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AI Adoption Readiness in Small and Medium-Sized Enterprises: Barriers, Assessment Criteria, and a Phased Implementation Framework

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Abstract

Small and medium-sized enterprises are repeatedly told that artificial intelligence is within reach, and repeatedly discover that it is not. This paper argues that the discrepancy is not explained by the dominant framings of adoption. Acceptance theory explains individual intention, and technology–organization–environment theory explains the contextual pressures on the adoption decision, but neither describes what an enterprise must have in place before an automated decision can be specified, operated and defended. Three claims are developed. First, readiness is an organizational property distributed across strategy, data, process, people and governance, rather than a property of a technology stack. Second, small and medium-sized enterprises are not scaled-down large firms: Because they cannot amortize a failed initiative, cannot run parallel workstreams, and have no dedicated data, governance or transformation function, readiness must be sequenced rather than assessed in parallel and remediated concurrently. Third, the binding constraint on adoption is usually process determinacy rather than data volume, because decision logic is typically undocumented and process variation is typically unmeasured. From these claims the paper derives three artifacts: A five-family taxonomy of adoption barriers, a Five-Domain SME AI Readiness Model with a four-level rubric across nineteen assessment criteria, and a five-phase implementation framework with explicit gate criteria. Eight propositions are stated for empirical testing. The contribution is conceptual; it has not been empirically validated, and the paper distinguishes throughout between claims that are evidenced and claims that are reasoned.

Keywords: AI Readiness, Small and Medium-sized Enterprises, Intelligent Process Automation, Process Standardization, Decision Logic, AI Governance, Implementation Framework

1. Introduction

The gap between the availability of artificial intelligence and its uptake in smaller firms is well documented in practitioner surveys such as IBM (2023), but explanations of it remain generic. The two dominant traditions, which are technology acceptance and the contextual, firm-level account of adoption reviewed in Section 2, are incomplete for this question: Neither describes the internal condition a small or medium-sized enterprise (SME) must reach before an automated decision can be built, operated, monitored, and defended. That condition is what the readiness literature has begun to formalize (Jöhnk *et al*., 2021; Uren & Edwards, 2023).

This paper extends that position and adds a claim about *sequence*. Readiness models are typically constructed as profiles assessed in parallel and remediated concurrently, which assumes an organization able to run several workstreams at once and to survive the failure of some. SMEs generally cannot. It is argued here that readiness dimensions stand in a dependency order for such firms, that the operating question is therefore *what is the binding constraint* rather than *what is our average maturity*, and that the implementation path must be phased against that constraint.

A second claim follows from the author's earlier work on the standardization of reporting and decision workflows, which held that decision logic and reporting definitions must be explicit and stable before they can be automated. SMEs commonly diagnose themselves as unready because they lack data (European Economic and Social Committee (EESC), 2021). The position taken here is that the more frequent and more tractable blockers are undocumented decision logic and unmeasured process variation, a condition that no volume of data can correct.

The sequencing claim has a theoretical warrant. If a firm's capacity to assimilate new external knowledge is a function of its prior related knowledge (Cohen & Levinthal, 1990), and if that capacity divides into a potential component that may never be converted into use (Zahra & George, 2002), then some readiness dimensions produce the internal knowledge on which others depend; and returns to a technology depend on organizational investments made alongside it (Brynjolfsson & Hitt, 2000; Bresnahan *et al*., 2002).

Three artefacts are contributed: a taxonomy of adoption barriers in five families, each sub-barrier grounded in literature or marked as an argued extension (Table 1); the Five-Domain SME AI Readiness Model, with nineteen criteria and a four-level rubric, together with a mapping of each domain to the theoretical constructs that ground it (Tables 2, 3 and 4); and a five-phase implementation framework with gate criteria (Table 5). The theoretical contribution is the sequencing argument together with the determinacy claim. Section 2 reviews the literature and states the gap, Section 3 states what kind of paper this is, Section 4 develops the framework, Section 5 illustrates it hypothetically, Section 6 reviews how the readiness constraints appear across applied domains, Section 7 discusses practice and validation, Section 8 states the limitations, and Section 9 concludes.

2. Background and related literature

2.1 What the dominant framings explain, and where each stops

Acceptance research explains use intention through perceived usefulness and ease of use (Davis, 1989) and through performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh *et al*., 2003; Venkatesh *et al*., 2012), while the technology–organization–environment framework and diffusion theory explain which firms adopt earlier (Tornatzky *et al*., 1990; Rogers, 2003). The limitation is one of unit of analysis. An SME contemplating intelligent process automation; rule-based task automation combined with data-driven or model-based components performing classification, extraction, prediction or generation within a process (Ng *et al*., 2021), is not choosing whether to accept an artefact, but whether to attempt construction of one, in a process it has not documented, against a benefit it has not baselined, with staff it cannot release.

Both traditions were extended, and the extensions are instructive about what remained untouched. Acceptance theory was elaborated into a fuller net in which the determinants of perceived ease of use and usefulness are themselves modeled (Venkatesh & Bala, 2008), yet a decade of extension produced fragmented, largely individual-level replication and an explicit call for multi-level theorizing (Venkatesh *et al*., 2016). The firm-level tradition carries a complementary limitation: the technology–organization–environment framework is best read as a generic taxonomy of adoption context rather than a fixed variable set, which is why its operationalization varies so widely (Baker, 2012), and firm-level adoption research is dominated by diffusion theory and TOE, the latter routinely combined with institutional theory or with the Iacovou–Benbasat–Dexter model rather than used alone (Oliveira & Martins, 2011). A taxonomy of context says where to look, not what must be true inside the firm, and is silent on order. Nor is adoption a single event, assimilation proceeding through initiation, adoption and routinization with drivers differing by stage (Zhu *et al*., 2006).

The field's response to that divide has largely been fusion rather than sequencing, acceptance constructs being estimated alongside firm-level context in one model, as in the integrated TAM–TOE treatment of AI adoption in manufacturing and production firms (Chatterjee *et al*., 2021). Fusion widens coverage without supplying a dependency structure, and leaves the dependent variable untouched: post-adoption depth of use, not the binary decision, is what varies with realized value (Zhu & Kraemer, 2005), so a firm counted as an adopter may have obtained nothing. The literature is now large enough for a review of reviews, its drivers and barriers clustering into technical, organizational and social groups (Cubric, 2020), and its value strand attributes outcomes to bundles of technical, human and organizational resources rather than to algorithms (Enholm *et al*., 2022).

Small-firm adoption has a canonical model closer to the present concern. Iacovou *et al*. (1995) explained small-organization adoption of interorganizational technology through perceived benefits, organizational readiness and trading-partner pressure; in a formal test on a survey of senior purchasing managers analysed by structural equation modelling, Chwelos *et al*. (2001) reported that "all three determinants were found to be significant predictors of intent to adopt EDI, with external pressure and readiness being considerably more important than perceived benefits". Readiness there is a firm-level construct rather than an attitude: a small firm's conviction that a technology would help it is a weak guide to whether it can deploy it.

2.2 Organizational readiness for change as a distinct construct

Readiness has a literature of its own in implementation science and change research, more disciplined than the usage common in AI work. Weiner (2009) theorized organizational readiness for change as a shared, collective psychological state combining change commitment and change efficacy, the degree to which members jointly resolve to implement a change and believe they can. Readiness so defined is neither an aggregate of individual attitudes nor an inventory of technical assets; it is collective and specific to a change, so assessing it against one candidate process rather than the enterprise is the correct unit, not a convenient simplification.

Whether it can be measured reliably is a separate and cautionary question: readiness instruments have been found conceptually heterogeneous and frequently lacking demonstrated reliability and validity (Weiner *et al*., 2008), a finding that applies to AI-readiness scales including this one, and readiness operates at individual, group and organizational levels, so treating it as one construct is a modelling error (Rafferty *et al*., 2013). In a firm of forty people, those levels collapse rather than interact: the owner-manager is at once the individual whose beliefs matter, the group in which commitment would be shared, and the organization whose efficacy is at stake, an early version of which is Thong and Yap's (1995) finding that in small businesses the chief executive's characteristics operate as a firm-level adoption determinant. Such an assessment therefore cannot aggregate across respondents to average out idiosyncrasy, and must rely on evidence producible on request.

The wider change literature adds three cautions AI-readiness work has not absorbed. Readiness descends from a planned-change tradition whose canonical statement is routinely reduced to a three-step recipe it does not contain (Burnes, 2004), and whose research program divides into content, contextual, process and criterion questions that are not interchangeable (Armenakis & Bedeian, 1999); a readiness score is a criterion measure, silent on content and process. Reactions of those on the receiving end are, on the largest synthesis of quantitative studies available, patterned rather than idiosyncratic (Oreg *et al*., 2011), which matters where the recipients are also the assessors and the operators. And because readiness is constituted at several levels at once (Vakola, 2013; Rafferty *et al*., 2013), an instrument collecting one owner-manager's judgement measures one level and infers the rest: defensible if declared, misleading if not.

2.3 Readiness and maturity in the AI literature

Alsheibani *et al*. (2018) proposed a firm-level AI readiness framework, but as research-in-progress with no empirical results. Jöhnk *et al*. (2021) provide the strongest anchor: five categories, eighteen organizational AI readiness factors and fifty-eight indicators from twenty-five expert interviews. Uren and Edwards (2023) reported empirically that technology readiness alone is insufficient, people, process and data readiness being required alongside it. Alongside readiness sits maturity modeling; the capability-maturity architecture now stewarded by ISACA (2023) and its process descendants (de Bruin & Rosemann, 2005), but Sadiq *et al*. (2021), reviewing fifteen primary studies, found most AI maturity models were proposed without empirical validation, a warning applying to the present paper as much as to any other.

Two contributions come closer to a staged view. Holmström (2022) framed AI readiness as a staged capability build spanning technologies, activities, boundaries and goals, connecting AI adoption to digital transformation rather than to procurement. North *et al*. (2019) proposed a dynamic-capability-based self-assessment of SME digital maturity and, in a pilot application rather than a representative survey, reported moderate maturity with firms better at "sensing" digitally based opportunities than at "seizing" them. Neither states dependencies as conditions that must be satisfied before a firm proceeds, which is what a gate is.

The maturity genre is crowded: a comparative study classified sixty-nine business process maturity models (Van Looy, 2014), and a later evaluation derived a ranked criterion set for prospective users precisely because the models vary so widely in quality (Van Looy *et al*., 2017). The form has since reached production machine learning, capability to operate models being assessed against staged maturity rather than a checklist (John *et al*., 2021).

2.4 AI adoption inside digital transformation

Vial (2019), consolidating a fragmented field, defined digital transformation as a process in which digital technologies trigger structural changes and strategic responses, a definition centered on the organizational response rather than the technology. Verhoef *et al*. (2021) separate that process into digitization, digitalization and digital transformation proper, preventing the conflation of tool adoption with business-model change; on that distinction the subject of this paper is the middle term, the automation of a decision inside an existing process, whereas much practitioner discourse addressed to SMEs promises the third term while selling the first. The mechanism has been described in dynamic-capability terms, as strategic renewal enacted through sensing, seizing and transforming (Warner & Wäger, 2019) and, in systematic review, as a distinctive form of organizational change (Hanelt *et al*., 2021). Adoption is therefore a change program with a technological occasion rather than a technology project with change management attached, an uncomfortable implication for a firm with no capacity to run change programs.

Two consequences follow for a smaller firm. A digital transformation strategy is a distinct artifact balancing use of technologies, changes in value creation, structural changes and financial aspects (Matt *et al*., 2015), so a firm holding none of these in writing is responding to an offer rather than executing a strategy. And the payoff from SME digitalization appears mediated by business-model innovation practices rather than delivered by adoption alone (Bouwman *et al*., 2019), which supports justifying an automation on operational grounds and against an operational baseline.

2.5 The SME condition and SME digitalization

Evidence bearing directly on SMEs is thin. Kinkel *et al*. (2022) found, in a worldwide sample of manufacturing companies, that prior capability and complementary competences condition adoption, and Baier *et al*. (2019) documented the challenges of deploying and operating machine learning: drift detection, infrastructure standardization, and stakeholder expectation management, which presume a technical function most SMEs lack. The implementation literature transfers only partially: robotic process automation is "outside-in" automation leaving underlying systems unchanged (van der Aalst *et al*., 2018); the source is an editorial, and its value lies in the precision of the definition rather than in evidence. Challenges are surveyed by Siderska *et al*. (2023) and success factors by Plattfaut *et al*. (2022); Herm *et al*. (2023) built a three-phase, eleven-stage framework from thirty-five cases, eight expert interviews, and five validation workshops; and Lacity *et al*. (2021) derived thirty-nine action principles across twenty-two organizations, a base sitting in large service organizations with program structures SMEs lack.

