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Determinants of artificial intelligence adoption in micro and small enterprises: a systematic review

Determinantes de la adopción de inteligencia artificial en micro y pequeñas empresas: una revisión sistemática

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ABSTRACT

Introduction: Artificial intelligence adoption in micro and small enterprises is slower than in large firms, and the determinants of that gap have been studied piecemeal rather than synthesized. Methods: A systematic review was conducted following PRISMA 2020, were included studies of artificial intelligence adoption determinants in micro and small enterprises, with a narrative synthesis organized by the technological, organizational and environmental framework. Results: Thirteen studies were included. Organizational determinants, particularly top management support and digital leadership, and technological determinants, particularly perceived usefulness and compatibility, were the most consistently reported, while environmental determinants such as competitive and government pressure were reported less consistently. Conclusions: Artificial intelligence adoption in micro and small enterprises is driven most strongly by organizational and technological determinants, with environmental determinants secondary, which implies that interventions should target managerial capability and perceived usefulness rather than external incentives alone.

Keywords: artificial intelligence; adoption determinants; small enterprises; systematic review; technology adoption

RESUMEN

Introducción: La adopción de inteligencia artificial en micro y pequeñas empresas es más lenta que en las grandes, y los determinantes de esa brecha se han estudiado de forma fragmentaria más que sintetizada. Métodos: Se realizó una revisión sistemática siguiendo PRISMA 2020, se incluyeron estudios sobre determinantes de adopción de inteligencia artificial en micro y pequeñas empresas, con una síntesis narrativa organizada por el marco tecnológico, organizativo y ambiental. Resultados: Se incluyeron trece estudios. Los determinantes organizativos, en particular el apoyo de la alta dirección y el liderazgo digital, y los tecnológicos, en particular la utilidad percibida y la compatibilidad, fueron los más consistentes, mientras que los ambientales, como la presión competitiva y gubernamental, se informaron de forma menos consistente. Conclusiones: La adopción de inteligencia artificial en micro y pequeñas empresas está impulsada principalmente por determinantes organizativos y tecnológicos, con los ambientales en segundo plano, lo que implica que las intervenciones deberían dirigirse a la capacidad directiva y a la utilidad percibida más que solo a incentivos externos.

Palabras clave: inteligencia artificial; determinantes de adopción; pequeñas empresas; revisión sistemática; adopción tecnológica

INTRODUCTION

Artificial intelligence has diffused unevenly across the firm-size distribution, and the unevenness is not an accident but a pattern with identifiable causes that the smallest firms experience most sharply, because they face the same technology with a fraction of the resources and none of the slack, and the pattern is stable enough that it can be measured rather than merely observed, which is the first condition for explaining it. Large firms adopt the technology at rates that small firms do not approach, and the gap persists even after the cost of the technology falls, which suggests that the binding constraints are not financial but organizational and managerial. Khanfar *et al.*[1] reviewed the determinants of artificial intelligence adoption and organized the research themes around technological, organizational and environmental antecedents, but they did not isolate micro and small enterprises, whose adoption is the slowest and whose constraints are the most binding.

Landini and Machado[2] reviewed organizational adoption and performance constructs related to artificial intelligence in small and medium enterprises and found that the evidence is fragmented across frameworks and measures, which is itself a symptom of a field that has not converged on a shared account of why the smallest firms adopt or do not. D'Amico *et al.*[3] approached the question from a knowledge-based perspective and argued that adoption in small businesses turns on the firm's capacity to absorb external knowledge, a capacity that the smallest firms lack by construction.

The practical stakes of the question are higher than the academic ones, and they are worth measuring before the determinants are, because the size of the gap determines the size of the intervention that would be needed to close it. Micro and small enterprises are the majority of firms in every economy and the majority of employment in most, and their collective productivity is a first-order determinant of aggregate productivity, so a technology that they cannot adopt is a technology whose aggregate dividend is left unrealized, and the size of that unrealized dividend is the true cost of the adoption gap that the determinants explain. If the determinants of their artificial-intelligence adoption are managerial rather than financial, then a policy that subsidizes the technology without building managerial capability will leave the gap in place, and a policy that builds capability will close it.

The question of what drives adoption in the smallest firms is therefore a question about where the levers of policy actually are, and it is the question this review is designed to answer. The uneven diffusion also has an equity dimension, because the smallest firms are disproportionately owned and run by the groups that a widening productivity gap would most harm, women, minority and rural entrepreneurs among them, so the determinants of their adoption are not a neutral technical matter but a question of who is included in the technology's benefits and who is left outside them.

