, data maturity, workforce competence, leadership commitment, financial capacity, AI governance, and external ecosystem support. Contemporary evidence confirms the relevance of this distinction. OECD research reports that SME AI adoption remains below that of larger enterprises, while Eurostat data for 2025 indicate that 17.0% of small EU enterprises and 30.4% of medium enterprises used AI technologies, compared with 55.0% of large enterprises. OECD survey evidence also shows growing use of generative AI among SMEs while identifying continuing barriers involving skills, legal uncertainty, data handling, and perceived relevance.

Because a verified firm-level dataset was not supplied, the present investigation adopts a simulation-based methodological design. A synthetic sample of 420 enterprises was created, comprising 180 micro, 150 small, and 90 medium-sized firms. AI readiness was measured on a 0–100 composite index across seven dimensions. The simulated overall mean was 57.2, indicating a developing but uneven readiness profile. Leadership commitment produced the highest dimensional score at 65.3, followed by digital infrastructure at 62.4 and ecosystem support at 61.4. AI governance recorded the lowest mean at 48.9, while workforce competence and data maturity also remained comparatively weak. Only 12 of the 420 simulated SMEs reached the advanced-readiness category, whereas 239 remained in emerging or developing stages. The findings suggest that AI readiness should be treated as a capability-development process rather than as a binary technology-adoption decision. The paper proposes a staged readiness model in which SMEs first establish digital and data foundations, then develop workforce and managerial competence, implement controlled AI use cases, and progressively institutionalize governance, monitoring, cybersecurity, and performance evaluation. The study concludes that sustainable SME AI adoption depends less on immediate access to powerful AI tools than on the ability to align technology with reliable data, skilled people, management processes, financial discipline, and responsible governance.

Keywords: artificial intelligence readiness, small and medium-sized enterprises, SMEs, AI adoption, digital maturity, organizational readiness, AI capability, technology adoption, responsible AI, digital transformation

1. Introduction

Small and medium-sized enterprises occupy a central position in contemporary economies, but their ability to benefit from technological change is frequently constrained by differences in scale, specialist capacity, and investment resources. Artificial intelligence has begun to reduce some traditional technology-entry barriers because sophisticated capabilities can now be accessed through cloud applications and relatively inexpensive generative AI services rather than through large in-house data-science departments. Yet adoption remains uneven. OECD evidence published in 2025 concludes that AI adoption among SMEs remains comparatively low relative to larger businesses and other established digital technologies. Eurostat's 2025 enterprise data demonstrate the size gradient particularly clearly: 17.0% of small EU enterprises, 30.4% of medium enterprises, and 55.0% of large enterprises reported using at least one AI technology.

The rapid diffusion of generative AI complicates conventional measures of organizational technology adoption. The OECD's cross-country survey found generative AI being used by the respondent or a colleague in approximately 30.7% of surveyed SMEs, with adoption ranging from 24% in Japan to 39% in Germany. Among SMEs using generative AI, 65.1% reported improved employee performance, while smaller proportions associated its use with cost savings, new tasks, new products or services, improved competitiveness, or higher revenue. At the same time, only 29% of generative-AI-using SMEs reported using it in core business activities, suggesting that widespread experimentation should not automatically be interpreted as deep organizational integration.

This distinction between use and readiness is fundamental. An enterprise may allow employees to use generative AI for drafting emails, creating marketing copy, summarizing documents, or brainstorming ideas while lacking the data architecture, employee competence, governance procedures, cybersecurity controls, performance indicators, or strategic coordination required for higher-consequence deployment. Jöhnk, Weißert, and Wyrtki conceptualize organizational AI readiness as a multidimensional problem involving resources, capabilities, awareness, strategic alignment, and organizational characteristics rather than as a simple procurement decision. Mikalef and Gupta similarly conceptualize AI capability as an organizational bundle of tangible, human, and intangible resources through which AI can contribute to performance.

The readiness challenge is particularly significant for SMEs because resource constraints coexist with rapidly expanding AI possibilities. OECD survey evidence shows that among non-users of generative AI, 57.3% reported that the technology was not suited to their work, 54.1% expressed copyright, legal, or regulatory concerns, 52.5% were concerned about information entered into AI systems, and 49.8% identified insufficient employee skills. Broader Eurostat evidence concerning enterprises that had considered AI but not adopted it similarly identifies lack of relevant expertise as the dominant barrier, cited by 70.9% of small enterprises and 69.2% of medium enterprises in 2025. Legal uncertainty, privacy concerns, data limitations, incompatibility, and cost also remained relevant.