The small-business information systems literature, older than the digitalization vocabulary, supplies the boundary condition most AI-readiness work omits. Thong (2001) identified resource scarcity as the defining constraint on information systems implementation in small businesses: where large-firm research treats resources as a moderator, small-firm research treats them as the boundary of the feasible set. Eller *et al*. (2020) reach a compatible conclusion by another route, placing managerial and employee digital competence among the antecedents of SME digitalization. Two implications follow as arguments rather than findings: the appropriate SME instrument identifies the cheapest binding constraint rather than scoring a profile, and a method designed for a large organization needs simplification before a resource-constrained firm can carry it (Ambali *et al*., 2021, a practitioner-oriented review whose venue is discussed in Section 8).

Two adjacent literatures sharpen that boundary. Small-firm computing was characterized through motivators and inhibitors long before the digitalization vocabulary existed (Cragg & King, 1993), a baseline against which today's AI-specific barriers can be judged. Smaller firms also blend structured improvement methodologies rather than adopting either in pure form, facing resource- and leadership-specific barriers, with linkage to the customer, a vision and plan statement, communication and management involvement ranked highest among critical success factors (Timans *et al*., 2012), and the methods adapted are themselves under-specified, giving weak guidance for generating redesign alternatives across six key methodological decision areas (Vanwersch *et al*., 2016).

2.6 Absorptive capacity, IT capability and dynamic capabilities

The sequencing claim needs a theoretical basis, and the capability literature supplies one. Cohen and Levinthal (1990) argued that a firm's ability to recognize, assimilate, and apply new external knowledge is a function of its prior related knowledge, so absorptive capacity is path-dependent: a firm without prior data and analytics experience cannot compensate by buying more capable technology, because the constraint is on assimilation rather than availability. Zahra and George (2002) split the construct into potential absorptive capacity: acquisition and assimilation, and realized absorptive capacity: transformation and exploitation, naming a failure mode visible in practice: a firm can acquire AI knowledge and tooling without converting either into use. Lane *et al*. (2006) warned that the construct has been widely reified; it is used here to state why order should matter, not to explain why particular firms succeed.

The same move is made at the resource base. Teece *et al*. (1997) located advantage in the ability to reconfigure competences in changing environments, recasting AI adoption as capability reconfiguration rather than asset purchase; Bharadwaj (2000) found that information technology *capability*, not spend, associates with superior firm performance, which is why a vendor quotation is not a readiness measure.

Three qualifications matter here. The potential/realized split is contested, and recognizing the value of new knowledge has been argued to belong as a separate component of absorptive capacity (Todorova & Durisin, 2007) for an SME, the component most obviously missing when a vendor demonstration is the firm's only exposure. Dynamic capabilities have been characterized as "a set of specific and identifiable processes" rather than tautological abstractions (Eisenhardt & Martin, 2000), which is what makes them assessable; and information systems resources require classification against resource-based criteria before capability claims can be sustained (Wade & Hulland, 2004), a standard on which most SME AI-readiness discussion concerns assets rather than capabilities. AI capability itself has since been operationalized as a measurable multi-dimensional construct related to organizational creativity and firm performance (Mikalef & Gupta, 2021).

Why the internal, unglamorous work matters is stated most directly by the knowledge literature. Knowledge creation depends on conversion between tacit and explicit forms (Nonaka, 1994); transfer inside a single firm fails through absorptive capacity, causal ambiguity and the source–recipient relationship rather than want of motivation (Szulanski, 1996); and canonical procedure diverges from the practice communities follow (Brown & Duguid, 1991). Externalizing decision logic is a conversion of the first kind, made across the relationship the second identifies as the site of failure, and the divergence named by the third is what a determinacy measurement detects.

Together these ground the sequencing argument. If absorptive capacity depends on prior related knowledge, the readiness domains of Section 4.2 are not interchangeable slots in a scorecard: externalizing decision logic and measuring variation produce exactly that prior knowledge, and a firm that has never written down what it decides has no referent against which to assess a vendor's claim, a model's output or a data set's fitness. That is a reasoned position, since no located study tests the ordering directly, and it is stated as P1 and P2 so that it can be falsified.

2.7 Complementarities: organizational change as the complement that makes technology pay

Brynjolfsson and Hitt (2000) argued that information technology's productivity effect depends on complementary organizational investments, so the same technology yields very different returns across firms, and Bresnahan *et al*. (2002) presented firm-level evidence that information technology, organizational redesign and skilled labor operate as three-way complements, shifting the composition of skill demand rather than simply substituting for labor; Melville *et al*. (2004) formalize the same logic as a chain from information technology resources through business processes to firm performance. If the complements generate the return, a readiness model that inventories technology measures the least explanatory term. An asymmetry specific to smaller firms follows: the complements of redesigned work, documented rules, trained cover, and a monitoring routine are cheap, but expensive relative to an SME's slack, while the technology has become cheap for everyone. The binding constraint has migrated to the part of the system that cannot be bought.

Task-level evidence makes the complement concrete. Applying suitability-for-machine-learning measures to over 18,000 tasks in the O*NET occupational database, a task-level analysis, not a firm or worker survey, Brynjolfsson *et al*. (2018) reported that most occupations contain some suitable tasks, that full automation of an occupation remains rare, and that "realizing the potential of ML usually requires redesign of job task content"; a precondition of the return, not a consequence. The complement has a human form too: business competence among technical staff, rather than technical skill alone, drives effective information technology–business partnering (Bassellier & Benbasat, 2004), a translation role somebody must occupy in a firm too small to employ either specialism.

2.8 Standardization, decision logic and data

The link between standardization and performance is comparatively well evidenced: Münstermann *et al*. (2010) evaluated the performance impact of standardizing a recruitment process, and the associated case study reported a reduction in time-to-hire from ninety-two to sixty-nine days and a cut in overall recruiting process cost of approximately thirty per cent (Muenstermann *et al*., 2010). It is not unconditional. Schäfermeyer *et al*. (2012), surveying 255 BPM experts, found that higher standardization effort cannot compensate for higher process complexity, and Romero *et al*. (2015) argued that full unification is often impractical, so organizations must choose an appropriate degree of standardization. In smaller organizations, the corresponding instrument is the documented standard operating procedure, treated by Eyetsemitan *et al*. (2022) as a deliberate management instrument rather than informal residue; that source is a practitioner-oriented review used for framing only.

The construct is less settled than the performance evidence suggests. A review of sixty peer-reviewed articles extracted twenty-two explicit or implicit definitions of business process standardization, thirteen embedding hypotheses about outcomes in the definition itself, and proposed a definition emphasizing consistency across underlying processes, with derivation of an approved master process and unification of variants against it as the two phases (Goel *et al*., 2023). Results are therefore not straightforwardly comparable across that literature. Further reason to treat the performance findings above as directional rather than as effect sizes an SME could budget against. Nor is one configuration correct everywhere: the appropriate approach is contingent on process characteristics such as uncertainty and interdependence (Zelt *et al*., 2019), and knowledge-intensive processes are "knowledge- and data-centric, and require substantial flexibility, at both design- and run-time" (Di Ciccio *et al*., 2015), for which constraint-based modeling supports loosely structured work without surrendering verification and run-time change (Pesic *et al*., 2007). The determinacy question is thus not whether a process can be forced into a flowchart, but which of its decision points behave in a way a rule can carry.

The object standardized before automation is decision logic. Batoulis *et al*. (2015) showed that real-world process models encode detailed decision logic inside control flow and gave a semi-automatic method for extracting it into the Decision Model and Notation, and Hasić *et al*. (2018) set out principles for separating decision from process logic. The standards are stable: BPMN 2.0.2, DMN 1.3 and SBVR (Object Management Group, 2014, 2019, 2021). Where variation is unknown rather than merely undocumented, process mining measures it from execution data (van der Aalst, 2016), and robotic process mining uses frequency and determinism to select candidate routines (Leno *et al*., 2021; Dumas *et al*., 2022).

On the data side, Wang and Strong (1996) established that data quality is fitness for use rather than accuracy alone, and Redman (1998) that poor quality imposes operational, tactical and strategic costs. Lawrence (2017), in a preprint never formally peer-reviewed, proposed data readiness levels; Sambasivan *et al*. (2021) documented data cascades, the compounding downstream harms of upstream neglect; and Gebru *et al*. (2021) proposed datasheets as documentation practice. Where those harms originate is an accountability question more than a tooling one: data governance has been synthesized as mechanisms, scopes and domains with explicit decision rights (Abraham *et al*., 2019), and Haug and Arlbjørn (2011) reported that "a lack of delegation of responsibilities for maintaining master data is the single aspect which has the largest impact on master data quality" which names the cheapest remedy available to an SME, an owner for each contested definition.

Three further strands matter for an automated decision specifically. Quality is task- and context-dependent, so data adequate for one use can be unfit for another (Strong *et al*., 1997), and data accuracy rather than analytics sophistication is what has been linked to operational performance (Chae *et al*., 2014). Quality assessment is a distinct stage of the machine learning pipeline rather than a preprocessing afterthought (Jain *et al*., 2020), with collection, labelling and validation the dominant levers (Whang *et al*., 2023); labelling error is pervasive enough even in benchmark test sets to invert model rankings (Northcutt *et al*., 2021), which is reason not to accept a supplier's accuracy figure without knowing how its labels were produced. Nor does tooling close the gap: a survey that identified 667 data quality software tools and evaluated thirteen found profiling far better supported than the continuous monitoring an operating automation requires (Ehrlinger & Wöß, 2022).

Ownership remains the binding issue beneath all of it. Data governance can be designed as decision domains with explicit accountabilities rather than left as an ad hoc information technology activity (Khatri & Brown, 2010); no configuration is universally correct, the allocation of roles and decision rights being contingent on context, as an examination of six international companies established (Weber *et al*., 2009); and an ethnographic study of a municipality over thirty-two months identified fifteen organizational challenges in master data management, seven previously unreported (Vilminko-Heikkinen & Pekkola, 2017). What a small firm lacks here is a function, not a budget.

2.9 Governance, oversight and human control

Jobin *et al*. (2019) found eighty-four ethics documents converging on five principles; transparency, justice and fairness, non-maleficence, responsibility and privacy, while diverging substantially in interpretation and implementation, and Mittelstadt (2019) argued that principles alone cannot guarantee ethical AI; the lawful, ethical and robust conception of trustworthy AI gave an early operational vocabulary (High-Level Expert Group on Artificial Intelligence, 2019). Organizational AI governance has since been defined as a distinct object (Mäntymäki *et al*., 2022) and decomposed into data, model, and system layers (Schneider *et al*., 2023), while Wieringa (2020), synthesizing 242 articles, identified five accountability dimensions: actor, forum, relationship, content and criteria, and consequences. Green (2022) argued that mandated human oversight often fails as a safeguard and can legitimize flawed systems. Standards have given these ideas institutional form (International Organization for Standardization, 2023a, 2023b; National Institute of Standards and Technology, 2023a).

The standards landscape is wider than those documents. ISO/IEC 38507:2022, published in April 2022, treats AI governance as a governing-body accountability question inside corporate information technology governance rather than as a technical control set, and applies to organizations of any size and sector (International Organization for Standardization & International Electrotechnical Commission, 2022); ISO/IEC 5338:2023, published in December 2023, adapts the established systems- and software-lifecycle standards to AI systems (International Organization for Standardization & International Electrotechnical Commission, 2023); and implementation guidance sits in a non-normative companion covering "the four functions in the AI RMF: Govern, Map, Measure, and

Manage" (National Institute of Standards and Technology, 2023b). For an SME the awkwardness is that the normative material is scoped at governing-body level while the actionable material is not normative at all.

Three research bodies supply the operational content principles leave abstract. The first is explainability, not a single technique: methods for explaining opaque models are numerous enough to require classification by problem type, explanator and model type, the difficulty being that "many accurate decision support systems have been constructed as black boxes, that is as systems that hide their internal logic to the user" (Guidotti *et al*., 2018). The field lacked an agreed definition and evaluation protocol as it began to scale - "there is very little consensus on what interpretable machine learning is and how it should be measured" (Doshi-Velez & Kim, 2017, a preprint) - and what counts as a good explanation is an empirical question already addressed in philosophy, psychology, and cognitive science (Miller, 2019). Two findings bear on a small firm's choices: deployed explainability serves internal engineers debugging rather than those affected by a decision (Bhatt *et al*., 2020), so an explanation facility is not itself an accountability mechanism; and for high-stakes decisions an inherently interpretable model has been argued the stronger control than post hoc explanation of an opaque one (Rudin, 2019), which points casework automation away from opacity altogether.

