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AI Adoption in Small and Medium Enterprises: Complementarity Thresholds and the Dual-Pathway Problem

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Abstract

AI has been touted as a technology that empowers small and medium enterprises (SMEs) to get into the game of doing what big business does. But the adoption evidence tells another story: AI adoption continues to be very firmly entrenched at the very top of the market, among the largest, youngest and most digital companies, and the adoption gap has not narrowed with the decreasing costs of tools. This paper proposes that the lack of progress towards closing the gap is not so much caused by awareness, cost and attitude the three factors that have been central in the SME adoption literature but by threshold effects in complementary assets that may influence whether this gap yields value or not. We create a Dual-Pathway Complementarity Threshold (DPCT) framework, separating embedded adoption (passive use of AI functions within vendor software) from deliberate adoption (reconfiguring processes and roles around the AI function). The two pathways have fundamentally different strategic implications: while the former (embedded) is accessible to almost all SMEs, and therefore does not provide a durable advantage after diffusion, the latter (deliberate) does provide an appropriable advantage, but would involve crossing thresholds of data adequacy, absorptive capacity, process formalisation, and governance that most SMEs would not cross. The framework generates six propositions, five structural asymmetries in the SME/large-firm adoption and a re-interpretation of the policy problem as complementary asset formation instead of technology diffusion. This paper does not gather firm-level data needed to produce credible estimates of these parameters; so no invented statistics are reported; instead, a clear simulation program is programmed which packages the threshold value function and rent dissipation dynamics with a template of estimation notation using placeholders.

Keywords: artificial intelligence; SMEs; technology adoption; complementary assets; absorptive capacity; digital transformation; productivity paradox; competitive advantage

1. Introduction

The mainstream media coverage of AI and SMEs is focused on the concept of ‘democratisation'. The AI tech that's used by today's businesses comes as a subscription service, which is in contrast to the previous generation of enterprise technology, where it needed capital spending, specialized staff and multi-year implementation programs. Experiments were once an expensive proposition, now available on a monthly subscription; once the capacity to deploy a data science team, foundation models are now available through a user-friendly interface; the marginal cost of experimenting has dropped to near zero. In this regard, the technology gap between large and small companies ought to be narrowing.

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The evidence of adoption is not in support of that expectation. However, large-scale firm-level survey evidence from the U.S. suggests that the use of AI is rather focused, with younger and larger firms being more likely to be utilizing AI, and that the geographical and sectoral distribution of firms using AI reflects established digital advantage, rather than eradicating it (McElheran et al., 2024; Zolas et al., 2021). These are similar findings across countries, as the OECD has been able to gather evidence from across the fields from which the conclusion is drawn: Smaller firms are less likely to adopt than larger firms in all countries studied (Calvino & Fontanelli, 2023). Similar patterns are observed at the firm level in Germany, as the adoption of AI is mainly linked to larger and research-intensive firms, and measurable innovation gains are shown to be mainly driven by firms that already have the capability to make use of AI (Rammer et al., 2022). So far the price drop has not brought convergence about.

This paper starts with that discrepancy. If the limiting factor for SME adoption was the cost or availability of the technology, the pattern observed would not be explainable. Where the binding constraint is the assets needed to make the technology useful, as theory suggests, the pattern is exactly that. The economic theory of general purpose technologies is a longstanding concept that has been present for many years and has been put forward by several researchers, such as Brynjolfsson et al., 2021 and Brynjolfsson & Hitt, 2000. The economics of general-purpose technology has been theorized for a long time and was first put forward by several researchers (Brynjolfsson et al., 2021; Brynjolfsson & Hitt, 2000). The systematic disadvantage faced by SMEs isn't in acquiring AI, rather, it's in making those complementary investments, which are lumpy, managerially intensive and hard to carve up.

A second discrepancy is the motivator for the analysis. A large proportion of the cases about SME AI use is not strategic AI use. If a small firm's accounting package has a new feature that detects anomalies, their CRM includes a lead scoring function, and their office suite has a new drafting assistant, then the firm has integrated AI but without choosing to. It is almost never recognized in the adoption literature that this embedded pathway is real and beneficial, but it also has a property: the ability to create durable advantage is not possible because every competitor gets the same ability from the same vendors on the same terms. It's the AI version of a classic debate on the strategic importance of infrastructural technology, as more and more of it becomes accessible. It's the AI version of a classic debate on the strategic value of infrastructural technology as it becomes more available (Carr, 2003). To consider embedded and deliberate adoption as two end points on a continuum is to merge two processes, one with a positive and one with a negative strategic connotation.