Against this background, the present study investigates Artificial Intelligence Readiness Among Small and Medium-Sized Enterprises through a multidimensional simulation framework. It conceptualizes readiness as the organizational capacity to select appropriate AI use cases, supply suitable data and infrastructure, develop workforce competence, finance implementation, govern technological risks, and integrate AI into measurable business processes. Rather than presenting adoption as an endpoint, the paper proposes a staged pathway from digital foundation to governed AI capability. The quantitative analysis is explicitly synthetic because no primary survey was conducted. Its purpose is to demonstrate a reproducible readiness-assessment architecture that future empirical researchers, SME associations, policymakers, business-support organizations, and enterprise managers can validate with real-world samples.

2. Objectives of the Study

2.1 To Assess the Multidimensional Nature of SME AI Readiness

The first objective is to examine AI readiness as a combination of technological, data, human, managerial, financial, governance, and ecosystem capabilities rather than reducing readiness to whether an enterprise currently uses an AI application.

2.2 To Identify Critical Readiness Gaps Across Different SME Sizes

The second objective is to determine how readiness may differ among micro, small, and medium-sized enterprises and to identify capability areas that are likely to constrain progression from experimentation toward operational and strategic AI integration.

2.3 To Develop a Staged AI Readiness Framework for SMEs

The third objective is to establish a practical maturity framework that SMEs can use to prioritize digital foundations, employee capabilities, governance, external partnerships, and investment before expanding AI into core or high-impact business activities.

3. Review of Literature

3.1 Organizational Readiness, Digital Maturity, and AI Capability

Organizational readiness literature provides an important conceptual foundation for AI adoption because technology implementation depends on complementary resources rather than technology availability alone. Jöhnk, Weißert, and Wyrtki identified five categories of organizational AI readiness and developed actionable indicators based on interviews with AI experts and triangulation with scholarly and practitioner literature. Their work emphasizes that organizations must consider whether their assets, organizational capabilities, and commitment are appropriate for the intended AI use case.

Mikalef and Gupta extend this resource-oriented perspective by conceptualizing AI capability as a combination of tangible resources, human skills, and intangible organizational resources. Their empirical work links AI capability with organizational creativity and firm performance, implying that business value is produced through resource orchestration rather than through isolated algorithms. Wamba-Taguimdje and colleagues similarly argue that organizational value from AI transformation depends on complementary elements including data, talent, domain expertise, external relationships, infrastructure, and organizational process transformation.

Digital maturity constitutes an especially important foundation for smaller businesses. Pirola, Cimini, and Pinto's study of Italian manufacturing SMEs found intermediate levels of digital readiness and emphasized investments in infrastructure, data availability, and employee expertise. More recently, Peretz Andersson's 2026 study of 246 Swedish manufacturing SMEs found substantial differences in digitalization maturity and reported positive associations between digital maturity and measures of organizational performance, particularly revenue-related outcomes. The study explicitly treats digitalization maturity as a technological foundation on which AI readiness can develop.

These findings indicate that AI readiness should not begin with model selection. SMEs with fragmented business systems, poorly structured data, inconsistent digital records, or weak cybersecurity may need to strengthen basic digital capabilities before adopting complex AI systems. This sequencing is particularly important because AI can amplify the weaknesses of the environment in which it is deployed.

3.2 Technology–Organization–Environment Factors in SME AI Adoption

The Technology–Organization–Environment framework provides a useful structure for understanding why otherwise similar firms differ in technology adoption. Within this perspective, adoption is affected by technological characteristics, internal organizational conditions, and environmental influences. Recent AI research continues to support this multidimensional interpretation. A 2025 meta-analysis involving 12 studies and 3,398 respondents found significant effects for seven of eight examined TOE factors. Compatibility and perceived relative advantage were important technological factors, organizational readiness and top-management support were positive organizational influences, while government support, competitive pressure, and vendor partnership were important environmental factors.