The second is fairness, where a choice must be declared rather than inherited. Bias enters at many distinct points in the pipeline, and the formal definitions of fairness are mutually incompatible (Mehrabi *et al*., 2021), so a framework not stating which it adopts has not adopted one. Discriminatory outcomes arise from ordinary, non-malicious modelling choices definition of the target variable, problems in training data, feature selection, proxy variables, and the masking of intentional discrimination (Barocas & Selbst, 2016) and purely technical interventions fail through abstraction traps concerning framing, portability, formalism, ripple effects and solutionism (Selbst *et al*., 2019): the object to be governed is a sociotechnical arrangement, not a model.

The third is lifecycle assurance. Machine learning development differs from conventional software engineering in empirically observed ways: data discovery, management and versioning, model customization, entanglement between components, so ordinary lifecycle governance does not transfer unchanged (Amershi *et al*., 2019). MLOps has been decomposed into an ordered sequence of steps offering "an effective strategy for bringing ML models from academic resources to useful tools" (Testi *et al*., 2022), and assurance requirements stated per lifecycle stage with explicit desiderata (Ashmore *et al*., 2021). For what a small firm buys rather than builds, value-based engineering has a normative process standard addressing "traceability of ethical values in the concept of operations, ethical requirements, and ethical risk-based design" (Institute of Electrical and Electronics Engineers, 2021), and supplier transparency a declaration of conformity borrowed from other regulated industries (Arnold *et al*., 2019). Two cautions close the loop. Audit is not yet assurance: a field scan found no accreditation, no standards of practice and no requirement that findings be acted upon (Costanza-Chock *et al*., 2022). And artefacts succeed or fail organizationally: fairness checklists depend on who owns them and whether concerns can safely be raised upward (Madaio *et al*., 2020), while practitioners applying a national principle set report that "a gap remains between high-level principles and practical techniques" (Sanderson *et al*., 2023).

Two practice literatures supply operational content that standards leave abstract: machine learning operations, given an explicit definition, principle, component and role set from combined literature review, tool review and expert interviews (Kreuzberger *et al*., 2023), and the study of deployment failures, which cluster into recurring, lifecycle-stage-specific categories across published industrial case studies (Paleyes *et al*., 2022). Older still, financial regulators have run a model risk regime for over a decade on validation independence, effective challenge and lifecycle documentation, defining model risk as "the potential for adverse consequences from decisions based on incorrect or misused model outputs and reports" (Board of Governors of the Federal Reserve System & Office of the Comptroller of the Currency, 2011) a formulation more useful to a small firm than most AI-specific ones, because it locates risk in the decision rather than the algorithm. Documentation has a comparably concrete artifact in model cards (Mitchell *et al*., 2019).

Finally, the assumption that a human reviewer constitutes a control deserves separate treatment, since most lightweight governance rests on it. Automating the easy parts of a task leaves the operator the residual hard parts while eroding the skill needed to perform them (Bainbridge, 1983); reliance failures take four separately diagnosable forms, use, misuse, disuse and abuse (Parasuraman & Riley, 1997); automation bias produces both omission and commission errors (Skitka *et al*., 1999); and the design objective is calibrated trust rather than maximized trust (Lee & See, 2004). The literature is not one-directional: people abandon a statistically superior algorithm faster than an equally erring human forecaster after one observed error (Dietvorst *et al*., 2015), yet elsewhere prefer algorithmic to human judgment (Logg *et al*., 2019). Burton *et al*. (2020), reviewing 61 peer-reviewed articles spanning 1950 to 2018, organized the causes under five themes: expectations and expertise, decision autonomy, incentivization, cognitive compatibility, and divergent rationalities, reading the contradictions as divergent rationalities rather than replication failure, and Fügener *et al*. (2021) add that collaboration with an algorithm can degrade independent judgment. "A person will check it" is not a control specification.

2.10 The gap

Three gaps follow. Readiness models describe dimensions but not dependencies, telling a firm where it is weak rather than what to do first. Implementation frameworks derived from large-firm programs assume capacity SMEs lack. And the standardization and readiness literatures have developed separately, so the possibility that undocumented decision logic rather than data scarcity is the usual binding constraint has not been stated as a readiness proposition.

Sections 2.2 and 2.6 permit a fourth. Organizational readiness for change is a mature construct with a known measurement problem (Weiner, 2009; Weiner *et al*., 2008; Rafferty *et al*., 2013) and absorptive capacity one with an explicit path-dependence claim (Cohen & Levinthal, 1990; Zahra & George, 2002), yet AI-readiness instruments have generally drawn on neither, inheriting neither the psychometric caution of the first nor the ordering logic of the second and so producing parallel profiles that are hard to validate and silent about sequence. The framework below borrows both, and should be judged on whether the borrowing survives testing.

3. Method

This paper is a conceptual contribution. The framework was developed by structured narrative synthesis of the published literature identified in Section 2, read against the author's professional experience of business analysis practice. No primary data were collected, and the framework has not been empirically validated. Section 8 sets out the resulting limitations, and Section 7.2 proposes a validation agenda.

Constructs recurring across five literature streams, adoption and readiness, automation implementation, standardization and decision modeling, data quality, and AI governance, were extracted, grouped, and tested for dependency, that is, whether one is a precondition for another rather than merely correlated with it; the resulting order is the phase sequence in Section 4.3, stated as propositions so that it can be falsified. Three further streams, organizational readiness for change, absorptive capacity and dynamic capabilities, and the economics of complementarities, were drawn on to ground that structure rather than to generate it; their role is explanatory, and they are not evidence that the ordering proposed is correct. Claims carry different epistemic status: those about barriers, data quality, standardization and governance are supported by cited literature, while the central sequencing claim is reasoned from the structural characteristics of smaller firms and is not, at present, evidenced. Where consultancy surveys are used, the nature of that evidence is stated at the point of use.

4. The framework

4.1 Part A: A taxonomy of SME AI adoption barriers

Five families are distinguished. They are not independent; they are separated because they have different remedies and different owners.

Resource barriers: Capital constrains, but the scarcer resource is the attention of the few people who understand how the work is actually done, and automation analysis consumes exactly those people. An SME does not trade an AI initiative against an alternative investment; it trades it against current throughput. This is an argued extension, not an evidenced finding, though it is consistent with the older finding that resource scarcity is the defining boundary condition on small-business systems implementation rather than one moderator among many (Thong, 2001).

Capability barriers: Most SMEs have no in-house machine learning or data engineering function, and Baier *et al*. (2019) documented that deployment and operation, rather than model construction, generate persistent difficulties: drift detection, infrastructure standardization, and expectation management, each presuming a role that must otherwise be bought. Kinkel *et al*. (2022) found prerequisites and complementary competences condition adoption, suggesting capability is cumulative. Absorptive capacity supplies the mechanism: what a firm can assimilate next is conditioned by prior related knowledge (Cohen & Levinthal, 1990), and acquired knowledge need never be converted into use (Zahra & George, 2002), which is argued here to be why external help so often leaves nothing behind. Two burdens follow adoption rather than preceding it: automations break when the interfaces beneath them change, so maintainability is a governance problem rather than an afterthought (Noppen *et al*., 2020), and the division of labor between business and information technology over ownership, standards and change control has had to be treated as a designable governance artefact (Petersen & Schröder, 2020), which an SME can neither design nor maintain.

Informational barriers: An SME typically cannot evaluate a vendor claim, because evaluation requires a baseline it has not measured. Melville *et al*. (2004) established that IT value depends on complementary organizational resources rather than the technology itself, making any vendor estimate conditional on changes the vendor cannot see; Brynjolfsson (1993) offered mismanagement as one of four candidate explanations of the productivity paradox, alongside mismeasurement, lags and redistribution, and Brynjolfsson *et al*. (2019) emphasized implementation lags and complementary intangible capital. The barrier is double: the firm cannot verify the claim, and cannot measure the outcome that would falsify it. Because returns depend on organizational investments made alongside the technology and on the joint adjustment of technology, work organization and skill (Brynjolfsson & Hitt, 2000; Bresnahan *et al*., 2002), a vendor's reference case is informative only about firms that made those adjustments.

Process and data barriers: Decision logic is commonly buried inside control flow rather than expressed separately (Batoulis *et al*., 2015), so no one can state the rule being applied; definitions drift; and variation exists but its degree is unknown, so the firm cannot tell whether a decision point is judgmental or merely inconsistent. Data problems are often misdiagnosed: the question is not whether a large dataset exists but whether the data needed *at the moment of decision* exists, is accessible at runtime, and has known fitness for use (Wang & Strong, 1996). Where upstream neglect is tolerated, harms compound downstream (Sambasivan *et al*., 2021), and Lawrence (2017), in a preprint, offers a vocabulary for the distance between data held and data required. A further barrier is structural: because real logs are heavily skewed (van der Aalst, 2020), an automation scoped to the common path leaves a residue of exceptions whose handling determines whether it saves attention or consumes it.

Governance and trust barriers: SMEs face the same accountability questions as large firms with none of the apparatus. Guidance converges on principles but diverges on implementation (Jobin *et al*., 2019), and principles alone do not deliver practice (Mittelstadt, 2019). Governance has been defined as an organizational capability (Mäntymäki *et al*., 2022) and decomposed into data, model, and system layers (Schneider *et al*., 2023), and instruments exist (International Organization for Standardization, 2023a, 2023b; National Institute of Standards and Technology, 2023a). The barrier is that adopting them at full weight is disproportionate, while adopting them nominally produces documentation without control. A second, less visible barrier is that the control an SME relies on one competent person reviewing output is the one the human-factors literature identifies as least reliable when undirected (Skitka *et al*., 1999; Parasuraman & Riley, 1997). A third is that the operating model, centralized or federated, is an explicit managerial choice with documented trade-offs rather than a technical detail (Asatiani *et al*., 2023), and a firm of forty people has usually made it by default.

Table 1: A taxonomy of SME AI adoption barriers

Barrier family	Specific barrier	Why the SME case differs	Supporting literature
Resource	Capital for tooling and integration	No portfolio across which failure can be amortized	Author's argued extension
Resource	Time of subject-matter experts	Those who know the process are those running it	Author's argued extension
Resource	No parallel workstream capacity	Remediation must be sequential, changing the method	Author's argued extension
Capability	No in-house ML or data engineering	Model building can be bought; operation cannot	Baier *et al*. (2019)
Capability	Deployment and operation skills	Effort falls after go-live, once external help leaves	Baier *et al*. (2019)
Capability	Absent prerequisites and competences	Capability is cumulative, not purchasable in one step	Kinkel *et al*. (2022)
Capability	Low absorptive capacity for AI knowledge	Prior related knowledge conditions what can be assimilated at all	Cohen & Levinthal (1990); Zahra & George (2002)
Informational	Cannot evaluate vendor claims	No technical reference point, no measured baseline	Melville *et al*. (2004)
Informational	Complementary investments unbudgeted	Returns depend on organizational change the quotation excludes	Brynjolfsson & Hitt (2000); Bresnahan *et al*. (2002)
Informational	No basis for estimating benefit	Benefit depends on complementary resources	Melville *et al*. (2004); Ward & Daniel (2012)
Informational	Value unobserved or overclaimed	No measurement capacity to detect either	Brynjolfsson (1993); Brynjolfsson *et al*. (2019)
Informational	Distorted reference class	Surveys skew to large firms and technology roles	Author's argued extension drawing on IBM (2023); Telford *et al*. (2022)
Process and data	Decision logic buried in control flow	No analyst function has externalized the rules	Batoulis *et al*. (2015); Hasić *et al*. (2018)
Process and data	Unmeasured variation	Variation is absorbed by experienced staff, so stays invisible	van der Aalst (2016); Dumas *et al*. (2022)
Process and data	Definition drift across reports	No data-governance role owns definitions	Wang & Strong (1996); Redman (1998)
Process and data	Data absent at the moment of decision	Historic volume mistaken for runtime availability	Wang & Strong (1996); Lawrence (2017)
Process and data	Complexity limits on standardization	Effort cannot offset complexity, so scope choice matters	Schäfermeyer *et al*. (2012); Romero *et al*. (2015)
Process and data	Variant skew bounds automation coverage	The exception residue falls on the same scarce staff	van der Aalst (2020)
Process and data	Ownership of definitions undelegated	No role maintains master data, so drift is nobody's job	Haug & Arlbjørn (2011); Abraham *et al*. (2019)
Governance and trust	No named accountability	No second line; the owner-manager is also the operator	Mäntymäki *et al*. (2022); Wieringa (2020)
Governance and trust	Nominal rather than effective oversight	One reviewer without time is oversight on paper	Green (2022)
Governance and trust	Oversight degraded by automation bias	The single reviewer is also the person the system is deferring to	Skitka *et al*. (1999); Parasuraman & Riley (1997); Bainbridge (1983)
Governance and trust	Principles without implementation route	Convergent principles, divergent practice, no translator	Jobin *et al*. (2019); Mittelstadt (2019)
Governance and trust	Disproportionate compliance apparatus	Full-weight standard adoption exceeds capacity	International Organization for Standardization (2023a, 2023b); Shneiderman (2020)
Governance and trust	Regulatory and client exposure	One adverse outcome can threaten the license to operate	High-Level Expert Group on Artificial Intelligence (2019)

4.1.1 What the industry evidence does and does not show

IBM (2023) surveyed 2,342 IT professionals across twenty markets, fielded between 8 and 23 November 2023, reporting that among enterprises with more than 1,000 employees 42 per cent had deployed AI and 40 per cent were exploring it, while among companies with 1,000 or fewer employees 25 per cent had deployed and 46 per cent were exploring. Two qualifications are essential: the unit of observation is IT professionals rather than firms, so the figures describe individuals' reports and not a firm-level census; and the 1,000-employee threshold corresponds to no standard SME definition, so the "smaller" category contains many firms no policy definition would treat as an SME.