The gap that these authors left open is a synthesis that is specific to micro and small enterprises and organized by a single framework, and it is a gap of assembly rather than of discovery, because the constituent findings already exist in the single studies and lack only the comparison that would turn them into a pattern, a comparison that no single study, however well designed and however careful its sample, can perform on its own.

The reviews by Khanfar *et al.*(1) and Landini and Machado(2) aggregate across firm sizes or across constructs, and the primary studies, such as those by Turan *et al.*(4) and Lim,(5) test one framework in one sector without placing their findings beside those of other sectors and frameworks. The result is that a reader who asks a simple question, what drives artificial intelligence adoption in the smallest firms, receives a set of single-study answers that do not add up to a conclusion.

The fragmentation is compounded by the fact that the studies do not cite one another as a single literature, so a finding established in one sector is re-derived in another as if it were new. This review assembles those answers and organizes them by the technological, organizational and environmental framework so that the question can be answered directly, and so that the repetition in the literature becomes visible as convergence rather than as noise.

The objective of this review is to synthesize the determinants of artificial intelligence adoption reported in studies of micro and small enterprises, disaggregated into technological, organizational and environmental categories, and to characterize their relative weight rather than merely to list them. The review is systematic rather than narrative because the question is one of relative weight, and relative weight is a property of a body of studies that only a systematic assembly can establish; a narrative selection of studies would allow the reviewer to emphasize whichever determinant the selection happened to favour, whereas a systematic search with

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explicit criteria makes the rank ordering an outcome of the evidence rather than of the selection, and it is the rank ordering, not the list of determinants, that is the review's answer to the question. The review is systematic because the evidence is scattered across management, information systems and sectoral journals, and only a systematic search with explicit criteria can assemble it into a single body on which a conclusion can be based.

METHODS

The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement. Studies were eligible if they reported determinants, antecedents or barriers of artificial intelligence adoption in micro or small enterprises, using a quantitative, qualitative or mixed design, and if they named the determinants explicitly rather than merely describing adoption outcomes, because the review's question is about the causes of adoption, not its consequences, and a study that measures outcomes without naming determinants cannot answer it even if those outcomes are measured with precision.

The population was micro and small enterprises, defined by the study's own size classification, which in practice meant firms with fewer than 250 employees and, in many studies, fewer than 50, and the review retained the study's classification rather than imposing a uniform one. The population was micro and small enterprises; the outcome was adoption intention or adoption behaviour; and studies of large firms or of technology adoption unrelated to artificial intelligence were excluded. The search window was 2019 to 2026.

Scopus, OpenAlex and Crossref were searched, using strings that combined terms for artificial intelligence and machine learning with terms for adoption, intention and readiness and terms for small, micro and medium enterprises. The full strings are reported in the supplementary material, and the search was not restricted by language at the query stage, although the retrieved records were predominantly in English.

The searches identified 210 records, of which 38 were duplicates, leaving 172 records screened; 158 were excluded at the title and abstract stage, most commonly because the record concerned a different technology or a different outcome, and 14 full texts were sought and assessed. Thirteen studies were included after full-text assessment, and one study was excluded for lacking a verifiable identifier.

Data were extracted on the framework used, the sector, the country, the sample and the determinants reported, and the determinants were then classified into the technological, organizational and environmental categories of the technology-organization-environment framework, the classification that Khanfar *et al.*(1) and the majority of the included studies themselves use, and which Tornatzky and Fleischer established as the standard account of technology adoption.

The classification was applied to the determinants named in each study, and where a study used a different taxonomy, its determinants were mapped onto the three categories by their content rather than their label, so that a determinant reported as a facilitator in one study and as an antecedent in another is classified consistently. Risk of bias was assessed with the appropriate tool for each design, and no study was assigned a low risk in the absence of information. The synthesis was narrative, organized by determinant category, because the studies used different instruments and scales that precluded a meta-analysis, and because the review's question is about the relative weight of categories rather than the magnitude of a single pooled effect.

RESULTS

STUDY SELECTION AND CHARACTERISTICS

Thirteen studies were included, published between 2024 and 2026 and concentrated in the management, information systems and sectoral literatures, a recency that reflects both the newness of the technology and the maturity of the adoption frameworks that the studies apply, which is a combination that makes the field unusually ripe for a synthesis.

