AI Enablement in SMEs: Why Theoretical Models Miss the Real Picture

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Abstract: Artificial intelligence is widely promoted as transformative for business competitiveness, yet adoption in small and medium-sized enterprises (SMEs) remains limited and poorly understood. While large corporations develop formal AI strategies backed by dedicated teams and budgets, micro and small enterprises face a different reality: constrained resources, fragmented knowledge and the absence of internal AI expertise. Most existing theoretical frameworks do not account for these differences, as they derive from large-enterprise contexts and assume conditions that rarely exist in smaller firms. This study investigates how AI enablement unfolds in the SME context and where theoretical predictions diverge from empirical evidence. The research employs an exploratory sequential mixed-methods design (QUAL→QUAN). This paper presents findings from the qualitative phase, based on reflexive thematic analysis of in-depth interviews with nine experts who implement AI solutions in SMEs as consultants, integrators or advisers, coded in two cycles and validated through member checks. The interviews were conducted between 2022 and 2025. The findings challenge several established assumptions. Strategy in SMEs is not a formal document but a dynamic process that emerges through collaboration with external IT consultants and incremental implementation. The primary barrier is not technology, which has become increasingly accessible, but knowledge gaps among SME managers about what AI can and cannot do. Innovation culture, treated in most frameworks as a distinct dimension, functions in SMEs as part of human-resource dynamics. Most notably, partnership with external IT consultants emerges as the central mechanism, operating through a three-tier model of consulting, joint planning and long-term support. Dynamic capabilities in SMEs are therefore realised relationally, through external partnerships, rather than through internal organisational processes. The paper contributes a partnership-based refinement of dynamic capabilities theory for smaller firms, and argues that supporting AI adoption in such firms requires partnership-oriented management and policy rather than technology-centric strategies that overlook how these enterprises actually function.

Keywords: Artificial intelligence, SMEs, AI enablement, Cooperation, Entrepreneurship

1. Introduction

Artificial intelligence (AI) is widely described as a general-purpose technology that will reshape competition across industries (Brynjolfsson and McAfee, 2014; Vial, 2019). Public policy, industry reports and the academic literature converge on a similar claim: firms that learn to integrate AI into their operations will outperform those that do not. Yet this narrative has been shaped mainly by the experience of large enterprises, which possess the internal resources, data assets and specialised teams required to translate AI potential into business value (Mikalef and Gupta, 2021; Simón, Revilla and Sáenz, 2024). When attention shifts to small and medium-sized enterprises (SMEs), which account for the majority of firms and employment in most economies, the picture becomes considerably less clear.

Recent systematic reviews confirm that AI adoption among SMEs lags behind that of larger firms, and that the gap does not close through broader availability of tools (Oldemeyer, Jede and Teuteberg, 2025; Schwaeke et al., 2025; OECD, 2025). Cloud AI services, low-cost APIs and generative assistants have reduced technical barriers to entry, yet many SMEs remain on the sidelines (Arroyabe et al., 2024; Mohib et al., 2025). This points to a puzzle: if technology is no longer the binding constraint, what is? And why do existing adoption frameworks, repeatedly validated in large-firm samples, explain so little of what happens in smaller firms?

Most contemporary models of AI adoption, including the Technology-Organization-Environment framework (Tornatzky and Fleischer, 1990; Badghish and Soomro, 2024) and AI-specific frameworks such as AI Readiness and AI Capability (Jöhnk, Weißert and Wyrtki, 2021; Mikalef and Gupta, 2021), rest on assumptions that rarely hold in SMEs. They assume a formal strategy, a distinct IT function, organisational slack for experimentation and internal data science competence. In a micro or small enterprise, none of these can be taken for granted. The owner-manager often doubles as strategist, IT lead and operational manager; external partners, not internal departments, carry most specialised knowledge (Ayinaddis, 2025).

This study addresses the resulting gap between theory and practice. The central research question is: how does AI enablement unfold in SMEs, and where do theoretical predictions diverge from empirical practice? The concept of AI enablement is used here in a broad sense, encompassing not only the decision to adopt specific AI tools but also the organisational, human and relational conditions that allow AI to be put to productive use.

Enablement is therefore closer to the notion of dynamic capabilities (Teece, 2007) than to a one-off technology adoption decision.

To address the research question, the study uses an exploratory sequential mixed-methods design, the qualitative phase of which is reported here. Nine experts with direct experience implementing AI projects in Lithuanian SMEs were interviewed between 2022 and 2025. Experts were chosen deliberately: they observe a wide cross-section of SME realities and can articulate patterns that individual managers often cannot. Thematic analysis produced 725 coded segments, 106 codes and seven themes, with inter-theme relations examined through segment-level code co-occurrence.

The contribution is fourfold: four divergences between large-firm frameworks and SME reality; a partnership-based refinement of dynamic capabilities, in which sensing, seizing and reconfiguring are realised through external consultants; a reframing of the technology-versus-knowledge debate showing that knowledge gaps dominate technological constraints; and grounded guidance for consultants, SME managers and policymakers whose interventions often rest on large-firm assumptions.

2. Theoretical Background

2.1 AI Enablement and Dynamic Capabilities

AI enablement is not yet a stable construct. It is used to describe the organisational conditions that allow AI to generate value, beyond the binary question of whether a tool has been adopted (Mikalef and Gupta, 2021; Bettoni et al., 2021; Acimovic, 2024). Enablement covers strategic orientation, human capital, data readiness, processes and the external relationships that sustain adoption over time. It is closer in spirit to the dynamic capabilities view than to traditional adoption frameworks (Hossain, Fernando and Akter, 2025; Simón, Revilla and Sáenz, 2024).