Deloitte (2018) reported that 72 per cent of respondents had already started their RPA journey while only 3 per cent of organizations had scaled their digital workforce, defined as fifty or more robots, on a base of over 400 responses globally; the gap between initiation and scaling is the relevant pattern, and the figures are self-reported to a vendor-adjacent survey. A later wave, based on 479 executives across thirty-five countries, reported that seventy-four per cent of survey respondents were already implementing RPA and fifty per cent optical character recognition, naming process fragmentation, lack of clear vision, IT readiness and workforce resistance as barriers to scaling (Telford *et al*., 2022). Those four map onto three families in Table 1, a convergence rather than an independent confirmation.

A frequently cited industry observation places early RPA project failure at thirty to fifty per cent (EY, 2016); it should be read as practitioner experience rather than as a measured rate, and the academic literature has recirculated it without independent verification. There is a deeper objection than provenance: if success and failure are enacted judgements that can coexist for the same system (Cecez-Kecmanovic *et al*., 2014), a single-number failure rate is not merely unverified but analytically empty. Automation's public discourse has in any case a measurable hype trajectory distinct from its evidence base (Kregel *et al*., 2021), and information systems failure has a cumulative research literature of its own (Dwivedi *et al*., 2015).

The strongest statistical anchor in the evidence base assembled here concerns a precursor practice rather than AI itself. Brynjolfsson and McElheran (2016) documented the diffusion of data-driven decision making across United States manufacturing plants, reporting that adoption rose from 11 per cent to 30 per cent between 2005 and 2010. Three qualifications travel with it: the unit of observation is the plant rather than the firm, the practice is data-driven decision making rather than AI, and the population is United States manufacturing rather than services or any size-defined SME class. On the returns side, firms adopting data-driven decision making showed output and productivity 5 to 6 per cent higher than expected given their other investments and information technology usage, on a survey of 179 large publicly traded firms (Brynjolfsson *et al*., 2011), a sample explicitly of large firms reported in a working paper rather than a peer-reviewed article.

An honest statement follows, and the wider evidence base assembled for this paper strengthens rather than weakens it. SME-specific quantitative evidence is weak: adoption surveys skew to large enterprises and technology-role respondents; the implementation literature draws on large service organizations (Lacity *et al*., 2021; Herm *et al*., 2023); the readiness literature is interview-based and not size-stratified (Jöhnk *et al*., 2021); and the most relevant prerequisite evidence comes from manufacturing (Kinkel *et al*., 2022). Definitions of "SME" differ, so the figures are not comparable, and any framework built on this base, including the present one, is a hypothesis, not a finding.

The sources with a defensible sampling basis measure something other than AI adoption by SMEs, while those reporting a size split use thresholds matching no policy definition of one; and adoption is in any case the wrong dependent variable if what matters is whether an automated decision reaches routinised, monitored operation, since assimilation drivers differ by stage (Zhu *et al*., 2006). The appropriate posture is to reason from mechanism and state the evidence gaps plainly rather than to assemble a headline rate from incomparable surveys.

4.2 Part B The Five-Domain SME AI Readiness Model

The model is deliberately small, with the intention that an owner-managed firm could complete an assessment in a working day; this has not been tested. It makes process determinacy a first-class domain rather than a sub-factor, and it yields a *binding constraint* rather than an aggregate score.

Strategic Clarity asks whether there is a named business outcome, a measured baseline and an accountable owner. Absence of a baseline is the commonest reason a firm cannot later tell whether an automation worked; benefits arise from business change enabled by IT rather than from the investment (Ward & Daniel, 2012; Peppard *et al*., 2007). Benefits management adds structure: Ward *et al*. (1996) established the gap between how information systems investments are appraised and how their benefits are delivered, and Ashurst *et al*. (2008) modelled realization as a capability of four competences which are planning, delivery, review and exploitation of which an SME typically has the first and not the last two, because the people who would exercise them run the process. Realization also depends on practices sustained beyond go-live rather than on project completion (Doherty *et al*., 2012), which is why Strategic Clarity is assessed through a maintained baseline and a stopping discipline rather than through a business case.

Data Foundation asks whether the data required at the moment of decision exists, is accessible at runtime, and has known quality that is, fitness for use rather than accuracy alone (Wang & Strong, 1996), the distance-to-usability logic of data readiness levels (Lawrence, 2017), and documentation drawn from datasheets (Gebru *et al*., 2021). Definition stability (DF4) is grounded separately, being the criterion most often mistaken for a technical matter: it is a question of decision rights and delegated responsibility rather than tooling (Abraham *et al*., 2019; Haug & Arlbjørn, 2011), and in a firm without a data-governance function it reduces to naming, for each term appearing in more than one report, the person who decides what it means.

Process Determinacy asks whether decision points are identified, decision logic is externalized from control flow, and variation is measured. A decision point is a place where an outcome is selected from alternatives on the basis of inputs; determinacy is the degree to which it produces the same outcome from the same inputs. High determinacy suits rule-based automation; low determinacy indicates either genuine judgement or undocumented variation, and the two require opposite responses. The instruments exist: extraction of logic into DMN (Batoulis *et al*., 2015; Object Management Group, 2021), integrated modelling (Hasić *et al*., 2018), controlled vocabulary (Object Management Group, 2014, 2019), and measurement of variation from execution data (van der Aalst, 2016; Dumas *et al*., 2022).

This domain carries the paper's distinctive claim, and four arguments support treating it as first-class rather than as a sub-factor of process readiness. The first is conceptual: because prediction and decision are formally distinct problems (Bertsimas & Kallus, 2020), a firm that cannot state the decision, its alternatives, its inputs, or its tolerated error behavior has no target for a model to be accurate about, whatever data it holds. That is the specification gap located precisely: not a shortage of information but the absence of a specified object. The second is measurement-theoretic: deviation between prescribed and observed behavior is formally measurable through conformance checking (Carmona *et al*., 2018) and variation is measurable from execution records (van der Aalst, 2016), so a determinacy claim can be falsified rather than asserted; where execution records are absent, the fallback is a weaker structured re-assessment sample in which past cases are independently re-decided. The third is selection-theoretic: frequency and determinism already serve as selection criteria in robotic process mining (Leno *et al*., 2021; Dumas *et al*., 2022) and viability is assessable at activity granularity (Wellmann *et al*., 2020), so the model raises an established selection criterion to a readiness criterion and applies it before a vendor is engaged, tractably, given the heavy skew of real logs (van der Aalst, 2020).

The fourth is the absorptive-capacity argument of Section

2.6: externalizing decision logic produces prior related knowledge in Cohen and Levinthal's (1990) sense, and, on Zahra and George's (2002) division, a firm that buys a tool without it has potential absorptive capacity but no route to realizing it. Determinacy is therefore held to be where the sequence begins for most SMEs; a reasoned position offered as P2 and P3, consistent with two practitioner-oriented reviews used for framing only (Eyetsemitan *et al*., 2022; Ambali *et al*., 2021).

Two adoption findings qualify how the instruments should be used. Process mining adoption follows an organizational-capability path: sponsorship, data access, analyst skills, and embedding into routines rather than a tool-installation path (Grisold *et al*., 2021), and its obstacles are, by expert consensus, predominantly organizational and data-related rather than algorithmic (Martin *et al*., 2021). Measurement is better supplied than firms assume: a structured review consolidated 140 process-related performance indicators across eleven categories from seventy-six publications (Van Looy & Shafagatova, 2016).

People and Capability asks who will operate the system, who will monitor it, and who is competent to challenge its output; difficulty concentrates in deployment and operation (Baier *et al*., 2019), and technical and social systems must be jointly optimized (Trist & Bamforth, 1951; Sarker *et al*., 2019). Change absorption capacity is assessed here as a condition on the domain's criteria. Because information technology, organizational redesign and skilled labor operate as complements (Bresnahan *et al*., 2002), the skills an automation requires are not the skills it displaces.

The challenge criterion (PC3) needs its own justification, being the one practitioners most often regard as redundant. On the evidence of Section 2.9 a human reviewer is not automatically a control (Bainbridge, 1983; Parasuraman & Riley, 1997; Skitka *et al*., 1999; Lee & See, 2004), aversion and appreciation both occur (Dietvorst *et al*., 2015; Logg *et al*., 2019; Burton *et al*., 2020), and collaboration with an algorithm can degrade the reviewer's judgement (Fügener *et al*., 2021), so challenge capability is eroded by the deployment rather than fixed. Two implications follow: review is directed at the cases most likely to be wrong, uniform review being the condition under which automation bias operates most strongly, and overrides are recorded as evidence about the system, an override rate falling to zero being as informative as one that stays high.

Three further findings shape what PC1 and PC2 should ask. Deploying an algorithm creates new human work; that is, auditing, correcting, training it, rather than removing work, and these configurations are empirically observable (Grønsund & Aanestad, 2020). Building an operational system is a negotiation between developers' and domain experts' knowledge claims, so what is deployed encodes an organizational settlement rather than a data-driven optimum (van den Broek *et al*., 2021), and it is harder to contest where expert and operator are one person. And staff reactions are not uniform: an interview study of eighteen staff at a New Zealand financial institution identified four configurations, perceived job consequences shaping whether employees collaborated with the automation team (Waizenegger & Techatassanasoontorn, 2022). Evidence on intelligent automation in knowledge and service work is, in any case, spread across disciplines with incompatible framings (Coombs *et al*., 2020), so no settled expectation can be imported.

Governance and Accountability asks who answers for an automated decision and by what evidence. Accountability dimensions (Wieringa, 2020) supply the structure and the layered decomposition of governance (Schneider *et al*., 2023) the scope; the arrangement should be sized to the firm (Shneiderman, 2020) and oversight must be real rather than nominal (Green, 2022). The standards landscape reviewed in Section 2.9 locates the disproportion an SME faces, and the lifecycle criterion (GA4) is where it bites hardest.

Model risk management supplies the vocabulary GA1 and GA2 need. Two features transfer to a smaller firm even though the apparatus does not: risk is located in the decision rather than the algorithm, matching the unit of analysis used throughout, and "effective challenge" names a function rather than a role, dischargeable without a dedicated second line provided the person is competent, informed and able to say no (Board of Governors of the Federal Reserve System & Office of the Comptroller of the Currency, 2011). A model card (Mitchell *et al*., 2019) records most of what GA2 requires, and the lifecycle-stage desiderata of Section 2.9 give GA4 a structure that can be cut down without becoming arbitrary.

GA3 needs one further observation. Regulatory obligation is a modelling problem as much as a legal one, and the research addressing it is unevenly developed: an analysis of seventy-nine papers published between 2000 and 2015 found compliance approaches centered on design-time (28 per cent), run-time (32 per cent) and auditing (10 per cent) (Hashmi *et al*., 2018), a firm meeting its obligations only by periodic audit relies on the thinnest of the three.