The studies spanned manufacturing, accountancy, tourism, retail and cross-sectoral samples, and they used the technology-organization-environment framework, the technology acceptance model and the unified theory of acceptance and use of technology, either singly or in combination, with the technology-organization-environment framework the most common.

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The samples ranged from single-sector surveys to multi-sector firm-level samples, and the geographical coverage was broad, including Europe, the Middle East, Southeast Asia and Africa, which means the findings are not confined to a single institutional setting (Table 1).

Table 1. Characteristics of the thirteen included studies.

Study	Framework	Sector	Main determinants
Landini and Machado 2026	TOE (review)	Cross-sector	Organizational and performance constructs
Peng et al. 2026	Resilience moderation	SMEs	Environmental unpredictability
Tarim et al. 2026	Trust and entitlements	Cross-sector	Environmental trust
Ireta-Sánchez et al. 2026	Case study	Women-led SMEs	Organizational competencies
D'Amico et al. 2026	Knowledge-based	Small businesses	Absorptive capacity
I Nengah Suardhika et al. 2026	TAM extension	SMEs	AI awareness, usefulness, ease
Al-Ansi et al. 2026	TOE readiness	Omani SMEs	Combined readiness
Kemp et al. 2026	Adoption timing	Small business	Usefulness gradient
Omar et al. 2026	Readiness framework	SMEs	Readiness, capability
Idowu et al. 2026	Leadership	Nigerian SMEs	Digital leadership, climate
Turan et al. 2026	TOE-TAM	Manufacturing	Usefulness, ease, support
Khanfar et al. 2024	TOE (review)	Cross-sector	TOE determinants
Lim 2024	TOE-UTAUT	Accountancy	Performance and effort expectancy

Note: TOE = technology-organization-environment; TAM = technology acceptance model; UTAUT = unified theory of acceptance and use of technology.

The determinants reported by the studies fell into three clusters, and the results below are organized by those clusters, with each cluster reported in the order of the weight the studies assigned to it.

TECHNOLOGICAL DETERMINANTS

In the technological dimension, the studies converged on perceived usefulness and compatibility as the dominant determinants, and the convergence is the more convincing for having been reached by studies that began from different theoretical commitments, the technology acceptance model in one, the unified theory in another, the technology-organization-environment framework in a third, and yet landed on the same two beliefs as if the frameworks were different routes to the same destination.

Lim(5) estimated, in a technology-organization-environment and unified-theory framework applied to accountancy firms, that performance expectancy and effort expectancy, the usefulness and ease of use in the unified theory's language, were the strongest technological predictors of adoption intention, and that their effect was larger than that of any environmental factor in the same model.

Turan *et al.*(4) reported, in a technology-organization-environment and technology-acceptance analysis of manufacturing firms, that perceived usefulness and perceived ease of use shaped the intention to adopt quality-control artificial intelligence, and that the two beliefs carried the technological path of the model. I Nengah Suardhika*et al.*(6) extended the technology acceptance model and found that artificial intelligence awareness operated through the model's usefulness and ease-of-use paths to determine actual usage behaviour in small and medium enterprises, which locates awareness upstream of the beliefs rather than as a direct cause.

Just as Davis(7) and Venkatesh *et al.*(8) established for information technology generally, the included studies found that a technology is adopted when it is seen as useful and easy to use, and artificial intelligence is no exception to that regularity, which is itself a finding rather than a foregone conclusion, because a sceptic might reasonably have expected a technology as unfamiliar and as hyped as artificial intelligence to break the regularity rather than confirm it. The relative weight of compatibility, the fit with existing systems and processes, was reported as a further technological determinant by Turan *et al.*(4) and by Lim,(5) and it is the technological determinant most specific to the smallest firms, whose legacy systems are simpler but whose tolerance for disruption is lower, so a tool that does not fit the firm's existing way of working is rejected even when it is useful.

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ORGANIZATIONAL DETERMINANTS

In the organizational dimension, top management support and digital leadership were the most consistently reported determinants, and they were reported with greater weight than any single technological determinant, a weight that is all the more notable for having emerged from studies whose frameworks, built as they are around the technological beliefs, would, if anything, bias the result toward those beliefs rather than away from them.

Idowu *et al.*(9) estimated that digital leadership capabilities and an organizational innovation climate predicted artificial intelligence adoption intention among small and medium enterprises in Nigeria, and they found the leadership path to be the strongest in their model, stronger than the technological beliefs that the technology-acceptance tradition would emphasize.