The paper has four contributions to make. It defines the concept of SME AI adoption, identifies the adoption pathways, and defines an adoption construct which goes beyond procurement. It recognizes five structural asymmetries which distinguish SME adoption from large-firm adoption, which is typically a simple scaling down of the former. It captures five structural asymmetries that distinguish SME adoption from large-firm adoption, which is typically a simple scaling down of the former. It creates the Dual-Pathway Complementarity Threshold framework and 6 testable propositions. It provides an analytical protocol of sorts: a simulation harness and an estimation template that provide a framework of evidence that would falsify the argument, instead of filling in illustrative figures for evidence not gathered.

2. Definitional Groundwork

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2.1 The SME category and its heterogeneity

The definition of SMEs is both qualitative and quantitative. European Union defines it as having less than 250 employees and an investment limit and/or turnover limit (European Commission, 2003), whereas India has a revised definition based on a combination of investment and turnover (Government of India, 2020). That is an arbitrary threshold that is analytically inadequate: it puts together a 2-person design consultancy and a precision manufacturer with 200 workers, whose data environments, decision structures and adoption constraints bear little relationship to each other. Thus, any general statement of adoption of AI by SMEs is a statement about a distribution not a type.

It is more important to consider the three facets of heterogeneity, rather than headcounts when dealing with adoption. The first is digital intensity of the existing operating model, since AI adoption is conditional on data that only accrues from prior digitalisation. The second, process formalisation: large and small firms alike have work that can be formalised and encoded into repeatable and documented processes, which AI can then work on, whereas other firms have work that is tacit routine, and on which AI cannot operate. The third is the role of the owner-manager in the decision, which in smaller businesses often merges strategic, technical and financial influence in one individual whose prior beliefs are then key in the decision-making process, a concept that is more than a decade old in the small-business information systems literature (Thong, 1999; Thong & Yap, 1995).

2.2 What counts as adoption

The adoption construct used in this literature is very non-conforming and this non-conforming has consequences. Survey instruments that ask about the use of AI also capture a combination of intentional use, exposure to AI due to software changes, and pilot activity that did not make the system to production. Research that developed over a period of time showed that binary adoption measures are not particularly good predictors of value and the explanatory power lies with the post-adoption depth of use (Assimilation research, 2004; Zhu & Kraemer, 2005). Table 1 thus lists a graded adoption construct, which differentiates five states in which indicators of adoption can be observed.

Table 1. A graded construct of AI adoption in SMEs

State	Description	Observable indicator	Strategic consequence
S0 Non-adoption	No AI capability in use	Absence of AI-enabled tooling in the software estate	None
S1 Embedded exposure	AI arrives inside general-purpose vendor software without a firm decision	Vendor feature availability; no procurement decision recorded	Efficiency parity at best; no advantage
S2 Point application	A discrete tool is deliberately procured for a bounded task	Named tool with an owner and a budget line	Localised gains; easily replicated by rivals

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State	Description	Observable indicator	Strategic consequence
S3 Process integration	Workflow and roles are reconfigured around AI output	Revised standard operating procedures; changed job content	Firm-specific gains begin to accrue
S4 Capability embedding	The firm systematically identifies, evaluates, and deploys new use cases	Internal evaluation routine; retained learning across deployments	Durable, imitation-resistant advantage

The distinction between S1 and S2 marks the pathway split developed below; the distinction between S2 and S3 marks the complementarity threshold. Most survey-based adoption rates aggregate S1 through S4, which is why reported adoption can rise steeply while measured productivity effects remain elusive.

2.3 The AI construct is not one technology

There is a parallel definitional issue relating to the technology. The term "adoption of AI" is now used to describe a variety of applications, including those that rely on supervised prediction of structured business data, computer vision systems performing processing tasks on a production line, robotics process automation with statistical elements, conversational interfaces based on foundation models, and generative support within office software. These differ in what data they require, the cost of integration, risk of regulatory exposure, and how they fail, and assuming they are all one type of object to be adopted will ensure that estimated antecedents remain constant with different samples of technology mixes. The presence of this heterogeneity has been noted in reviews of the AI business-value literature as a constant cause for inconsistent results (Enholm et al., 2022; Mikalef & Gupta, 2021).

For SMEs, the difference that can make the difference is between the two types of technology, where the capability needs to be developed from the firm's own data and where the capability is pre-trained. The former has a threshold on how much data they require which most small businesses do not have the capacity structurally; the latter does not. This is the only difference that explains a large part of the discontinuity that can be observed between the pre- and post-2022 adoption pattern, and it is the foundation of the fifth proposition developed below. One of the reasons why firm-level readiness assessment has been challenging to put into practice is the lack of clarity regarding AI (Jöhnk et al., 2021; Kinkel et al., 2022).