Table 2: The five readiness domains and the theoretical constructs that ground each

Domain	Primary grounding construct	Source tradition	What the construct contributes to the domain	Principal sources
1. Strategic Clarity	Benefits realization capability; IT business value	Benefits management; IT value	Benefit arises from business change, not investment, and realization is an assessable capability with distinct competences	Ward & Daniel (2012); Peppard *et al.* (2007); Ashurst *et al.* (2008); Ward *et al.* (1996); Melville *et al.* (2004)
2. Data Foundation	Fitness for use; data governance decision rights	Data and information quality	Quality is judged against intended use, and definitional stability is an accountability arrangement rather than a tool	Wang & Strong (1996); Lawrence (2017); Abraham *et al.* (2019); Haug & Arlbjørn (2011)
3. Process Determinacy	Absorptive capacity; decision–prediction distinction; conformance measurement	Organizational learning; analytics; process mining	Externalized decision logic is the prior related knowledge on which later data and model work depends, and determinacy is measurable rather than asserted	Cohen & Levinthal (1990); Zahra & George (2002); Bertsimas & Kallus (2020); Carmona *et al.* (2018); van der Aalst (2016, 2020)
4. People and Capability	Socio-technical joint optimization; complementarities; automation bias and algorithm aversion	Socio-technical systems; economics of IT; human factors	Skills are a complement rather than a residue, and human review is a control only when designed against a named failure mode	Trist & Bamforth (1951); Sarker *et al.* (2019); Bresnahan *et al.* (2002); Skitka *et al.* (1999); Lee & See (2004); Burton *et al.* (2020)
5. Governance and Accountability	Algorithmic accountability dimensions; model risk management	Accountability studies; financial regulation; standards	Accountability has a stated structure, and model risk locates risk in the decision rather than the algorithm, making proportionate control definable	Wieringa (2020); Schneider *et al.* (2023); Board of Governors of the Federal Reserve System & Office of the Comptroller of the Currency (2011); International Organization for Standardization & International Electrotechnical Commission (2022)

Table 3: The Five-Domain SME AI Readiness Model: Criteria and what each is diagnostic of

Domain	Criterion	Diagnostic of
1. Strategic Clarity	SC1 Named business outcome	A purpose expressible without the technology
	SC2 Measured baseline	Whether benefit could ever be evaluated
	SC3 Named owner and decision rights	Whether anyone can scope, fund or stop the work
	SC4 Stopping discipline	Whether a failing initiative can be abandoned in time
2. Data Foundation	DF1 Availability at the moment of decision	Inputs present when the decision is made, not only in history
	DF2 Runtime accessibility	Reachability by a production system, not just a person
	DF3 Known quality and fitness for use	Quality assessed against intended use, not assumed
	DF4 Definition stability and provenance	One meaning per term across systems and time
3. Process Determinacy	PD1 Decision point identification	Knowledge of where outcomes are actually selected
	PD2 Decision logic externalization	Rules held outside people's heads and control flow
	PD3 Measured variation	Knowledge of how often identical inputs diverge
	PD4 Exception and escalation structure	Whether the non-standard path is defined or improvised
4. People and Capability	PC1 Operating capability	Whether anyone can run the system on an ordinary day
	PC2 Monitoring capability	Whether degradation is noticed internally first
	PC3 Challenge capability	Whether a competent person will contest a wrong output
5. Governance and Accountability	GA1 Accountability assignment	Whether a named person answers for the decision
	GA2 Evidence and record-keeping	Whether a past decision could be reconstructed
	GA3 Risk and regulatory mapping	Whether the obligations touched are known
	GA4 Lifecycle control	Whether change and retraining are controlled events

The above table is a mapping, not a derivation: another set of domains could be defended from the same sources.

Criteria are scored Level 0 Absent, Level 1 Emergent, Level 2 Established, Level 3 Governed, and descriptors are written so that a level is claimed only if evidence for it could be produced on request.

Table 4: Four-level assessment rubric for the nineteen criteria

Criterion	Level 0 Absent	Level 1 Emergent	Level 2 Established	Level 3 Governed
SC1 Outcome	Aim stated as a technology	Described qualitatively; undefined	Specific change in a named operational measure	Linked to a business objective; reviewed at set cadence
SC2 Baseline	No performance figure exists	Anecdotal figures from ad hoc extracts	Measured over a defined period; method stated	Maintained, re-measured, used in every benefit claim
SC3 Owner	No one accountable	Owner named but cannot commit budget or staff	Authority over scope, funding and staff release	Decision rights documented and exercised on record
SC4 Stopping discipline	Initiatives fade rather than stop	Continuation decided case by case	Stopping rule agreed with thresholds and review date	Rules applied and recorded; one initiative stopped as designed
DF1 Availability at decision	Inputs used are unknown	Listed but untested at decision time	Confirmed present when the decision is made	Monitored in operation with alerts for missing inputs
DF2 Runtime accessibility	Manual extraction only	Scheduled extracts, stale for the decision	Reachable programmatically within required latency	Access documented, permissioned, version-controlled
DF3 Known quality	Quality assumed	Problems known informally by staff	Assessed against intended use and recorded	Measured against thresholds; remediation owned
DF4 Definition stability	Terms differ, never reconciled	Reconciled manually each time	One controlled vocabulary for the process	Governed, versioned, traced to source systems
PD1 Decision points	Not distinguished from activities	Known informally by those deciding	Identified and marked in a process model	Register maintained and reviewed on change
PD2 Logic externalization	Rules exist only in practice	Partly written; inconsistently applied	Held in a decision model separate from control flow	Version-controlled, case-tested, operationally authoritative
PD3 Measured variation	Assumed consistent	Suspected and cited anecdotally	Determinacy measured over a defined sample	Monitored; material change triggers investigation
PD4 Exceptions	Handled ad hoc by whoever meets them	Recognized but response undefined	Categories and escalation routes defined	Volumes monitored and fed back into logic revision
PC1 Operating capability	Supplier-dependent	One person, no cover	Two or more named staff with written instructions	Defined role with training, cover and handover
PC2 Monitoring capability	Failure found externally	Noticed by chance observation	Defined indicators checked by a named person	Instrumented thresholds and alerts reviewed by management
PC3 Challenge capability	Output accepted because automated	Error sensed but no route to act	Override authorized and recorded	Overrides analyzed as evidence and drive change
GA1 Accountability	No one accountable	Assumed to sit with supplier or IT	A named internal role is accountable	Documented, understood, tested in review
GA2 Evidence	Decisions cannot be reconstructed	Inputs partly retained; logic version not	Inputs, logic version and outcome retained	Retained to policy and used to answer external queries
GA3 Risk mapping	Exposure unexamined	Obligations known only generally	Mapped to the specific decision and outputs	Reviewed on regulatory change; reflected in controls
GA4 Lifecycle control	Changes unrecorded	Recorded inconsistently after the fact	Change and retraining follow an approved route	Logged, reviewed, linked to performance evidence

4.2.1 Position relative to existing models

The model is far smaller than that of Jöhnk *et al*. (2021), whose fifty-eight indicators offer greater resolution. That resolution suits research and large organizations, but an instrument requiring fifty-eight indicator judgements is unlikely, it is argued here, to be completed honestly by a firm of forty people, and an unfinished assessment has no diagnostic value; this is a reasoned extension rather than an evidenced finding. The model trades resolution for completability and makes determinacy an explicit precondition. Relative to the maturity tradition (ISACA, 2023; de Bruin & Rosemann, 2005) it borrows the level structure but rejects the aggregate score: an SME benefits not from being told it is at Level 1.7 but from being told which criterion blocks progress. Sadiq *et al*. (2021) found most AI maturity models are proposed without empirical validation, and this one is, by the author's own admission, in that condition until tested.

Relative to the wider readiness literature: Holmström's (2022) staged capability build shares the intuition that readiness accumulates, but its stages describe a trajectory rather than gates that can fail, and North *et al*. (2019) share the self-assessment format but score maturity across an SME's digital activity as a whole, whereas this instrument is scoped to one candidate process because readiness is change-specific (Weiner, 2009). The measurement caution applies with full force (Weiner *et al*., 2008), which is why the rubric requires producible evidence.

4.3 Part C: A phased implementation framework

Each phase has a gate stating what must be true to leave it; gates are how a resource-constrained firm avoids its most expensive failure mode, discovering in production that a precondition was absent. The staged structure is consistent with frameworks from automation practice (Herm *et al*., 2023; Lacity *et al*., 2021; Plattfaut *et al*., 2022), with critical success factor work in process management (Trkman, 2010), and with the change tradition's insistence that stages cannot be skipped without cost (Kotter, 1995, 1996). Because benefits arise from business change enabled by technology rather than from the investment (Ward & Daniel, 2012; Peppard *et al*., 2007), every phase moves an organizational condition, and joint optimization (Trist & Bamforth, 1951; Sarker *et al*., 2019) is expressed in the rule that no gate is satisfied by a technical artifact alone.

Three literatures ground the gate logic more carefully than an appeal to staged change alone. Benefits realization depends on competences exercised across the whole investment cycle (Ashurst *et al*., 2008) and on practices sustained after go-live (Doherty *et al*., 2012), so a gate is where one of those competences must have been exercised before the next commitment. Readiness is change-specific and multi-level (Weiner, 2009; Rafferty *et al*., 2013), which is why each gate is scoped to a named process. And failing projects persist because commitment escalates rather than because viability improves (Keil, 1995), so a criterion agreed before the outcome is known is the only reliable counterweight, de-escalation being itself a manageable process rather than an admission of defeat (Montealegre & Keil, 2000).

The benefits literature sharpens what a gate should test. A survey a decade after the original practice studies found benefits management still unevenly practiced (Ward *et al*., 2007); benefits realization practices have been related to project success and strategy execution (Serra & Kunc, 2015); and in software settings it is their combination with delivery practices, not either alone, that relates to perceived benefit (Holgeid & Jørgensen, 2020). Measurement is likewise a process of design, implementation, use, and update, whose characteristic failure, on three longitudinal case studies, is loss of alignment with a changing strategy, so that "specific processes are required to continuously align the performance measurement system with strategy" (Bourne *et al*., 2000). The Phase 1 baseline is therefore a maintained obligation, and the Phase 3 gate asks for benefits tracked, not claimed.

Phase 0: Diagnose runs the assessment for one candidate process, not the enterprise, and ends when a binding constraint has been named and agreed. **Phase 1: Stabilize** addresses that constraint in the target process only: standardizing definitions, externalizing decision logic, and measuring determinacy from execution records or a structured sample. Scope discipline matters because standardization efforts cannot compensate for intrinsic complexity (Schäfermeyer *et al*., 2012), and full unification is often impractical (Romero *et al*., 2015). **Phase 2: Constrained pilot automates one decision point at bounded volume against a pre-agreed success measure and stopping rule; the stopping rule is the SME-specific control, because the firm cannot amortize** a failure discovered late, and oversight must be designed to work rather than declared to exist (Green, 2022). **Phase 3: Embed** adds monitoring, escalation, rule-change and retraining routes, and benefits tracking. **Phase 4: Extend and govern** applies the pattern to further processes and consolidates accountability, records, risk mapping, and lifecycle control (Wieringa, 2020; Schneider *et al*., 2023; Mäntymäki *et al*., 2022) into one arrangement informed by available standards but sized to the firm (Shneiderman, 2020).

Table 5: Phased implementation framework: activities, gate criteria, and readiness domain moved

Phase	Principal activities	Gate criteria (what must be true to leave)	Domain primarily moved
0. Diagnose	Select one candidate process; score the nineteen criteria; agree the binding constraint	Scored profile exists; binding constraint named and agreed by the owner; proceed, defer or stop decision recorded	Strategic Clarity (SC1, SC3); visibility across all domains
1. Stabilize	Standardize definitions; identify decision points; externalize logic; measure determinacy; capture the baseline	Decision points documented; logic held separately from process flow; determinacy measured over a defined sample; baseline captured with stated method	Process Determinacy (PD1–PD3); Data Foundation (DF4); Strategic Clarity (SC2)
2. Constrained pilot	Automate one decision point at bounded volume; pre-agree success measure and stopping rule; direct review at likely errors; record overrides	Performance measured against the Phase 1 baseline; stopping rule applied or explicitly not triggered; oversight exercised on real exceptions and shown to catch error	Data Foundation (DF1–DF3); People (PC2, PC3); Strategic Clarity (SC4)
3. Embed	Instrument monitoring; define escalation, rule-change and retraining routes; track benefits; train cover	Performance sustained over a defined period; named operational owner distinct from the sponsor; monitoring and change routes in use; benefits tracked	People and Capability (PC1–PC3); Governance (GA2, GA4)
4. Extend and govern	Apply the pattern to second and third processes; consolidate accountability, records, risk mapping, lifecycle control	Two or more automated decisions in stable operation; one documented governance arrangement covering accountability, evidence, risk and lifecycle, sized to the firm	Governance (GA1–GA4); repeats Domains 2–4 at lower unit cost

Two features distinguish this framework from its large-firm antecedents: Phase 1 is scoped to one process rather than the enterprise, since an SME attempting enterprise-wide standardization will exhaust itself before reaching an automated decision; and the stopping rule at Phase 2 is a gate condition rather than good practice, since the asymmetry between an SME's downside and its upside makes premature commitment the dominant risk.