Recent SME-specific evidence reinforces this pattern. D'Amico and colleagues' 2026 research examines AI adoption among smaller businesses from a knowledge-based TOE perspective and finds that investments in technological, organizational, and external knowledge shape adoption. The study emphasizes that SMEs' AI adoption cannot be understood solely through investment in one technical resource because different knowledge-building activities interact with one another.

OECD policy research reaches a similar conclusion from a practical perspective. Its 2026 study of SME technology adoption in the United Kingdom identifies cost, perceived relevance, and trust in technology vendors as significant constraints, while peer learning, supply chains, and intermediary organizations operate as important diffusion channels. The report also notes gaps in management and technological skills as barriers to AI adoption.

Environmental readiness is therefore particularly important for SMEs because smaller firms may compensate for limited internal expertise through cloud providers, consultants, technology-transfer organizations, industry associations, universities, government programs, and supply-chain partners. Readiness should consequently measure not only what the firm owns internally but whether it can obtain trustworthy expertise and support externally.

3.3 Skills, Responsible AI, and the Readiness–Adoption Gap

Employee competence represents one of the most persistent constraints on AI adoption. Eurostat's 2025 evidence indicates that lack of relevant expertise was the dominant reported reason for non-adoption among enterprises that had previously considered AI. The OECD's SME generative-AI survey likewise identifies employee skills among the major barriers and reports that twice as many SMEs associated generative AI with increasing the need for higher skills as with decreasing that need.

Skills requirements extend beyond technical model development. SMEs increasingly need employees who can identify appropriate use cases, assess output quality, protect commercially sensitive information, recognize hallucinated or misleading outputs, supervise automation, interpret AI-assisted analysis, and understand relevant legal or contractual restrictions. The OECD's SME survey found that only a minority of AI-using firms had undertaken systematic preparation through training, legal research, or internal guidance. For example, 35.6% of SMEs using generative AI reported researching copyright, legal, or regulatory issues.

Responsible-AI readiness is therefore becoming inseparable from adoption readiness. Soudi's review of ethical AI readiness within SMEs concludes that smaller businesses often lack the expertise and resources available to larger firms and recommends more SME-sensitive guidance, training, risk-based assessment, and cooperation among business, government, academia, and civil society. NIST's AI Risk Management Framework provides a complementary organizational perspective through its Govern, Map, Measure, and Manage functions, emphasizing that AI risk management should be integrated across organizational activities rather than treated as a final technical compliance check.

The literature therefore reveals an important readiness–adoption gap. AI tools can be adopted rapidly at the employee level, particularly when they are inexpensive and easy to access, but organizational readiness develops more slowly because it requires coordinated investments in data, skills, managerial processes, governance, and learning. The present study builds its analytical framework around this gap.

4. Research Methodology

4.1 Research Design and Synthetic SME Sample

The study adopts a quantitative simulation-based cross-sectional design. A synthetic sample of 420 SMEs was constructed to demonstrate how an AI readiness assessment could be implemented before conducting an empirical survey. The sample consisted of 180 micro enterprises, 150 small enterprises, and 90 medium-sized enterprises. The size categories are analytical simulation groups and are not presented as a legal SME classification for any particular jurisdiction.

Seven readiness dimensions were evaluated using a 0–100 scoring system. Dimension scores were designed to represent multiple questionnaire indicators converted to standardized values. The overall SME AI Readiness Index was calculated as the unweighted arithmetic mean of the seven dimensions. Equal weights were used to avoid claiming that one dimension has empirically proven superiority in the absence of real validation data.

4.2 AI Readiness Measurement Framework

The readiness framework integrates technological, organizational, and environmental factors with responsible-AI considerations. The first two dimensions—digital infrastructure and data maturity—represent foundational technological capacity. Workforce competence, leadership commitment, financial capacity, and governance represent internal organizational capabilities. Ecosystem support represents the firm's ability to use external expertise and institutional resources.