3. Theoretical Lenses

There are four theoretical traditions relevant to the problem and they can be viewed as a partition of the explanatory burden, not competition. The decision to adopt is explained by diffusion of innovations and technology-organisation-environment framework, where attributes of the innovation, organisational readiness and environmental pressure are identified as antecedents (Rogers, 2003; Tornatzky & Fleischer, 1990). Acceptance models describe the use intention of an individual, which is more akin to the organisational decision than large firms (Davis, 1989;

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Venkatesh et al., 2003), and is the level considered in owner-managed firms. Absorptive capacity refers to the firm's capacity to identify, internalise and exploit external knowledge, and is the simplest way of understanding why the same know-how produces different value in different firms (Cohen & Levinthal, 1990; Zahra & George, 2002). Complementary-asset and complementarity theory provides an explanation to who appropriates the value an innovation creates and why the answer depends on assets the innovator may not own (Milgrom & Roberts, 1990; Teece, 1986).

Table 2 outlines what each lens illuminates and what it doesn't. This paper argues that the SME AI literature has been heavily inspired by the first two of these traditions intentions explained while less so by the latter two outcomes explained. This is because intention is measurable by survey, while complementary stocks of assets and absorptive capacity are not.

Table 2. Theoretical lenses on SME AI adoption

Lens	Explains	Key constructs	Silent on	Applicability to SMEs
Diffusion of innovations	Rate and pattern of spread across a population	Relative advantage, compatibility, complexity, trialability	Value realised after adoption	High for embedded pathway; weak for capability formation
Technology-organisation-environment	Firm-level adoption decision	Technological, organisational, and environmental readiness	Post-adoption depth and appropriation	Widely applied; risks treating readiness as continuous
Acceptance models (TAM, UTAUT)	Individual use intention	Perceived usefulness, ease of use, social influence	Organisational reconfiguration and returns	Unusually apt where the owner-manager is the decision unit
Absorptive capacity	Conversion of external knowledge into internal capability	Prior related knowledge; assimilation and exploitation routines	Market structure and rent capture	Central; explains persistent inter-firm variance
Complementary assets and complementarities	Who appropriates the value created	Co-specialised assets; complementarity clusters	Individual-level behaviour	Central; explains why cheap technology need not help small firms

4. Five Structural Asymmetries

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In most cases, the adoption of SMEs is modeled as a form of large-firm adoption, based on smaller coefficients. If the difference is structural, then there are five asymmetries. These are briefly summarized in Table 3 and explained below.

Data thinness. Performance of machine learning algorithms is determined by the volume of data as well as the method, and in some classical applications, the amount of data available has proven to be as important as the sophistication of the machine learning method (Halevy et al., 2009). You can't train a churn model for a two hundred customer SME, not, because they're not skilled, it's because there aren't enough events. This is not a resource constraint, it's a hard constraint, and is why most of the pre-2022 AI wave missed small companies. The foundation-model shift has introduced a significant ease in this regard, as capabilities are now gained through pre-training on shared corpora and can be recalled by using a few or no specific examples of the capability from the given context (Bommasani et al., 2021; Brown et al., 2020). The binding constraint shifts, not from data to integration, but to data.

Resource indivisibility. Complementary investments are not proportional. One can't hire one twentieth of a data engineer; the minimum viable governance structure for dealing with personal data has a size component that is fairly constant across firm sizes. As size decreases, the effective threshold as a percentage of turnover increases rapidly as a result of these costs in comparison to SME turnover, without the need to make any assumption about the less capable or less willing of small firms.

Owner-manager centrality. Large companies have an adoption that is distributed and occurs through a combination of specialist functions, formal business cases, and spread knowledge. However, in smaller companies the owner-manager is the only person who constitutes the entire evaluation apparatus, and the prior knowledge of the company owner/manager is the almost sole determinant of the firm's absorptive capacity (Thong, 1999). This produces high variability and specific failure modes rapid adoption when the owner is technically savvy, near-total inertia when they are not, and limited internal corrections in both scenarios.

Slack deficiency and the experimentation problem. The deployment of AI is highly uncertain upfront on what will work and most of the time it will be a portfolio approach with most of the deployments failing cheaply. If the business is big, they use organisational slack to do it. SMEs normally don't have the luxury of this, and a single deployment that fails costs them more than the experimentation budget, because it changes their attitude about the entire technology class and the owner-manager's belief that it's a viable technology to use. It makes sense, then, that under-adoption is not conservatism, but is a reaction by a person who cannot diversify.