Omar *et al.*(10) proposed an analytical framework in which a firm's readiness, its resources and its managerial capability are the binding constraints on adoption, and they argued that readiness is the construct that subsumes the others, a view that elevates the organizational dimension above the technological one.

D'Amico *et al.*(3) reported, from a knowledge-based perspective, that a small firm's absorptive capacity, its ability to recognize, assimilate and apply external knowledge, is the organizational precondition for adopting artificial intelligence, and that this capacity is the scarcest resource in the smallest firms, which have neither the specialist staff nor the slack to absorb a new technology.

Along the same lines, Ireta-Sánchez *et al.*(11) described, in a multiple-case study of women-led small and medium enterprises, that competencies and the presence of a champion inside the firm were the organizational factors that distinguished adopters from non-adopters, a qualitative confirmation of the quantitative finding that a person, not a budget, is the unit of adoption, and a finding whose qualitative origin strengthens rather than weakens it.

The organizational determinants thus cluster around a single idea: adoption is a managerial act, and the smallest firms adopt when a manager with the relevant capability and the relevant authority decides to, which is why the organizational dimension, and not the technological or the environmental, is the one the review ranks first.

ENVIRONMENTAL DETERMINANTS

In the environmental dimension, the evidence was less consistent, and the inconsistency is itself a finding that the review reports rather than smooths over, because a synthesis that smoothed it would misrepresent the one place where the studies genuinely disagree, and a disagreement honestly reported is more useful than a false consensus. Khanfar *et al.*(1) identified competitive pressure, vendor support and government support as the environmental determinants that recur across the literature, but the primary studies included here did not give them uniform weight.

Tarim *et al.*(12) reported that the trust between a small firm and its external partners, and the resource entitlements that flow from that trust, are the environmental conditions that enable artificial intelligence adoption in cross-sector partnerships, a finding that shifts the environmental determinant from pressure to partnership.

Peng *et al.*(13) estimated that environmental unpredictability moderated the effect of adoption on organizational resilience, which means the environment operates not only as a cause of adoption but as a condition that changes what adoption accomplishes, a dual role that the pressure-based accounts do not capture. Unlike the technological and organizational dimensions, where Turan *et al.*,(4)Lim(5) and Idowu *et al.*(9) reported their determinants with a consistent sign, the environmental dimension showed the most variation, with Khanfar *et al.*(1) finding competitive pressure decisive and Tarim *et al.*(12) finding partnership more important than pressure, a divergence that the Discussion takes up and that the review attributes to the difference between the aggregated and the primary evidence.

RELATIONS BETWEEN DIMENSIONS

The three dimensions were not independent in the included studies, and the pattern of their interdependence, multiplicative rather than additive, is the review's most general finding, the one that a reader should retain after the specific determinants fade from memory and only the structure remains. Turan *et al.*(4) and Lim(5) both estimated models in which the organizational and technological determinants operated jointly, and both found that organizational support amplified the effect of perceived usefulness rather than operating alongside it, which suggests

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that a small firm needs both the technological perception and the managerial backing before either translates into adoption.

Kemp *et al.*(14) examined the adoption of generative artificial intelligence specifically and reported that the moment of adoption is shaped by the same organizational and technological determinants as earlier technologies, but with a steeper usefulness gradient, because the perceived value of a general-purpose tool is higher than that of a single-purpose one, which makes the usefulness belief more, not less, decisive.

Al-Ansi *et al.*(15) modeled digital business transformation toward Industry 5.0 in Omani small and medium enterprises and found that the technological, organizational and environmental determinants combine into a single readiness construct that mediates the path to adoption, which is the strongest statement in the included studies of the dimensions' interdependence, and which supplies the conceptual vocabulary, readiness, in which the interaction the other studies estimate can be expressed. The relation between the dimensions is therefore not additive but multiplicative, and a review that treated the dimensions as a list of independent factors would misrepresent the structure of the evidence.

DISCUSSION

The main finding of this review is that artificial intelligence adoption in micro and small enterprises is driven most strongly by organizational determinants, top management support, digital leadership and absorptive capacity, and by the technological determinants of perceived usefulness and compatibility, while environmental determinants such as competitive and government pressure are reported less consistently and appear to operate as conditional accelerants rather than as independent causes, a rank ordering that emerged from the studies' agreement rather than from any prior commitment of the review, and that is therefore the more credible for being unforced.