Table 1: Proposed Measurement Framework for SME AI Readiness

Readiness Dimension	Principal Indicators	Readiness Interpretation
Digital infrastructure	Cloud use, integration, cybersecurity, software interoperability, connectivity	Ability to technically support AI-enabled workflows
Data maturity	Data quality, accessibility, governance, structured records, analytical availability	Ability to supply reliable information for AI applications
Workforce competence	AI literacy, analytical skills, prompt/use competence, verification ability, training	Human capacity to use and supervise AI
Leadership commitment	Strategic alignment, executive sponsorship, defined business cases, change support	Management willingness and capacity to guide adoption
Financial capacity	Investment budget, implementation affordability, recurring cost tolerance, ROI evaluation	Ability to fund adoption sustainably
AI governance	Internal policies, privacy, security, legal	Ability to use AI responsibly and

Readiness Dimension	Principal Indicators	Readiness Interpretation
	awareness, vendor assessment, human oversight	manage risk
Ecosystem support	Vendors, consultants, government support, industry networks, universities, peer learning	Ability to supplement limited internal capabilities

Source: Developed by the author from the study's conceptual synthesis. The framework is proposed and requires empirical validation.

4.3 Analytical Procedure, Classification, and Research Ethics

The synthetic observations were generated to produce plausible differences in readiness associated with SME size while maintaining substantial within-group variation. Micro enterprises were assigned the lowest average readiness distribution, small enterprises an intermediate distribution, and medium enterprises the highest average distribution. This modeling choice is illustrative and is not claimed to represent actual population differences.

Composite readiness scores were classified into four maturity bands. Scores below 40 were classified as Emerging, scores from 40 to 59.9 as Developing, scores from 60 to 79.9 as Operational, and scores of 80 or above as Advanced. These thresholds are methodological conventions created for this study and have not been externally validated.

No human participants were recruited, and no identifiable company records were processed. Consequently, the study makes no claim of informed consent, institutional ethics approval, or real-enterprise fieldwork. Future empirical validation should preregister the instrument where appropriate, recruit a sufficiently diverse SME sample, report sector and jurisdiction characteristics, evaluate reliability and construct validity, and examine whether the proposed readiness dimensions predict subsequent adoption quality or business outcomes.

5. Analysis

5.1 Overall AI Readiness Profile

The synthetic sample produced an overall mean AI readiness score of 57.2 out of 100, placing the average enterprise in the developing-readiness category. The result suggests an organizational profile in which many firms possess enough digital capacity to begin experimenting with AI but have not yet developed the integrated capabilities required for advanced deployment.

Leadership commitment generated the highest dimensional mean at 65.3, indicating comparatively strong managerial interest and strategic recognition. Digital infrastructure followed at 62.4, while ecosystem support recorded 61.4. These values suggest that access to digital tools and external services may progress more rapidly than internal institutionalization.

5.2 Readiness Differences by Enterprise Size

The simulated size-group analysis indicates a progressive readiness gradient. Micro enterprises recorded a mean composite score of 49.5, small enterprises 59.6, and medium-sized enterprises 68.8.
The difference is especially visible in maturity classifications.

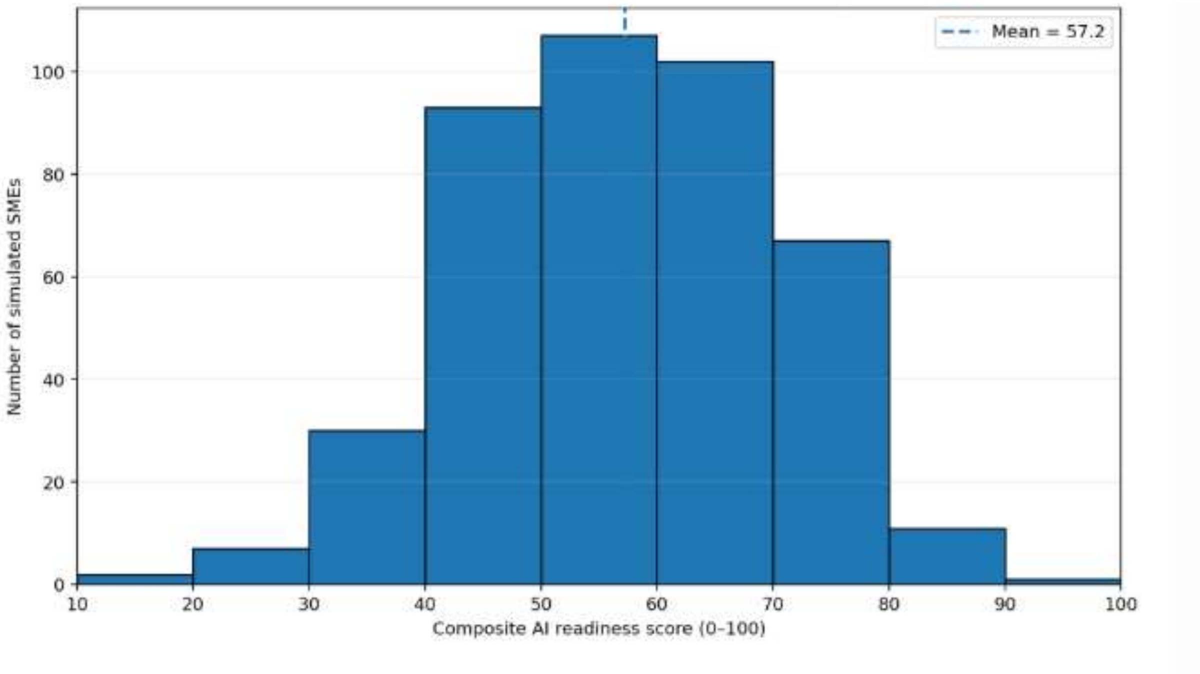
Table 2. Simulated SME AI Readiness Categories by Enterprise Size