Vendor dependence and the maintenance burden. SMEs don't have the internal capacity and therefore they rely on vendors to adopt, and the focus then moves from building to selecting and integrating. This is important because it is not the model that makes production ML so challenging; it's the infrastructure, monitoring and accumulated maintenance workload (Baier et al., 2019; Sculley et al., 2015). By purchasing a solution that the SME cannot sustain, the SME end up with a liability with delayed effect without having internal capacity to assess the risk at the time of purchase.

Table 3. Structural asymmetries between SME and large-firm AI adoption

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Asymmetry	Large-firm condition	SME condition	Consequence for adoption	Effect of the foundation-model shift
Data thinness	Sufficient volume for firm-specific training	Too few events for supervised learning	Excludes many classical applications entirely	Substantially relaxed; capability is pre-trained
Resource indivisibility	Complementary investments spread over a large base	Lumpy costs large relative to turnover	Effective threshold rises steeply as size falls	Partially relaxed; integration cost remains lumpy
Owner-manager centrality	Distributed evaluation across specialist functions	Single decision-maker constitutes absorptive capacity	High variance; limited internal correction	Unchanged; possibly amplified by ease of trial
Slack deficiency	Portfolio of experiments absorbs failure	One failure exhausts budget and updates beliefs	Rational under-adoption; premature abandonment	Improved; trial costs are now low
Vendor dependence	Build-or-buy genuinely available	Buy is effectively the only option	Constraint shifts to selection and maintenance capability	Unchanged; vendor proliferation raises selection difficulty

5. The Dual-Pathway Complementarity Threshold Framework

5.1 Structure

The framework asserts that the adoption decision of an SME can be summarized in two main paths, which have strategic implications that are of a very different nature (Figure 1). Pathway A (embedded or consumptive adoption) is when AI is integrated into general purpose vendor software. Its threshold is almost zero and its diffusion is therefore very fast and universal. Deliberate or integrative adoption (Pathway B) refers to the reconfigured processes and roles that involve the output of AI and result in firm-specific tacit know-how and thus appropriated advantage. Four complementarity thresholds data adequacy, absorptive capacity, process formalisation and governance capacity limit access to Pathway B.

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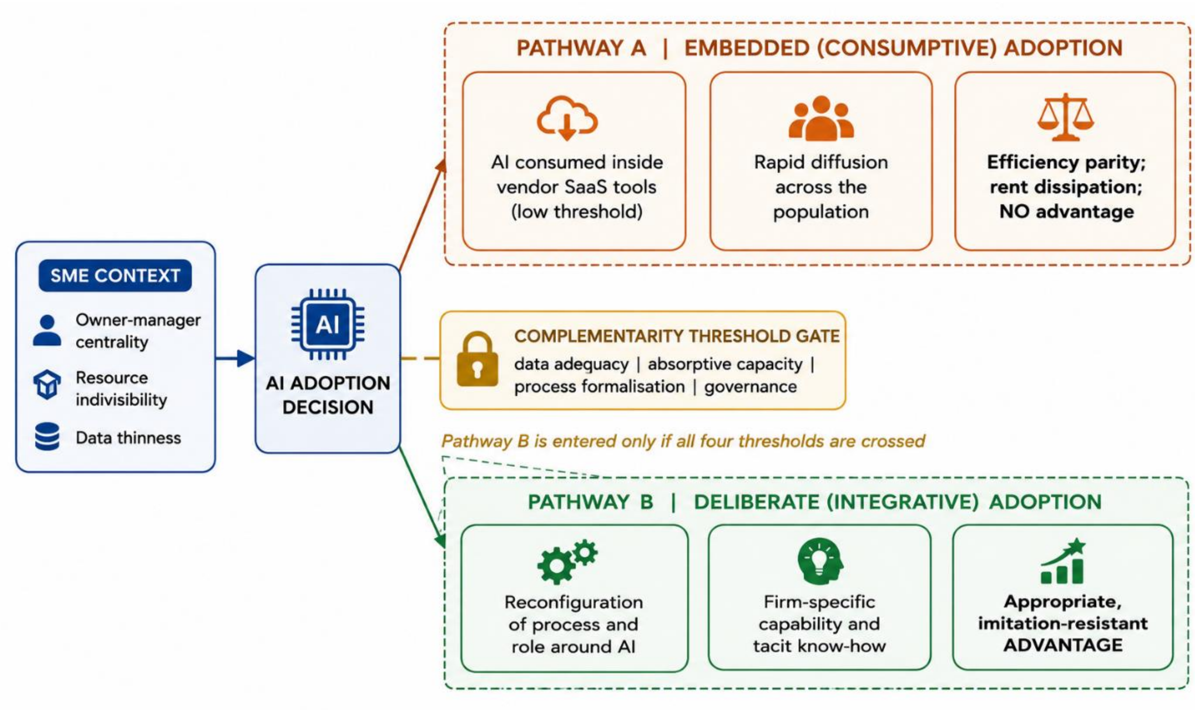