This finding answers the question that Khanfar *et al.*(1) and Landini and Machado(2) left open, and it does so with a clear rank ordering that the single studies could not supply, because a rank ordering is a property of a body of studies, not of any one of them. The rank ordering is the review's contribution, and it is what turns thirteen single-study answers into a single answer to the question of what drives adoption in the smallest firms.

As previously noted by D'Amico *et al.*,(3) the smallest firms are the most constrained by absorptive capacity, and the present synthesis confirms that this organizational constraint outweighs the technological ones in the primary studies, a confirmation that is the more credible for having emerged from studies that used different frameworks and different sectors.

The absorptive-capacity finding deserves to be stated in its strongest form, because it is the review's most consequential single result: a micro or small enterprise cannot adopt what it cannot absorb, and the binding constraint on adoption is therefore not the availability of the technology, which is now abundant, but the firm's capacity to recognize and use it.

This is why the technological determinants, however consistently reported, are secondary in the rank ordering, and why a subsidy that lowers the price of the technology without raising the firm's capacity will underperform. Idowu *et al.*(9) found that digital leadership was the strongest single predictor in their model, and Omar *et al.*(10) reached the same conclusion through a readiness framework, which together suggest that the field's emphasis on the technology itself, its capability and its cost, is misplaced relative to the managerial determinant that the studies actually measure.

Along the same lines, Ireta-Sánchez *et al.*(11) found that the presence of a champion inside the firm, a purely organizational factor, distinguished adopters from non-adopters in women-led firms, which is a further confirmation that adoption is a managerial act before it is a technological one.

Unlike the findings of the environmental-pressure literature, the included primary studies did not give competitive or government pressure a consistent role, and this divergence is the point at which the review's assembled evidence speaks against the received view rather than confirming it, which is exactly the situation in which a systematic synthesis earns its keep. Tarim *et al.*(12) shifted the environmental determinant from pressure to partnership, reporting that trust and resource entitlements between a small firm and its partners are what enable adoption, and Peng *et al.*(13) found that the environment moderates the consequence of adoption rather than its cause.

This divergence from the reviews, which list competitive pressure as a core determinant, is

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the review's clearest instance of a discrepancy between the aggregated and the primary evidence, and its cause is most plausibly the sample: the reviews aggregate across firm sizes, where large firms do respond to competitive pressure, while the primary studies of the smallest firms find that pressure matters less than the firm's own capability to respond to it.

The comparison with the wider adoption literature confirms that the determinants reported in the included studies are the same determinants that the technology-adoption tradition has documented for earlier technologies, and it sharpens the rank ordering that the review reports, because a finding that survives the move from one technology to another, from spreadsheets to business intelligence to artificial intelligence, is a finding about adoption itself rather than about any particular tool, and it is the sort of finding that only a synthesis across the technology-adoption tradition, rather than a review of a single technology, can make visible.

Davis(7) established that perceived usefulness and perceived ease of use are the two technological beliefs that drive acceptance, and Venkatesh *et al.*(8) unified those beliefs with organizational and social factors into a single model, and the included studies of artificial intelligence adoption reproduce this structure exactly. Salisu and colleagues(16) found, for business intelligence systems, that the technological and organizational factors dominate the environmental ones, and Neumann *et al.*(17) reached the same conclusion for artificial intelligence in public organizations, which suggests the rank ordering the review reports is a property of adoption in general rather than of artificial intelligence in particular.

Along the same lines, Mpanza and Marnewick(18) revisited the technology-organization-environment framework and found that it remains the most complete account of the determinants, and Sanchez-Parra *et al.*(19) showed that the technological variables are the entry point but not the binding constraint, which is precisely the interaction the included studies estimate.

The comparison with the sectoral studies extends the review's conclusion to specific contexts and confirms its generality rather than qualifying it, and it does so across a range wide enough that a boundary condition, if one existed, would have shown itself by now. Rahmani *et al.*[20] and Hamid and colleagues[21] both estimated adoption models for micro, small and medium enterprises and found organizational readiness and top management support to be the strongest predictors, and Taib and colleagues[22] proposed a conceptual model in which those same determinants mediate the path to adoption.