Enterprise Size	Simulated n	Emerging (<40)	Developing (40–59.9)	Operational (60–79.9)	Advanced (≥80)	Mean Readiness
Micro enterprises	180	35	115	30	0	49.5
Small enterprises	150	4	68	75	3	59.6
Medium enterprises	90	0	17	64	9	68.8
Total	420	39	200	169	12	57.2

Source: Author's synthetic simulation. Values are illustrative and do not represent surveyed enterprises. Of the 420 simulated enterprises, 39 were classified as emerging and 200 as developing. Together, these groups represented 239 firms, or approximately 56.9% of the simulated sample. A further 169 firms were operationally ready, while only 12 reached the advanced level.

5.3 Distribution of SME AI Readiness

Graph 1: Simulated Distribution of AI Readiness Scores Among SMEs



The histogram provides a different analytical perspective from an average score by showing the distribution of readiness across all 420 synthetic SMEs. The distribution is concentrated primarily between scores of approximately 40 and 80, with a smaller lower-readiness group and only a limited advanced-readiness tail.

The dashed vertical line represents the overall simulated mean of 57.2. The distribution illustrates why a single average may be insufficient for policy or managerial decision-making. Two SME populations can have the same mean readiness while containing very different proportions of firms at emerging, operational, or advanced stages.

The graph also reinforces the distinction between universal AI-policy advice and maturity-sensitive support. Enterprises clustered below 40 require different interventions from firms already approaching an 80-point readiness level. The former may need foundational digitalization, structured data, basic AI literacy, and business-case identification, whereas comparatively mature firms may require model governance, advanced cybersecurity, vendor controls, process redesign, and performance monitoring.

6. Discussion

6.1 AI Readiness Is a Capability-Building Process Rather Than a Technology Purchase

The central implication of the study is that SME AI readiness cannot be reduced to purchasing software or allowing employees to use generative AI. The simulated pattern in which leadership commitment and digital infrastructure exceed workforce, data, and governance maturity reflects a plausible transition problem: technological availability can expand faster than organizational capability. This interpretation is consistent with Jöhnk, Weißert, and Wyrtki's multidimensional organizational-readiness framework and with Mikalef and Gupta's argument that AI capability emerges from bundles of technical, human, and organizational resources. SMEs may therefore achieve more sustainable results when AI adoption is treated as a sequence of capability investments rather than a one-time technology acquisition.

Digital maturity provides an especially important starting point. Peretz Andersson's 2022 study of Swedish manufacturing SMEs demonstrates significant variation in technological maturity and treats integrated processes and usable organizational data as foundations for future AI readiness. This finding implies that SMEs should resist pressure to begin with the most sophisticated available AI application when basic systems remain disconnected. A company that maintains inconsistent customer records across spreadsheets, separate accounting applications, email systems, and manually maintained files may extract more long-term value from improving data architecture than from immediately procuring a complex predictive model. Readiness assessment can therefore help management distinguish a genuine AI requirement from a broader unresolved digitalization problem.