Figure 1. The Dual-Pathway Complementarity Threshold (DPCT) framework, showing the embedded and deliberate adoption pathways, the four-part complementarity threshold gate, and their divergent strategic outcomes.

The framework differs from the traditional maturity models in two aspects. First, the gate is a conjunction one, not a compensation one. Strength in one area doesn't compensate for weakness in the other: if a company has great data and no formalisation, then AI output is useless for them to act on, and if a company has formalised processes and no capacity for governance then they have nothing to deploy in any function involving personal or regulated data. Averaged maturity indices thus tend to overestimate the maturity of unbalanced companies. Secondly, the pathways are not linear processes. The fact that SMEs build up significant exposure to AI just by being on Pathway A doesn't necessarily mean there is an increase in their capability.

5.2 The strategic paradox

The main idea of the framework is not very pleasant for the democratisation story. The pathway into which an SME can go does not give them any advantage, and the pathway into which an SME can go if it does give them an advantage is not readily accessible. Pathway A has real gains but is competitively temporary: as the capability becomes available to all firms from the same vendors for the same price, the gains are diffused through to customers as the capability spreads, but there are no gains in efficiency. This is the "classic appropriation problem": the ability of the innovator to capture value is determined by control over complementary assets, not access to the technology; that is, the innovator has to own these complementary assets as well (Teece, 1986). The persistence of pathway B is due to the fact that the entity being duplicated is not a tool, but an operating model that is reconfigured, and that is socially complex and causally ambiguous, as the RBV suggests are protective attributes.

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An important qualification helps to make this not a counsel of despair. There are other factors to consider besides advantage. For many SMEs, Pathway A adoption is a defensively required step: if they do not capture efficiency opportunities, competitors do and this creates a disadvantage even if it does not create an advantage for those adopting Pathway A. The right management framing is then asymmetric. The concept of embedded adoption should be seen as a starting point, not a target, and should be done at a low cost without much deliberation; scarce managerial attention should be focused on limited processes in where deliberate integration is possible in a firm, because of its threshold position.

Another qualification is related to the source of SME advantage. The adoption literature often understates the offsetting strengths of small firms, with shorter decision chains, direct access to customers, and the absence of legacy systems and internal political constraints slowing the reconfiguration of large firms. The trade-off between resource disadvantage and behavioural advantage is not a new phenomenon in the field of innovation research of small firms (Nooteboom, 1994). The implication for Pathway B is specific and not general. If the integration is deliberately sought after and involves making large investments, the SME will be at a disadvantage, while if the integration involves a rapid change in the process and the large company is unlikely to make such a change, the SME will be at an advantage. However, the realistic SME opportunity is to be narrowly integrated, deeply connected applications in processes that the firm has under its end-to-end control rather than simply replicating scaled analytics functions.

5.3 Propositions

Table 4. Propositions of the DPCT framework

Proposition	Statement	Theoretical warrant	Focal constructs
P1	Realised value from AI is a threshold rather than linear function of the complementary asset stock, exhibiting negligible returns below the threshold and rising returns above it.	Complementarity theory; productivity J-curve	Complementary asset stock; realised value
P2	The gate is conjunctive: value is bounded by the weakest of data adequacy, absorptive capacity, process formalisation, and governance capacity, not by their average.	Complementarities; O-ring logic	Dimension minima; composite maturity index
P3	Performance differentials from embedded adoption dissipate as population diffusion proceeds, whereas differentials from deliberate adoption persist or widen.	Appropriation; resource-based view	Diffusion share; performance differential; persistence

Proposition	Statement	Theoretical warrant	Focal constructs
P4	Owner-manager prior technical knowledge predicts SME adoption depth more strongly than firm size, sector, or perceived cost.	Absorptive capacity; small-firm IS research	Owner knowledge; adoption state S0 to S4
P5	Foundation-model availability shifts the binding constraint from data adequacy to process formalisation, so that post-2022 adoption variance is better explained by the latter.	Data-scale arguments; general purpose technology theory	Constraint identity; period interaction
P6	Subsidy directed at technology acquisition produces smaller adoption-depth gains than equivalent subsidy directed at complementary asset formation.	Complementarity theory; policy design	Subsidy type; movement across adoption states

6. Barriers, Enablers, and the Policy Problem

This body of barrier literature is voluminous and mostly descriptive, with the result that a sort list of cost, skills, awareness, data quality and trust is mostly the result. According to the DPCT framework, these lists are inappropriate because they combine various types of barriers and the difference is important for policy. Table 5 categorises those barriers that are commonly reported as inhibiting access to Pathway A, access to Pathway B and the value that is derived from that pathway.