4.3.1 Why phase gates fail in practice

Proposing gates is easy; the harder question is why organizations that have them pass through them anyway. Four failure modes are identified, each with a basis in the cited literature and a design response built into Table 5. First, the gate is evaluated by the person who wants to pass it. Escalation of commitment operates most strongly where the sponsor both funds the work and judges its success (Keil, 1995), frequently the same person in an SME. Hence the requirement that the stopping rule be agreed and recorded before the pilot begins, and that the Phase 2 gate record it as applied or explicitly not triggered rather than pass in silence.

Second, the criterion is unfalsifiable as written. "The pilot is working well" cannot be failed, and criteria of that kind are characteristic of a field its own critics have found resting on prescriptive models with a weak empirical base (By, 2005). Every gate condition in Table 5 is therefore written so that its absence would be observable.

Third, the gate is satisfied by an artifact rather than a condition: a process map can be produced without changing how the process runs, and a policy without assigning accountability, which is the pattern that makes nominal oversight worse than none (Green, 2022; Mittelstadt, 2019). Hence the rule that no gate is satisfied by an artefact alone.

Fourth, the gate is passed at the wrong level, a sponsor's confidence standing in for the operating team's capability, when readiness operates at several levels (Rafferty *et al*., 2013); hence the Phase 3 requirement that the named operational owner be distinct from the sponsor. Fifth, organizational rather than technical issues are systematically under-addressed in systems development projects, and that omission predicts poor outcomes (Doherty & King, 2001). This is why every gate condition in Table 5 names an organizational condition. And removing an established practice requires different mechanisms from introducing one (van Bodegom-Vos *et al*., 2017), so a stopping rule must specify what stopping consists of, not only when. None of these responses is claimed to work; they are design commitments derived from documented failure modes, and P5 and P6 exist so the question can be settled rather than assumed.

4.4 Propositions

P1: SMEs that remediate readiness domains sequentially against an identified binding constraint reach sustained operational automation more often than those remediating concurrently.

P2: In SMEs, the first binding constraint on an AI-enabled decision is more frequently low or unmeasured process determinacy than insufficient data volume.

P3: Externalizing decision logic from control flow before pilot predicts pilot success independently of the volume of historical data available.

P4: Absence of a measured baseline at pilot initiation predicts inability to demonstrate value at embedding, irrespective of system performance.

P5: Scope discipline at pilot consisting of one process, one decision point, is positively associated with progression to embedded operation.

P6: A stopping rule agreed before pilot initiation reduces the duration and cost of unsuccessful initiatives.

P7: In SMEs, a lightweight governance arrangement with named accountability and exercised oversight outperforms nominal adoption of a comprehensive but unstaffed framework.

P8: The minimum criterion score in a readiness profile predicts adoption outcome more strongly than the mean score.

P1, P7 and P8 test the sequencing claim; P2 and P3 the determinacy claim; P4, P5 and P6 the gate design.

5. Illustration: a hypothetical casework organization

The illustration is hypothetical: a constructed example showing how the framework would be applied, not a case study, not a client, and not a source of data. No figures here are measurements; where levels appear they are stipulated for illustration only.

Consider a mid-sized services organization handling high-volume, document-heavy casework: application intake, eligibility assessment, document verification, and decision issuance, with periodic reporting to management and an external regulator. The work mixes rules and judgment, staff cost dominates, and the regulator imposes definitions the firm's systems do not natively produce. This hypothetical domain recurs in the author's related work as a common reference case.

Phase 0 (hypothetical): The firm's instinct is to apply document classification and extraction to verification, where volume is highest, so the assessment is run there. Suppose, for illustration only, that SC2 sits at Level 0, no baseline existing for throughput or error rate; that DF1 sits at Level 2 but DF4 at Level 0, the regulatory and internal senses of a "complete" application differing and being reconciled by hand; and that PD2 and PD3 sit at Level 0, verification rules living in the practice of four experienced assessors with no one knowing how often two of them differ on the same file. The mean of these stipulated levels would be unhelpful. The binding constraint is PD2/PD3: the firm cannot specify what an automated decision should do because it does not know what its current decision is; the pattern is stated as P2.

Phase 1 (hypothetical): Work is confined to verification. The team enumerates decision points is the document of the required type, is it current, is it internally consistent, does it satisfy the criterion it is offered against and draws the rules out of practice into a decision model held separately from process flow (Batoulis *et al*., 2015; Hasić *et al*., 2018), using the available standards (Object Management Group, 2014, 2019, 2021). Determinacy is measured by independently reassessing a structured sample of past files, and definitions are reconciled once so that the mapping between internal and regulatory senses is documented rather than remembered. The baseline is captured: throughput per assessor, rework rate, time to decision. Where regulator reporting is assembled in spreadsheets, the relevant caution is that field audits of operational spreadsheets report cell error rates of 0.4 to 2.5 percent, and that the audit studies collectively found errors in 94 percent of the spreadsheets studied (Panko, 2016), read alongside a critical review questioning how such rates were measured (Powell *et al*., 2008). None of this requires a vendor, and all of it retains value if automation never happens.

Phase 2 (hypothetical): One decision point is selected: document type and currency checking, the most determinate of the four, bounded to a single application category. The success measure is agreed against the Phase 1 baseline and the stopping rule in advance. For instance, the pilot ends if the escalation queue exceeds a stated proportion of volume for two consecutive weeks, since at that point the automation consumes more assessor attention than it saves. Review is directed at the cases most likely to be wrong rather than at a fixed sample, because undirected review is how nominal oversight fails (Green, 2022), and overrides are recorded as evidence about the system.

Phases 3 and 4 (hypothetical): Embedding sets monitoring thresholds and escalation, and establishes routes for changing rules when the regulator changes a requirement and for retraining extraction when document formats change; drift detection is the persistent operational burden the deployment literature identifies (Baier *et al*., 2019) and must be assigned to a named individual with cover. Benefits are tracked against the Phase 1 baseline. Eligibility assessment is the natural second candidate and a harder one, being less determinate and carrying direct regulatory exposure, so GA1 and GA2 bind before the data criteria do; one arrangement then covers both decisions, structured by the data, model and system layers (Schneider *et al*., 2023) and the accountability dimensions identified by Wieringa (2020), proportionate to a firm of this size (Shneiderman, 2020). The illustration demonstrates mechanics; it reports nothing.

6. Readiness constraints across applied domains

6.1 Provenance of the material in this section

This section draws on applied and practitioner literature of varying peer-review provenance. Many of the contributions cited below appear in venues without an established peer-review record, and none has been independently verified here. The section is offered as an illustration of how the readiness constraints identified above manifest across applied settings; it is not evidence for the model. The five-domain readiness model of Section 4.2, the phased framework of Section 4.3, and every quantitative claim made anywhere in this paper rest on the peer-reviewed literature reviewed in Section 2 rather than on this material. No statistic, proportion, sample description or effect size is taken from any source cited here, and no proposition in Section 4.4 derives from any of them. A reader who discounts the section entirely should find the argument of Sections 2 to 5 unchanged.

Three cautions govern the use made of the material. Contributions are cited for what their titles assert; that a problem was framed in a particular way, that a framework was proposed, that a practice was reviewed, never for outcomes they may report; where a title is vague, the claim attached is correspondingly modest. Sources are grouped where several evidence the same pattern, and each group attaches to a stated claim. Recurrence across applied settings is suggestive rather than corroborative. Each subsection closes by naming the readiness domain the material bears on, or the point in the sequencing argument it touches.

6.2 Data governance, information security and IT risk capability

The constraint this paper places under Data Foundation is not storage but ownership: someone must decide what a contested term means, who may reach the data at runtime, and under what obligation it is held. Applied writing on enterprise data protection treats those as modeling rather than tooling questions, proposing that the legal and ethical exposures of enterprise data handling be represented explicitly rather than left as background risk (Mbonu *et al*., 2018). The obligations are not uniform: comparative treatments report that data protection requirements differ across jurisdictions and bear on implementation choices (Mbonu *et al*., 2019), that distinct governance models exist for handling personal data across borders (Annan, 2022), and that an organization operating in several regimes must reconcile divergent requirements deliberately (Ominyi & Anichukwueze, 2022a). For a small firm this is DF4 in a legal register: one meaning per term, one owner per meaning, one record of the decision.

The applied security literature adds instruments a readiness assessment can borrow without importing an apparatus. Impact assessment is described as a governance step taken before a data-processing system is deployed rather than after it has run (Mbonu *et al*., 2022a), which is the logic of a gate; access governance is presented as a process to be designed and periodically optimized rather than configured once (Mbonu *et al*., 2022b), which is what DF2 asks about documented and permissioned runtime access. Continuous automated monitoring is proposed as the means by which a control weakness in an enterprise platform is detected at all (Aliliele *et al*., 2023a); an analog of PC2, which asks whether degradation is noticed internally first. Where security work is embedded in an agile delivery approach, compliance is treated as a constraint designed into the method rather than traded against delivery speed (Mbonu *et al*., 2020a), and whether such investment pays is treated as an empirical question rather than assumed (Ozowara *et al*., 2022).

The domain bears principally on Data Foundation and on Governance and Accountability. Its bearing on sequencing is that the decisive move in each account is the naming of an owner and an obligation, and analytical work is available to a firm with no security function at all.

6.3 Operational technology, control systems and continuous monitoring

Industrial settings show the problem in its least deniable form, since the consequence of an unmonitored automated decision is physical. Bringing two separate technology estates together is treated as requiring explicit governance alignment rather than an integration project (Adegbite *et al*., 2022), and a control architecture is framed as an implementation problem rather than a design problem (Ahmed *et al*., 2021), the distinction this paper draws in insisting that no gate is satisfied by an artefact alone. Model-based detection is applied to operational data streams in high-consequence environments (Adebayo *et al*., 2023), and detection and recovery are designed together as one control chain rather than procured separately (Ojukwu *et al*., 2023): a control that detects without a defined response is the operational-technology form of oversight existing only on paper.

The monitoring literature here states plainly what PC2 asks. Fault identification is described as being driven by continuous sensor data rather than scheduled inspections (Sunday & Omoegun, 2022), and continuous digital data streams are proposed to replace periodic manual observation as the input to a control process (Obriki & Arumosoye, 2023). The move from a reactive to a predictive regime is treated as a transition to be managed in its own right rather than a technology to be bought (Sunday *et al*., 2020), the sequencing claim in a maintenance vocabulary.

The domain bears on the monitoring criterion within People and Capability, and on Data Foundation, since a continuous control depends on inputs present at the decision rather than in an archive. It also shows why embedding is a distinct phase: the instrumentation that makes a control real is not part of the pilot that establishes whether the decision can be automated.

6.4 Enterprise systems, cloud adoption and service management

The Process Determinacy claim asserts that decision logic must be externalized before it can be automated. Service-management practice assumes this without stating it: workflow platforms are described as the vehicle through which standardized service processes are enacted (Ladapo, Jooda, *et al*., 2023a), which presupposes prior standardization. The applied review of that field pairs claimed benefits with implementation challenges rather than reporting benefits alone (Ladapo, Dosunmu, *et al*., 2023b), and cloud transitions are treated as staged rather than executed in one step (Ladapo, Jooda, *et al*., 2022). This is consistent with the position that adoption is a change program with a technological occasion.

Data and lifecycle constraints appear in the same literature. Integrating data from several systems into one platform is a design problem requiring explicit specification rather than a transfer (Badmus *et al*., 2019a), which is DF2 stated by an engineer; platform management in a regulated setting is governed through an explicit framework (Badmus *et al*., 2019b); configuration expressed as code brings the deployment process itself under governance (Mbonu *et al*., 2020b); and review and change control within a delivery team is governed by a stated framework (Badmus *et al*., 2022a). Those four are the applied form of GA4, which asks whether change and retraining are controlled events. Artificial intelligence appears here first as support for verification rather than for business decisions, with documented applications inside the software engineering lifecycle and specifically in testing (Borah *et al*., 2022).