The World Bank's 2021 AI foundations framework provides a complementary macro-level perspective through its four Cs: connectivity, compute, context in the form of data, and competency in the form of skills. Although developed at ecosystem level rather than specifically as an SME maturity model, these foundations correspond closely with the present study's infrastructure, data, skills, and external-support dimensions. The convergence suggests that sustainable AI adoption depends on interconnected prerequisites operating at both enterprise and ecosystem levels.

6.2 Skills, Data, and Governance Represent the Most Important Readiness Bottlenecks

The comparatively low simulated scores for workforce competence, data maturity, and AI governance identify a second important implication. These dimensions are difficult to address through technology procurement because they depend on organizational learning and repeated managerial practice. OECD research confirms that skills remain a significant SME constraint. In its 2020 generative-AI survey, approximately half of non-user SMEs reported that employees lacked the appropriate skills, while Eurostat's broader survey found lack of relevant expertise to be the dominant reason for non-adoption among enterprises that had considered AI. Training should therefore move beyond general awareness and develop task-specific competence in output verification, data handling, process redesign, risk recognition, and appropriate escalation.

Data maturity is equally important because AI outputs are constrained by the quality, relevance, and governance of the information on which systems depend. The Eurostat evidence shows that enterprises considering AI also identify data availability and quality as a significant barrier, while privacy and data-protection concerns remain prominent. For SMEs, this means that data readiness should not be interpreted as accumulating the largest possible dataset. The more useful goal is establishing reliable, appropriately governed, accessible information that supports a defined business use case. In some cases, a smaller, well-structured dataset may be more operationally valuable than a large collection of fragmented records whose provenance and accuracy are uncertain.

Governance appears to be the most easily neglected component of readiness because many inexpensive AI tools can be adopted without formal procurement or centralized technical approval. OECD research found substantial concerns among SMEs regarding copyright, legal, regulatory, and information-handling issues, while only a minority of AI-using SMEs had undertaken corresponding formal preparation. Responsible-AI readiness therefore requires proportionate controls that smaller businesses can realistically maintain. NIST's Govern, Map, Measure, and Manage structure provides a useful principle because it frames governance as a continuous organizational activity rather than a one-time compliance exercise. SME governance need not replicate the bureaucracy of a multinational corporation, but it should clearly identify permitted and prohibited uses, sensitive data restrictions, human-review requirements, vendor responsibilities, accountability for consequential decisions, and procedures for reporting problems.

6.3 A Staged Readiness Strategy Can Reduce the SME AI Adoption Gap

The simulated distribution indicates that a single AI adoption strategy would be inappropriate for SMEs at different readiness levels. Emerging firms should initially prioritize digital records, basic cybersecurity, reliable connectivity, management awareness, and identification of low-risk business problems suitable for experimentation. Developing firms can progress toward structured data practices, employee training, approved AI tools, small pilot projects, and basic usage policies. Operationally ready firms should integrate selected AI applications into recurring workflows, monitor performance, establish data and vendor controls, and evaluate measurable business value. Advanced firms can move toward more deeply integrated AI, customized models, systematic risk management, and continuous capability development.

This maturity-sensitive strategy is consistent with OECD evidence showing that AI diffusion across SMEs remains heterogeneous and that differences in digital maturity, complexity of use, and scope of application are useful for distinguishing SME adopter types. OECD's 2026 UK technology-adoption work further demonstrates that peer learning, intermediaries, supply chains, trusted vendors, skills development, and financial or advisory support can influence smaller firms' technology uptake. Policy interventions should therefore avoid assuming that every SME requires the same subsidy, course, or technological solution. Foundational firms may need digital advisory support, whereas advanced adopters may benefit more from innovation partnerships, compute access, specialized technical expertise, or governance assistance.

The readiness framework also changes how AI success should be evaluated. Adoption rates are useful but incomplete because they do not indicate whether AI is being used in core operations, whether employees can assess outputs, whether the system creates measurable value, or whether risks are managed. The OECD's finding that only 29% of generative-AI-using SMEs reported use in core business activities demonstrates this limitation directly. A stronger policy and management objective is therefore to increase productive and responsible AI capability, not simply the percentage of firms reporting some AI use. Such an orientation is more likely to convert technological experimentation into durable improvements in productivity, innovation, decision quality, and competitiveness.