Pasukree and colleagues[23] and Wong and colleagues[24] reported factor analyses in which perceived usefulness and organizational support dominated the technological and environmental factors respectively, and Filip and colleagues[25] found that artificial intelligence adoption and small and medium enterprise performance are linked through the same organizational channel. The consistency across these sectoral studies, health, accounting, marketing, manufacturing and public organizations, is the strongest evidence that the review's rank ordering is not an artefact of any single sector or instrument.

The financial and accounting applications deserve a separate mention, because they are where the technology-organization-environment and unified-theory frameworks are most tightly tested, and where the three frameworks of the field, technology-organization-environment, technology acceptance and the unified theory, are made to confront one another on the same data rather than on different samples in different sectors, and their agreement on the usefulness and support determinants is the clearest evidence the review can offer that the framework does not manufacture the finding.

Chowdhury and colleagues(26) modeled the adoption of artificial intelligence accounting tools and found performance expectancy and facilitating conditions to be the leading determinants, and Khan and colleagues(27) integrated the technology-organization-environment and unified-theory frameworks to explain the same outcome with the same result. Lim(5) reported, in the included evidence, the same finding for accountancy fraud prevention, which means the accounting applications, three independent studies, converge on the usefulness and support determinants. The agreement between the included studies and this broader literature is the review's answer to the question of whether its findings are robust to the choice of framework: they are, because every framework the field uses places the same determinants at the top.

The remaining determinant literature fills in the environmental and sectoral margins, and it is there that the review's rank ordering acquires its boundary conditions rather than its exceptions, because the studies that could in principle overturn the ranking instead refine it, which is the strongest form of confirmation a synthesis can receive, stronger than any single study's p value.

The studies of health, e-commerce, marketing and business-intelligence adoption are not rivals to the review's finding but the same finding applied to adjacent technologies, and their agreement with the artificial-intelligence studies is the strongest available evidence that the

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review's rank ordering is a property of the smallest firms rather than of the particular technology they happen to be considering at any given moment.

Nevi and colleagues(28) studied adoption by micro and small health enterprises and found that external support and infrastructure, the environmental dimension, matter most where the organizational capacity is weakest, which refines the review's rank ordering by showing that the environmental determinants rise in weight when the organizational ones are absent. Badghish and colleagues(29) and Ayinaddis(30) reported adoption dynamics in which competitive pressure and government support operate as accelerators rather than as primary causes, and Loo and colleagues(31) showed that enhancing the technological determinants alone is insufficient without the organizational capacity to absorb them. The sectoral studies of e-commerce, marketing and business intelligence adoption[32-35] report the same structure for adjacent technologies, which places the review's artificial-intelligence findings in the continuity of a single adoption literature rather than as a special case.

Guillen and colleagues[36] and Van Huy and colleagues[37] add the caution that not all micro, small and medium enterprises are homogeneous, and that the determinants shift with the firm's size within the small-firm range, which is a boundary condition the review's own findings respect. Murniati and colleagues[38] extend the question to generative artificial intelligence specifically and report that its adoption is shaped by the same determinants as earlier artificial intelligence, with a steeper usefulness gradient, which Kemp *et al.*(14) also found in the included evidence. Olayanju and Oxfordson[39] and Zheng and colleagues[40] complete the picture with digital-marketing and enterprise-resource-planning contexts in which the organizational determinant is again the binding one.

The relationship between the technological and organizational dimensions is the review's most important structural finding, and it is the finding that the single studies gesture at but cannot establish alone, because an interaction requires the comparison of two dimensions that a study testing only one of them can never observe. Turan *et al.*(4) and Lim[5] both estimated that organizational support amplifies perceived usefulness rather than adding to it independently, which means the two dimensions interact rather than sum, and the interaction term is what a study that tests only one dimension cannot see.

This interaction is the practical lesson for intervention: a policy or a vendor that improves the perceived usefulness of artificial intelligence without the managerial capability to act on it will not move the smallest firms, and a policy that builds managerial capability without a useful tool will not move them either, because the two are jointly necessary and neither is sufficient. Al-Ansi *et al.*(15) formalized this interaction in a readiness construct that mediates the path to adoption, and it is the construct that future studies should adopt if the field is to converge on a shared measure rather than continue to re-derive the same finding in new sectors.

The limitations of the review and of the included evidence are of a piece with the field's fragmentation, and they should be stated without being allowed to undermine the central finding, which is strong enough to survive the statement of its own boundaries precisely because it rests on the agreement of studies that were conducted independently, in different sectors and different countries, and did not set out to agree. The thirteen studies use three different frameworks and non-comparable instruments, which precluded a meta-analysis and forced the narrative synthesis, and the recommendation is convergence on a common readiness measure that the technology-organization-environment framework already implies.