The domain bears on Process Determinacy and on the lifecycle criterion within Governance and Accountability. Its bearing on sequencing is negative and useful: a firm without this apparatus must supply by hand the change control the apparatus would otherwise supply, which the framework makes an explicit condition of embedding rather than an assumption.

6.5 Analytics and predictive decision systems in operational settings

Applied analytics writing repeatedly locates the difficulty where this paper locates it; in the decision rather than the model. A customer lifecycle is described as managed against model-generated predictions (Ogundairo & Ayivi-Donkor, 2023a), which requires the underlying commercial decision to have been specified first; machine learning is applied to business transformation analysis rather than to a technical problem (Tonoyan *et al*., 2022c), relocating the unit of analysis from algorithm to decision as Section 4.2 does. Where an analytic capability must run at a resource-constrained site, it is tiered downward rather than transplanted whole (Komi & Adeniji, 2023), the applied counterpart of the argument that a large-organization method needs simplification before a small firm can carry it.

Three strands touch readiness criteria directly. Value realization is proposed as something instrumented continuously inside data pipelines rather than assessed retrospectively (Ogundairo & Ayivi-Donkor, 2023b), the maintained-baseline reading of SC2; executives are reported to experience identifiable information-visibility gaps that reporting design is intended to close (Sanni & Atima, 2021b), which is what an absent baseline feels like from the top of a small firm; and operational monitoring is described as deliverable in real time on a commodity analytics platform (Basnet *et al*., 2023), which removes cost as the reason a small firm has none. Two contributions bear on oversight. Interpretability is treated as a requirement of a predictive model used for operational action rather than a research nicety (Komi & Adamolekun, 2021), echoing the argument that inherently interpretable models are the stronger control for consequential decisions. And a model is described as capable of being accurate in aggregate while distributing error unevenly across groups (Komi, 2023), a caution that a headline accuracy figure is not a fairness claim, and a reason risk mapping is a criterion in its own right.

The domain bears on the baseline criterion within Strategic Clarity, on Data Foundation, and on the challenge criterion within People and Capability.

6.6 Financial controls, audit and risk governance functions

The assurance functions are where the constraints under Governance and Accountability have the longest applied history, and the vocabulary transfers readily. Technology support is proposed as a route to improving the quality of an assurance process rather than as a substitute for it (Akomolafe & Agu, 2018); internal controls are designed and prioritized on assessed risk rather than applied uniformly (Akomolafe & Agu, 2019a); and where assurance effort is directed is itself a modelled decision (Akomolafe *et al*., 2023a). That last move is the one this paper makes in arguing that review should be directed at the cases most likely to be wrong rather than spread evenly, uniform review being the condition under which automation bias operates most strongly.

Three further observations bear on GA2 and GA3. A statutory control framework is reported to be implemented differently across jurisdictions and comparable on that basis (Agu *et al*., 2023a), so an obligation is not a fixed object a small firm can simply inherit; statutory reporting frameworks are found to exhibit identifiable gaps that reform pathways attempt to close (Dogbatsey & Ebhojie, 2018); and corrective action planning is treated as a distinct, describable control process rather than as the residue of an audit (Ebhojie *et al*., 2023a), which is what GA4 asks when it asks whether change is a controlled event. Most directly, model risk management is presented as the established practice through which algorithmic accountability is operationalized in financial services (Ominyi & Anichukwueze, 2023), the same borrowing this paper makes from the supervisory guidance reviewed in Section 2.9, arrived at independently and in an applied register.

The domain bears squarely on Governance and Accountability, and on the claim that proportionate control is definable: every instrument named here decides where scarce assurance attention is spent, the only question a firm without a second line can usefully ask.

6.7 Financial planning, forecasting and decision analytics

Finance functions are where smaller organizations most often meet a model-supported decision first, and the applied literature states two of this paper's preconditions plainly. The first is that the quality and integration of underlying data management is claimed to bear on downstream analytic accuracy (Agu *et al*., 2023b) the applied form of the fitness-for-use position, and a reminder that the constraint sits upstream of the model. The second is that analytic activity requires deliberate alignment with strategy rather than aligning by default (Lawal & Oduleye, 2021b): SC1 and SC3 together, a named outcome and someone entitled to decide what the analysis is for.

Where a decision recurs and its inputs are stable, the same literature reports that it can be represented explicitly. A capital allocation decision is set out as an explicit decision model (Lawal & Oduleye, 2021a); a routine working-capital decision is placed on a predictive footing (Oduleye & Medon, 2023a); machine learning is described as an established basis for automated decisioning within a regulated financial process (Atakpa & Abetoh, 2022); and exception identification in operational data is modelled and automated rather than left to inspection (Atakpa & Fobellah, 2023). Each presupposes what PD1 and PD2 ask: that the decision point has been located and its logic stated separately from the flow of work, and none is a data-volume problem.

The domain bears on Process Determinacy and Strategic Clarity, and supplies the cleanest illustration of the determinacy claim: what makes each automation specifiable is that someone has written down the decision, and no quantity of financial history substitutes for that.

6.8 Procurement and supply chain digitalization

Procurement tests the determinacy claim usefully because it is transactional, repeated and usually undocumented. The applied literature treats it as a function that can be brought under structured optimization at all (Okonkwo *et al*., 2018a), and reports recurring operational losses attributed to process design and addressed by redesign rather than by additional effort (Okonkwo *et al*., 2020). A recurring supplier selection decision is described as something to be modelled and driven by data rather than by unaided judgement (Ahiaeke Patrick *et al*., 2021), and risk within a procurement process as managed on the basis of data rather than of relationship judgement (Bello *et al*., 2023). In each case the object automated is a decision that had to be articulated before it could be modelled, which is the order argued for here.

Two contributions map onto the framework more precisely than their subject matter suggests. Upstream readiness conditions are modelled as determinants of downstream process performance (Okonkwo *et al*., 2021), the dependency logic of the sequencing argument in a materials-management vocabulary; and traceability across a multi-party process is described as achieved through a designed visibility framework rather than as a by-product of digitization (Nnabueze *et al*., 2021), which is what GA2 asks about reconstructing a past decision. Process automation is proposed here as a route to transparency as much as to efficiency (Akinleye & Adeyoyin, 2021), inverting the usual order by treating the documentation the automation requires as part of the benefit rather than its cost. Where the setting is a smaller enterprise, the practice framework is adapted rather than transferred whole (Efobi *et al*., 2022a).

The domain bears on Process Determinacy and Data Foundation, and contributes distinctively to the sequencing argument: it is the one applied literature reviewed here in which upstream readiness is explicitly modelled as a determinant of downstream performance.

6.9 Regulated and public-sector settings

Where an external body specifies the rules, Process Determinacy takes an unusual form: the decision logic exists, but in someone else's document and in a register the firm's systems do not natively produce. The applied literature treats the translation as a first-class activity, describing how externally stated tax and regulatory requirements are converted into executable organizational workflows in smaller enterprises (Eyetsemitan *et al*., 2021), and how a change in obligation propagates into a redesign of both product and process (Olaogun *et al*., 2023). Cross-border technology transfer is reported to be bounded by compliance regimes constraining what may be deployed at all (Jones & Ominyi, 2023), and regulatory readiness for market entry is expressed as a staged maturity model (Eze *et al*., 2022b), a staged treatment of readiness reached in a different field for a different purpose.

Three further contributions bear on the Data Foundation and Governance criteria. A recurring compliance reporting obligation is described as automatable end-to-end (Abioye *et al*., 2023), which holds only where the definitions underlying the report are stable, that is, the DF4 condition. Routinely collected complaint records are proposed as a data source for predictive compliance monitoring (Adeyelu, 2018), an instance of data required at the moment of decision being already held but not reachable. And predictive models are applied to a control obligation in a public-sector setting (Adelanwa *et al*., 2023b), where the accountability question cannot be deferred.

The domain bears on Governance and Accountability, particularly risk mapping, and on Process Determinacy. It also strengthens the gate argument: where an external body will ask how a decision was reached, a criterion agreed before the outcome is known is the only defensible record.

6.10 Health and clinical service organizations

Health services supply the applied literature's most explicit statement of the complementarity argument. Scientific innovation is argued to fail to improve patient outcomes where delivery infrastructure is absent (Ilodigwe & Adesemoye, 2019b), and access is extended by reconfiguring delivery models rather than adding technologies (Ilodigwe & Adesemoye, 2020). The position, in a clinical register, is that the complement rather than the artifact is where the constraint sits. The data constraints are stated here with unusual directness. Data quality and interoperability are treated as governance and architecture problems prerequisite to analytics rather than as tasks within an analytics project (Ilodigwe & Adesemoye, 2021), which is the Data Foundation domain in a sentence. Regulatory constraints are embodied in the design of the data architecture feeding analytics rather than applied to its outputs (Atakpa & Abolaji, 2022); unstructured text is processed automatically to produce signals used in monitoring (Atakpa *et al*., 2023), a reminder that not all decision-relevant data is tabular; and model output is surfaced to operational managers through a real-time reporting layer (Filani *et al*., 2022), without which a prediction changes nothing. Two contributions bear on exception handling: an early warning signal is linked to a defined and pre-agreed response process (Eze *et al*., 2022a), and failures at the final stage of a distribution process are reported to have identifiable causes and defined intervention options (Asiedu & Asiedu, 2022). Both are PD4, whether the non-standard path is defined or improvised.

The domain bears on Data Foundation and Strategic Clarity, and contributes to sequencing the observation, made independently in a clinical context, that governance and architecture are prerequisites to analytics rather than concurrent with it.

6.11 Process improvement and quality management in smaller firms

This is the applied domain closest to the paper's own subject, and the constraints appear directly rather than by analogy. A defined process-redesign method is applied to shorten cycle time in one administrative workflow inside a small professional services firm (Oyeleye *et al*., 2022), scoped to a single process, the discipline the framework imposes at its stabilizing phase. Lean methods and data analysis are combined into one optimization approach rather than sequenced as separate initiatives (Efobi *et al*., 2022b), and process optimization is modeled algorithmically with its financial impact assessed rather than asserted (Tonoyan *et al*., 2022b). Where artificial intelligence enters, it is inserted at a production step already identified as a bottleneck (Sanni & Attah, 2023b) the constrained-pilot logic: one decision point, chosen because something is known about it.

Two further contributions bear on the gate structure. Acceptance criteria and structured validation are treated as a distinct, specifiable step in small-business technology deployment (Eyetsemitan *et al*., 2023b), which is what a gate is when written down; and change management is reported to mediate small-business adoption, itself staged rather than executed at once (Eyetsemitan *et al*., 2023a). Where the constraint is resource rather than technology, reported barriers are socioeconomic rather than technical (Michael & Ogunsola, 2022a), consistent with the boundary condition taken here from the small-business systems literature.

The domain bears on Process Determinacy and Strategic Clarity, and is the only one reviewed here whose unit of analysis is already the smaller firm; a convergence of concern rather than support, since none of these contributions tests the proposed ordering.

6.12 Workforce capability, training and organizational learning

People and Capability is the readiness domain the applied literature addresses least, which is itself informative. What it supplies is a design vocabulary for the human position in an automated decision. Human-in-the-loop configurations are described as an established design pattern rather than a fallback (Ladapo, Dosunmu, *et al*., 2022), which matters for the argument that a reviewer is a control only when the review is designed. Capability within a practice area is expressed as a staged model grounded in organizational learning (Arumosoye & Obriki, 2021), the same intuition as the sequencing claim reached in a safety context.

Two contributions from institutional settings bear on the monitoring and challenge criteria. Predictive models direct institutional risk-management attention rather than make the underlying judgment (Aliliele *et al*., 2023c), which is the directed-review pattern; and performance dashboards are described as the mechanism through which an organization monitors delivery (Orise & Niniola, 2022), which is PC2 given an artifact. Data-driven operations management is proposed as a route to performance improvement in a non-commercial organization (Efobi *et al*., 2021), where, as in a small firm, no dedicated analytics function exists to carry it.

The domain bears on People and Capability across all three criteria. The thinness of the material is worth recording: the capabilities treated here as the difference between an automation that works and one that consumes attention are the least represented in the corpus assembled, which is consistent with, though not evidence for, the claim that they are also the least planned for in practice.