7. Conclusion

Artificial intelligence has lowered some traditional barriers to advanced digital technology, making sophisticated analytical and generative capabilities accessible to enterprises that could not previously finance large-scale AI development. Yet easier access does not eliminate the organizational requirements associated with meaningful AI adoption. Current evidence shows that adoption remains strongly differentiated by firm size and that skills, legal uncertainty, data handling, cost, relevance, and organizational capacity continue to constrain smaller businesses.

The present study therefore conceptualizes AI readiness as a multidimensional organizational capability comprising digital infrastructure, data maturity, workforce competence, leadership commitment, financial capacity, governance, and ecosystem support. The synthetic analysis produced an overall readiness score of 57.2 and showed that more than half of the simulated firms remained within emerging or developing maturity stages. Leadership interest and basic digital infrastructure were comparatively strong, whereas AI governance, workforce competence, and data maturity formed the principal weaknesses.

These findings are illustrative rather than empirical, but they demonstrate why SME AI strategies should be sequenced according to maturity. Firms with weak digital foundations should not be encouraged to pursue complex AI deployment merely because tools have become inexpensive or fashionable. SMEs should first identify business problems, improve the reliability of relevant data, develop workforce competence, select proportionate technologies, establish clear governance responsibilities, and evaluate limited pilots before progressively embedding AI into core processes. External vendors, universities, peer networks, business associations, government programs, and technology intermediaries can provide important complementary capacity where internal resources remain constrained. OECD evidence indicates that such external diffusion channels can play an important role in SME technology adoption.

The overall conclusion is that AI readiness precedes sustainable AI value. Technology access may initiate experimentation, but durable business outcomes depend on whether SMEs can combine technology with people, data, management, finance, governance, and external knowledge. Future empirical research should validate the proposed readiness instrument with real SME samples across sectors and countries, test whether readiness scores predict adoption depth and organizational outcomes, and examine how firms move between readiness stages over time. A maturity-oriented approach can help ensure that SME AI adoption develops as disciplined organizational capability rather than fragmented technological experimentation.

References

1. Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press.
2. Tornatzky, L. G., & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington Books.
3. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540
4. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
5. Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation, 14*(1), 110–121.

6. Awa, H. O., Ojiabo, O. U., & Orokor, L. E. (2017). Integrated technology-organization-environment framework for technology adoption. *International Journal of Innovation and Technology Management*, *14*(4), 1750038. https://doi.org/10.1142/S0219877017500388
7. Zhu, K., Kraemer, K. L., & Xu, S. (2006). The process of innovation assimilation by firms in different countries: A technology diffusion perspective. *Management Science*, *52*(10), 1557–1576. https://doi.org/10.1287/mnsc.1050.0487
8. Zhu, K., Kraemer, K. L., & Xu, S. (2003). Electronic business adoption by European firms: A cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems*, *12*(4), 251–268. https://doi.org/10.1057/palgrave.ejis.3000475
9. Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, *37*(2), 471–482. https://doi.org/10.25300/MISQ/2013/37:2.3
10. Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003
11. Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52*(3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001
12. Kane, G. C., Palmer, D., Phillips, A. N., Kiron, D., & Buckley, N. (2015). *Strategy, Not Technology, Drives Digital Transformation*. MIT Sloan Management Review and Deloitte University Press.
13. Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research*, *70*, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004
14. Bughin, J., LaBerge, L., & Mellbye, A. (2017). Artificial intelligence: The next digital frontier? *McKinsey Global Institute Discussion Paper*.
15. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108–116.
16. Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). *Reshaping Business With Artificial Intelligence: Closing the Gap Between Ambition and Action*. MIT Sloan Management Review.
17. Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*, *97*(4), 62–73.
18. OECD. (2019). *Artificial Intelligence in Society*. OECD Publishing. https://doi.org/10.1787/eedfee77-en
19. European Commission. (2020). *White Paper on Artificial Intelligence: A European Approach to Excellence and Trust*. European Commission.
20. OECD. (2019). *The Digital Transformation of SMEs*. OECD Publishing.