Table 5. Reclassification of commonly reported barriers

Reported barrier	Which pathway it actually impedes	Underlying constraint	Appropriate instrument
Cost of technology	Pathway A entry	Cash constraint at low absolute values	Diminishing relevance; subscription pricing largely resolves it
Shortage of specialist skills	Pathway B entry	Absorptive capacity; indivisible hiring	Shared or brokered expertise; sector intermediaries
Poor or fragmented data	Pathway B entry	Prior digitalisation deficit	Support for basic systems and data discipline, not AI itself

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Reported barrier	Which pathway it actually impedes	Underlying constraint	Appropriate instrument
Undocumented processes	Pathway B entry	Process formalisation deficit	Operational improvement support; process mapping
Regulatory and privacy uncertainty	Pathway B entry and appropriation	Governance capacity; fixed compliance cost	Template governance instruments; safe harbours; sectoral guidance
Lack of awareness of use cases	Pathway A and B entry	Information asymmetry	Demonstration and peer-learning networks
Difficulty selecting vendors	Appropriation	Evaluation capability deficit	Assurance, certification, and independent evaluation
Inability to maintain deployed systems	Appropriation	Technical debt; no internal ownership	Managed-service models; realistic total-cost disclosure

This means, interpreted in this way, the main policy measure used in most jurisdictions is untargeted. Constraints which have already been overcome are dealt with through grants and vouchers to acquire technology, whereas the constraints that are real in limiting technology transfer are poorly addressed (absorptive capacity) or not addressed at all (process formalisation and governance capacity). This is P6 in policy form, and it is testable the number of P6 adoption-depth movement across the states of Table 1 should be different in a systematic way between the firms that receive acquisition subsidy compared to the firms that receive the equivalent value of capability support.

A second policy implication is with regards to intermediaries. The binding constraints are at the firm level, but not at the population level, thus institutions that aggregate demand can break constraints that individual SMEs cannot. The common data infrastructure, sector-level template governance, brokered access to expertise and sector-level demonstration networks all transform a fixed cost per firm into a fixed cost per sector. The OECD's analysis of SME digital transformation is equally pointing in a similar direction, highlighting the role of ecosystem and diffusion institutions, rather than financial support provided to the firm (Bianchini & Michalkova, 2019; OECD, 2021).

A third implication is related to Assurance. The quality of the vendor market is more important than any other firm level variable in determining the quality of the SME adoption since SMEs procure, not build, and they don't necessarily have the expertise to evaluate the products they are purchasing. When the ability to evaluate is not present, the protection of the firm should be provided by the market's institutions: independent certification, transparency of total cost of the protection (including maintenance costs), and interoperability guarantees to avoid lock-in. They are the traditional market failure remedies applied to an information asymmetry and will deal with

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the appropriation column of Table 5, but not by any means by firm level training. In recent years, the scholarly literature has started to focus on the governance and trust conditions that shape the value realised from AI in organisations, instead of compliance overhead (Dwivedi et al., 2021).

7. Analytical Protocol

7.1 Simulation harness

Two of the framework's claims concern functional form rather than sign, and are therefore better exhibited than asserted. Figure 2 reports a simulation harness with declared parameters. Panel (a) contrasts a linear value function with a threshold function net of the cost of complementary investment, generating the negative-return valley that the productivity J-curve literature predicts and that firm-level evaluations conducted too early will detect as failure (Brynjolfsson et al., 2021). Panel (b) formalises P3 by simulating the relative performance differential of firms on each pathway as embedded AI diffuses through the population, showing dissipation for Pathway A firms and accumulation for Pathway B firms. Table 6 records the parameters and the estimation template.