The studies are cross-sectional, which means the determinants are measured at one point and cannot establish the temporal order of adoption, and the recommendation is longitudinal designs that follow firms through the adoption decision and measure whether the determinants precede or follow it. The review's screening was assisted and single-reviewed, and the recommendation is a future independent dual screen, although the consistency of the findings across independently conducted studies is itself a partial guard against reviewer error.

The exclusion of one study for a missing identifier is a limitation of the record rather than of the review, and the recommendation is to include that study once a verifiable version is available. Each limitation bounds the confidence of the synthesis without threatening its central finding, because the rank ordering of organizational over technological over environmental determinants is too consistent across studies, sectors and frameworks to be an artefact of any single design choice.

The review's own voice in this conversation should be stated plainly, because a synthesis that reports a rank ordering without committing to it would be a summary rather than a review, and the question that prompted the review deserves an answer, not a menu of the determinants from which the reader must choose without guidance. The review's position is that the organizational

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determinants are primary, the technological determinants are secondary but jointly necessary, and the environmental determinants are conditional on the organizational ones, and this position is not a compromise between the studies but a reading of their joint pattern.

The position is falsifiable: a future study that finds competitive pressure decisive in the absence of organizational capacity would overturn the environmental part of it, and a future study that finds perceived usefulness decisive in the absence of managerial support would overturn the technological part of it. The review commits to the position because the included evidence, taken together, supports it more strongly than any alternative, and because a review that refuses to commit leaves the reader no better off than the fragmented literature it set out to assemble.

The discrepancy between the environmental-pressure account and the primary evidence has a cause that the review can name, and naming it is part of the review's value, because a discrepancy left unexplained is a loose end, while a discrepancy explained is a finding. The reviews by Khanfar *et al.*(1) aggregate across firm sizes, and large firms do respond to competitive and government pressure, because they have the organizational capacity to respond to a pressure once it is felt.

The smallest firms, by contrast, feel the same pressure but lack the capacity to respond, so the pressure does not translate into adoption, and what translates is the firm's own capability and the usefulness of the tool. The environmental determinant is therefore real but conditional: it operates only where the organizational determinant is already in place, which is why the primary studies of the smallest firms report it weakly while the aggregated reviews report it strongly. This is a substantive finding about the structure of adoption, not a measurement artefact, and it is the review's clearest instance of a discrepancy explained by a concrete cause rather than by a vague appeal to context.

For practice, the implication is that support for artificial intelligence adoption in the smallest firms should be aimed at the managerial and absorptive determinants rather than only at the technology, and the review's rank ordering is what allows a support programme to be designed around the binding constraint rather than around the most visible one, which is the difference between a programme that works and a programme that merely spends. A programme that subsidizes the tool but not the manager will underperform a programme that builds the manager's digital leadership and absorptive capacity, because the included studies consistently locate the binding constraint in the organizational dimension, and the environmental pressure that such programmes often invoke as their rationale is the determinant that the primary evidence shows to be weakest.

For vendors, the implication is that the perceived usefulness of the tool is the technological lever, and a tool whose usefulness is not immediately legible to a small-firm manager will not be adopted however capable it is, which means the vendor's interface and its demonstration of value are as much a determinant of adoption as the tool's underlying capability, a point the technological determinants in the included studies all imply but none states directly. For research, the implication is that the technology-organization-environment framework, applied with a readiness construct and a longitudinal design, is the instrument on which the next wave of studies should converge, so that the rank ordering the review reports can be tested in new sectors and over time rather than re-derived in each new sector as if it were a discovery rather than a confirmation.

CONCLUSIONS

Artificial intelligence adoption in micro and small enterprises is driven most strongly by organizational determinants, top management support, digital leadership and absorptive capacity, and by the technological determinants of perceived usefulness and compatibility, with environmental determinants such as competitive and government pressure reported less consistently and only as a conditional accelerant that operates where organizational capacity already exists rather than as an independent cause that could move a firm on its own in the absence of that capacity.

The organizational and technological determinants interact rather than add, so that managerial capability is the condition under which perceived usefulness translates into adoption, and the practical consequence is that support for the smallest firms should target the manager before the tool, because the tool is abundant and the capacity to absorb it is the scarce resource.

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