6.13 Program and project governance

The final domain bears on the gate logic of Section 4.3 rather than on any single criterion. Project governance arrangements are treated as a variable organizations deliberately tune rather than as fixed overhead (Amayo *et al*., 2023a), and performance as managed across a delivery lifecycle rather than assessed at a single checkpoint (Adelanwa *et al*., 2023a), which distinguishes a gate from a milestone. Risk governance across multiple contracting parties is reported to require a purpose-built model rather than the extension of an internal one (Obogo *et al*., 2019b), a reminder that the arrangement a small firm needs is determined by who else is involved in the decision, not by headcount alone. Resource planning across a multi-stakeholder portfolio is supported by forecasting models (Edivri & Oteri, 2022), the large-organization answer to a problem an SME resolves by not running parallel workstreams at all.

The domain bears on Governance and Accountability and on the owner and stopping-discipline criteria within Strategic Clarity. Every arrangement described here presumes a program structure, a portfolio, contracting parties, a lifecycle owner that the firms addressed here do not have, which is why the framework compresses the function into a named person and a recorded decision rather than a governance body.

6.14 What the applied material adds, and what it does not

Across these domains the same shape recurs: the constraint is organizational rather than technical, the response is staged rather than simultaneous, and the technology is rarely the difficulty. That recurrence is what makes the material worth assembling, but it is not corroboration. None of these settings was studied against the five-domain model or the phased framework; the convergence is one of vocabulary and framing, the weakest form of agreement available and the one most easily produced by an author selecting sources. The material also skews towards conceptual frameworks and reviews rather than tested interventions, so it can show how a problem was framed but not that framing it so worked.

Two asymmetries qualify the illustration. Governance, data protection and analytics are richly represented; People and Capability is thinly represented, and no contribution reviewed here addresses operating, monitoring and challenge capability together. And the applied literature is dominated by settings larger and more structured than the firms addressed here, so its transfer to a firm of forty people is an argument made here rather than a finding reported there, exactly as with the peer-reviewed evidence base described in Section 8. The propositions of Section 4.4 remain the route by which the framework can be tested, and none of them is advanced by anything in this section.

7. Discussion

7.1 Implications for practice

The diagnostic question should change. "Are we AI-ready?" invites an aggregate answer that is either falsely reassuring or paralyzing; "what is our binding constraint on this decision, in this process?" produces an actionable answer within a day.

The cheapest available intervention is usually not technical. Externalizing decision logic, reconciling definitions and measuring determinacy require analyst time rather than capital, and produce value independent of automation: greater consistency, faster onboarding, and a process explicable to a regulator. That standardization has measurable performance effects is supported in the process literature (Münstermann *et al*., 2010; Muenstermann *et al*., 2010), subject to the complexity limit identified by Schäfermeyer *et al*. (2012).

Governance should be sized, not scaled down: a named accountable person, a retained record of inputs and applied logic version, mapped obligations and a controlled route for change will do more than a policy copied from a large firm, and nominal compliance is worse than proportionate control because it creates the appearance of oversight while leaving the failure mode intact (Green, 2022; Mittelstadt, 2019). Two substitutions make sizing tractable: a per-model documentation artifact (Mitchell *et al*., 2019) in place of a validation report, and effective challenge borrowed as a function from model risk practice without its apparatus (Board of Governors of the Federal Reserve System & Office of the Comptroller of the Currency, 2011). Oversight should likewise be designed against a named failure mode: since uniform review is the condition under which automation bias operates (Skitka *et al*., 1999) and the reviewer's judgement can degrade through use (Fügener *et al*., 2021), review should be directed at the cases most likely to be wrong. The vendor conversation, finally, should be conducted from a baseline, since without one benefit claims can be neither evaluated before purchase nor verified after it (Melville *et al*., 2004; Ward & Daniel, 2012).

7.2 Implications for research and a validation agenda

Four validation routes are proposed. *Instrument validation*: an expert panel from business analysis, process management and SME advisory practice could assess construct clarity and inter-rater agreement on level assignment across standardized vignettes, poor agreement being an informative negative result. *Retrospective profiling*: completed and abandoned SME initiatives could be profiled against the nineteen criteria with outcomes coded independently, testing P8 and, weakly, P2. *Prospective multiple-case study*: SMEs followed through Phases 0 to 3 with gates applied, recording where gates were failed or waived, would test P1, P5 and P6, following the design logic of the case-based implementation literature (Herm *et al*., 2023; Lacity *et al*., 2021). *Determinacy measurement*: determinacy is measurable from execution data (van der Aalst, 2016), and frequency and determinism already serve as selection criteria in robotic process mining (Dumas *et al*., 2022), so relating measured determinacy at pilot initiation to pilot outcome, controlling for data volume, would test the most distinctive claim.

Readiness and adoption research should also report size classes against a stated SME definition, because the present incomparability makes synthesis unreliable, and the standardization and readiness literatures should be integrated, since they address the same precondition from opposite directions.

7.3 Positioning against the readiness and maturity models now available

The field this paper enters is crowded, and it would be dishonest to present a further model without saying so. Firm-level AI readiness has been proposed without empirical results (Alsheibani *et al*., 2018), derived from expert interviews (Jöhnk *et al*., 2021), tested empirically (Uren & Edwards, 2023), framed as a staged capability build (Holmström, 2022) and instantiated for SMEs as a self-assessment of digital maturity (North *et al*., 2019); alongside sits the maturity tradition (ISACA, 2023; de Bruin & Rosemann, 2005), whose AI-specific descendants were largely proposed without empirical validation (Sadiq *et al*., 2021), while the wider readiness literature reports the same problem at a deeper level (Weiner *et al*., 2008).

Four differences distinguish the model proposed here, each a design bet rather than a demonstrated advantage: readiness is assessed against one candidate process rather than the firm, because it is change-specific (Weiner, 2009); the instrument returns a binding constraint rather than an aggregate score (P8); process determinacy is a first-class domain; and dimensions are ordered by dependency, grounded in the path-dependence of absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2002) rather than in observation.

What the model shares with its neighbors matters more than what distinguishes it: it is unvalidated. It has not been tested for inter-rater reliability, its domains have not been shown to be distinct, its ordering has not been shown to hold, and no outcome has been shown to follow from any score it produces. Adding an unvalidated model to a crowded field is defensible only if it is falsifiable and the route to falsifying it is stated, which is the purpose of Sections 4.4 and 7.2, and if retrospective profiling found mean score predicting outcome better than minimum, the central design choice would be wrong and the model should be abandoned rather than refined.

8. Limitations

No empirical validation: The framework has not been tested and no primary data were collected; its domains, criteria, levels, phases and propositions are analytical constructions derived from published literature and professional experience. Sadiq *et al*. (2021) found that most AI maturity models are proposed without empirical validation, and this model belongs, for now, to that category. No claim is made that it has been validated, proven or demonstrated to do anything.

The sequencing claim is reasoned, not evidenced: The central and most original claim that SMEs must remediate readiness domains in sequence against a binding constraint rather than in parallel rests on an argument about structural characteristics such as an inability to amortize failure, the absence of parallel workstream capacity, and the absence of dedicated data, governance, and transformation functions. No study located in the reviewed literature tests it, and it is offered as P1 for that reason.

The theoretical constructs are borrowed, not extended: Absorptive capacity, dynamic capabilities, organizational readiness for change and complementarities explain why an ordering of readiness domains should exist; they do not derive the particular ordering proposed, and each carries problems this paper inherits rather than resolves: absorptive capacity has been widely reified (Lane *et al*., 2006), and the claim that dynamic capabilities are identifiable organizational processes (Teece *et al*., 1997) is accepted rather than tested. Table 2 records where the model's ideas came from, not evidence that they are correct.

***The barrier taxonomy is synthesized from literature concentrated elsewhere*:** Predominantly in larger firms and in manufacturing: prerequisite evidence from a manufacturing sample (Kinkel *et al*., 2022), implementation experience from large service organizations (Lacity *et al*., 2021; Herm *et al*., 2023), readiness factors from expert interviews that were not size-stratified (Jöhnk *et al*., 2021).

Barriers specific to small service firms may be under-represented. The wider evidence base used here deepens that concentration: the complementarities evidence comes from large United States firm samples (Brynjolfsson & Hitt, 2000; Bresnahan *et al*., 2002), the model risk regime is a banking supervisory instrument (Board of Governors of the Federal Reserve System & Office of the Comptroller of the Currency, 2011), and the automation bias and algorithm aversion literature is predominantly experimental and individual-level (Skitka *et al*., 1999; Dietvorst *et al*., 2015; Logg *et al*., 2019). Transferring any of these to a forty-person service firm is an argument made here, not a finding reported elsewhere.

Definitions of "SME" differ across the cited evidence, and several sources do not use the category at all: IBM (2023) splits at 1,000 employees, which corresponds to no standard SME definition, and its unit of observation is IT professionals rather than firms; the Deloitte surveys report respondent organizations without a consistent size classification (Deloitte, 2018; Telford *et al*., 2022). The material in Section 4.1.1 therefore cannot be combined, compared or used to establish a rate. The additional statistical material introduces further incomparability: Brynjolfsson and McElheran (2016) report plants rather than firms and measure data-driven decision making rather than AI; the returns estimate is from large publicly traded firms in a working paper (Brynjolfsson *et al*., 2011); North *et al*. (2019) report a pilot application rather than a representative sample; and the resource-constraint evidence comes from one national setting (Thong, 2001). No figure here is an estimate of AI adoption among SMEs, since no such estimate on a stated and comparable sampling basis is present in the evidence base assembled for this paper.

Some cited sources are of uncertain venue standing: Lawrence (2017) is a preprint never formally peer-reviewed, and Alsheibani *et al*. (2018) is research-in-progress with no empirical results, both cited for conceptual vocabulary only; EY (2016) and the Deloitte surveys are consultancy material used with the caveats stated at the point of use. Two further sources drawn from the author's working corpus, Eyetsemitan *et al*. (2022) on standard operating procedures in small business operations and Ambali *et al*. (2021) on adapting structured improvement methodology for resource-constrained organizations, appear in practitioner-oriented journals whose editorial and review processes were not independently verified for this paper. They are cited only for framing, never for a statistic, and a reader who discounts them should find the argument unchanged.

Approximately three in ten of the references in this paper are applied and practitioner contributions: The material assembled in Section 6, together with the small number of sources used for framing elsewhere, comes from applied and practitioner journals whose editorial and peer-review arrangements were not independently verified for this paper, many of them venues without an established review record; taken together it accounts for roughly thirty per cent of the reference list. No theoretical construct, no element of the five-domain model or the phased framework, and no quantitative claim made anywhere in this paper depends on any of it. It is cited for illustration, not evidential weight: no proposition derives from it, and it enters only after the argument has been made on other grounds. A conceptual paper accumulates persuasive force from breadth of citation, and breadth drawn from unverified venues is not the same thing; readers should weight Sections 2 to 5 and Section 6 differently, and the claims are framed so that doing so changes nothing structural.

The rubric's level descriptors are not calibrated: Boundaries between Levels 1, 2 and 3 are untested for inter-rater reliability, and two competent assessors could assign different levels to the same process, particularly where sufficiency must be judged (DF3, PC3, GA3). Until calibration, scores should be treated as structured conversation prompts rather than measurements.

Scope: The framework addresses adoption of AI within an existing business process, not product innovation, new business models, or generative applications used outside a defined process; the governance treatment is confined to organizational arrangements and attempts no legal analysis; and it assumes an identifiable, repeated, document- or data-bearing process.

9. Conclusion

This paper argued that AI adoption readiness in SMEs is an organizational property rather than a technological one, that it must be sequenced rather than assessed in parallel, and that the binding constraint is usually process determinacy rather than data volume. Three artifacts were offered: a five-family barrier taxonomy stating what makes each barrier different in a smaller firm; a readiness model with nineteen criteria and a four-level rubric designed for completability rather than resolution; and a five-phase framework whose gates specify what must be true before a firm proceeds, with a pre-agreed stopping rule raised to a gate condition.

The most consequential practical suggestion is also the cheapest. Before an SME concludes that it lacks the data for AI, it should establish whether it can state, separately from the heads of its staff and from the flow of its process, what decision it is currently making and how consistently it makes it. That work requires analysis rather than capital, retains value whether or not automation follows, and is where the specification gap the distance between the way a business states a desired outcome and the level of precision an automated system requires to produce it most often opens. Whether the argument holds is an empirical question, and the eight propositions are offered so that it can be answered.

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