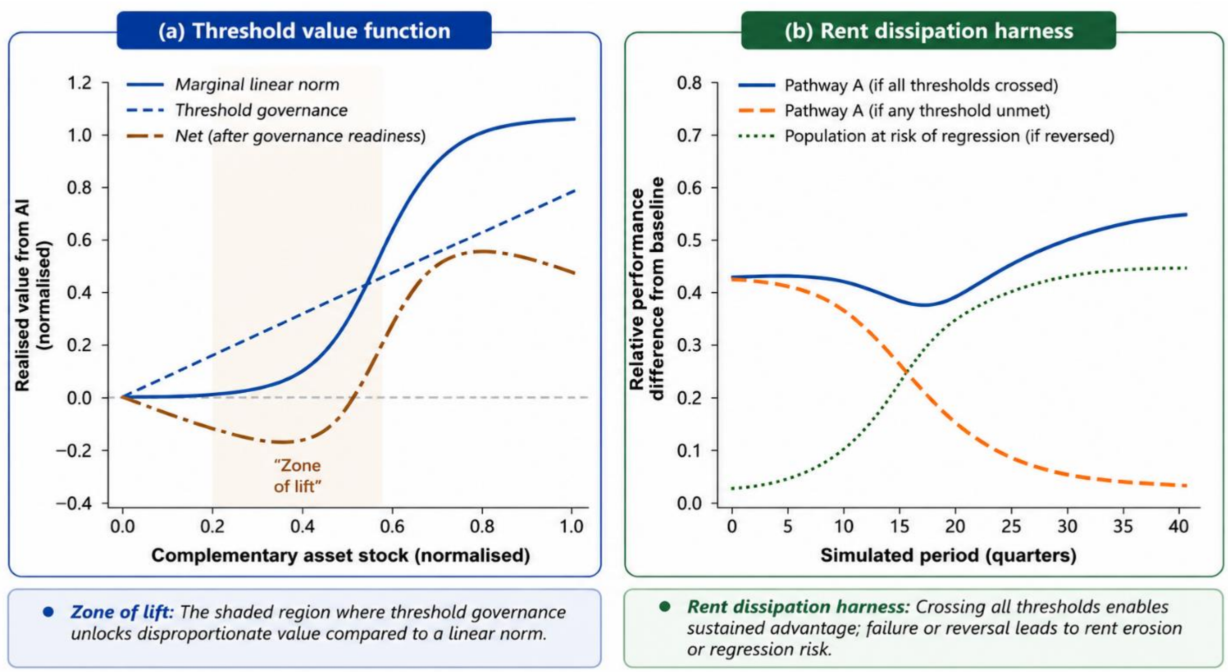

Figure 2. Panel (a) threshold value function net of complementary investment, showing the J-curve valley. Panel (b) simulated relative performance differential by adoption pathway as embedded AI diffuses. All values are generated from declared parameters and illustrate model behaviour only; they are not empirical estimates.

Table 6. Simulation parameters and estimation template with placeholder notation

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Element	Specification	Declared value or placeholder	Role
Threshold location	Complementary asset level at the inflection of the value function	0.55 of normalised stock	Sets where returns begin
Threshold steepness	Logistic slope of the gross return function	14	Governs discontinuity sharpness
Complementary investment cost	Cumulative cost as a function of asset stock	0.55 per unit, linear	Generates the J-curve valley
Diffusion rate	Logistic spread of embedded AI across the population	0.30 per period, midpoint at period 16	Drives rent dissipation
Capability accrual	Rate at which Pathway B firms accumulate retained advantage	0.22 per period, ceiling 0.55	Distinguishes the pathways
P1 test	Spline or threshold regression of value on complementary asset stock	Threshold location [k1]; slope contrast [b1]	Rejects linearity if the contrast is significant
P2 test	Minimum versus mean of the four dimensions as competing predictors	Coefficients [b2min], [b2mean]	Conjunctive gate implies [b2min] dominates
P3 test	Performance differential regressed on diffusion share by pathway	Interaction [b3]	Negative for Pathway A, non-negative for Pathway B
P4 test	Owner knowledge, size, sector, and cost perception entered jointly	Standardised coefficients [b4]	Relative predictive weight on adoption state
P5 test	Constraint indicators interacted with a pre- and post-2022 period term	Interaction [b5]	Tests the shift in binding constraint
P6 test	Subsidy type on movement across adoption states	Treatment effect [b6]	Randomised or quasi-experimental allocation preferred

7.2 Measurement cautions

There are four cautions to be observed in empirical work here. The S1-S3 distinction, which has a theoretical load, should be replaced by the graded construct of Table 1, which cannot be detected by binary adoption measures. Self-reported adoption is influenced by social desirability, and by

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true uncertainty on the part of the respondents about whether embedded features are considered to be AI, the case for instrument-level verification of the software estate rather than perception items. A major concern of cross-sectional adoption surveys is survivorship bias because of firms that have failed in their deployments, which don't report or exist. Finally, endogeneity is ubiquitous: firms that make a deliberate choice to adopt are systematically different from firms that don't, and thus observational estimates of the impact of adoption on performance will reflect selection unless we get identification from a policy discontinuity, staggered availability of vendors, or random selection of vendors (Podsakoff et al., 2012).

8. Discussion

8.1 Theoretical implications

The main theoretical shift in the framework is to shift the focus on SME AI adoption to appropriation. The predominant research programme is centered on what drives or facilitates the adoption of a firm, but the more important question is what is the impact of adoption on value that a firm can sustain. This will make the longstanding adoption disparities less mysterious. They are scarce, indivisible, and scarcity is related to firm size for structural reasons not fixed by cheaper technology, complementary assets. Any policy or research programme based on technology cost will thus continue to witness poor results and overlook both awareness as well as attitude.

The framework also provides a balanced interpretation of the generative AI transition one that isn't skeptical and one that isn't advertising. Indeed, one of the five asymmetries (historically the most absolute) can be addressed with foundation models: data thinness, which can be addressed by training large networks with a small number of examples (Bommasani et al., 2021; Brown et al., 2020). Empirical studies of generative AI in the workplace have identified significant productivity benefits, often greater for less senior employees, that may extend beyond their current tasks to other aspects of the job, a positive development for employers with shallower expertise in specialist benches (Brynjolfsson et al., 2023; Noy & Zhang, 2023). However, the same evidence highlights the inconsistent results of the tasks performed, and the challenge of predicting which tasks lie within the capability frontier (Dell'Acqua et al., 2023). What is being done by relaxing the data constraint is not so much to remove the constraint, but to shift it to the process of formalisation the substance of P5, and the need for which democratisation of access hasn't led to democratisation of outcome.

8.2 Practical implications

For practice there are three implications. First, SMEs should consider the two pathways as asymmetric decision costs: Embedded AI decisions should be made somewhat lightly, because the value is small, but the cost is low and not being stepped up is a risk; deliberate integration should be only one or two of the processes considered because they are at the right level of feasibility and not because of big headlines. Second, for most of the SMEs, the investment in the preparatory stage most likely is not in AI technology itself but in documentation of the process and basic data discipline these two dimensions are the most frequent ones that are binding and have a long lasting value, irrespective of the technology used. Third, there needs to be a room for the J-curve in evaluation horizons. Any firm that observes negative returns for a deliberate deployment in the valley displayed in Figure 2 will find that it will stop implementing well-thought-out projects, and in SMEs, the abandonment will update a single decision-maker's beliefs against the entire technology class, which is more harmful than it will be elsewhere.

8.3 Limitations

There are three restrictions which need to be clearly stated. This is a conceptual paper: the propositions are not empirically tested, but in the simulation they are internally consistent. It has its parameters declared, and Figure 2 should not be interpreted as a forecast or an estimate. Second, in Sections 1 and 8, the characterizations of the empirical literature do not include numerical estimates, but readers are referred to the cited literature for magnitudes; also, the adoption statistics in this field are especially subject to the wording of the adoption question, which is part of the argument. Third, the framework is created with the bulk of the evidence drawn from environments that have high levels of connectivity, formalisation and enforcement, and its application to contexts where these variables are materially different should be tested—and not assumed. The process formalisation threshold is more likely to hit - and to hit hard - earlier and harder in economies where most of this evidence comes from those with large informal or semi-formal SME populations.

9. Conclusion

Artificial Intelligence is inexpensive and small businesses haven't yet adapted. This explanation is given because it is believed that price never proved to be a limit. Value from AI is only realised when data is deemed adequate, absorptive capacity is sufficient, processes are formalised, and there is a governance capacity that is sufficient and these thresholds cannot be broken down in a structural way that is proportionate to penalising the smaller firms. The way that almost every SME can participate in adoption, as a feature of vendor software, provides some efficiency but not a lasting benefit since it's ubiquitous, meaning that the rents it generates are spread thin. This route of benefit will involve a restructuring of the organisation, a move that most SMEs are not able to make at this juncture.

This is not for the pessimists, nor even a reason to wait, but rather an argument for SMEs to proceed with care. It's a case for redirecting effort. The most productive preparation that can be done for a firm is the hard work on process and data that is productive regardless. The instruments of importance to policy are not subsidies for the purchase of the technology but subsidies on the complementary assets and shared intermediary institutions that make any purchased technology worth having. The DPCT framework, its six propositions and the analytical protocol provided here are designed to be testable, and thus refutable rather than just plausible, claims.

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