Dynamic capabilities theory (DCT) defines the firm's ability to sense opportunities and threats, seize them through appropriate resource commitments, and reconfigure its asset base as conditions change (Teece, Pisano and Shuen, 1997; Teece, 2007). AI is a natural test case for DCT because its value depends less on the technology itself than on the organisation's ability to perceive new use cases, commit to them and reshape routines accordingly. However, Teece's original formulation was based on observations of large multinational firms where sensing, seizing and reconfiguring are distributed across specialised units. Whether the same mechanisms operate in a firm of fifteen employees is an open question.

2.2 Large-firm Frameworks and Their Assumptions

Two families of models dominate the AI adoption literature. The TOE framework (Tornatzky and Fleischer, 1990) distinguishes technological, organisational and environmental factors; applied to AI, it typically highlights perceived usefulness, top management support, data infrastructure and competitive pressure (Badghish and Soomro, 2024; Schwaeke et al., 2025). More recent AI-specific frameworks, notably AI Readiness (Jöhnk, Weißert and Wyrtki, 2021) and AI Capability (Mikalef and Gupta, 2021), build on these foundations while adding constructs such as data availability, algorithmic maturity and AI governance. Systematic reviews show that these frameworks have been extended to SME samples, but typically through measurement-level adaptation rather than conceptual revision (Oldemeyer, Jede and Teuteberg, 2025; Ayinaddis, 2025).

Despite their differences, these frameworks share a set of implicit assumptions that reflect their large-firm origin. They assume that a firm has an identifiable strategy that can be captured in a document; that roles are differentiated, so that top management support, IT leadership and operational execution are distinct variables; that innovation culture exists as a separate organisational property, independent of individual relationships; and that adoption is an internal process in which external actors are, at most, suppliers. Evidence from SMEs, reviewed below, challenges each of these assumptions (Arroyabe et al., 2024; Mohib et al., 2025).

2.3 The SME Context

SMEs differ from large firms in ways that matter for AI enablement. Resource constraints are chronic, so AI decisions compete directly with payroll, inventory and marketing (Mohib et al., 2025). The owner-manager typically concentrates strategic, operational and technical roles in a single person, which compresses decision cycles but removes the specialised functions that large-firm frameworks assume. Formal strategic planning is rare, not because managers do not think strategically, but because the horizon is short and the environment changes rapidly. Internal AI expertise is almost absent; where technical competence exists, it is usually generalist

IT competence rather than data science (Arroyabe et al., 2024). External partners therefore carry a disproportionate share of the knowledge on which adoption decisions depend (Ayinaddis, 2025).

Recent systematic reviews document low adoption rates, knowledge barriers and reliance on external providers (Oldemeyer, Jede and Teuteberg, 2025; Schwaeke et al., 2025), but few offer a coherent framework that captures how enablement unfolds when most of the conditions assumed by adoption models are absent. Empirical work on European SME samples shows that digital capabilities and innovation routines, rather than technology access as such, differentiate adopters from non-adopters (Arroyabe et al., 2024). This study contributes to the same gap by treating SMEs not as scaled-down large firms but as organisations with their own logic, in which dynamic capabilities may be realised through fundamentally different mechanisms (Hossain, Fernando and Akter, 2025).

3. Methodology

3.1 Research Design

The study uses an exploratory sequential mixed-methods design (Creswell and Plano Clark, 2018), chosen because existing AI enablement instruments are large-firm artefacts whose fit with SMEs cannot be assumed: constructs must be surfaced before they are measured, especially where practice-based knowledge is not readily articulated in pre-formed survey items. The design proceeds in two phases (Figure 1). Phase 1, reported here, uses in-depth expert interviews to reconstruct how AI enablement unfolds in SMEs from practitioners with cross-firm exposure. Phase 2, currently under data collection, operationalises the emergent constructs into a survey of Lithuanian SME managers analysed by PLS-SEM, and will specifically test whether managers themselves perceive partnership as the central mechanism, whether knowledge gaps dominate technological barriers in self-reported data, and whether innovation culture loads as a distinct construct or collapses into human-resource items.

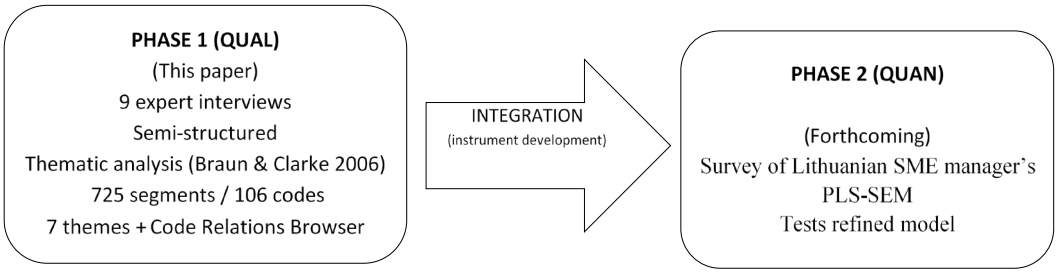


Figure 1: Exploratory sequential mixed-methods design. The qualitative phase reported here informs the instrument for the forthcoming PLS-SEM phase

3.2 Sampling

Purposive criterion sampling (Patton, 2014) was used to recruit nine experts who implement AI solutions for Lithuanian SMEs. Experts were chosen rather than SME owners because each draws on cross-firm experience that reveals systemic patterns invisible to single-firm informants (Yin, 2018); their outsider vantage reduces self-presentation effects; and they observe implementation from first contact to ongoing support. Experts varied in seniority (three to over twenty years), organisation type and client portfolio (micro firms to mid-sized manufacturers). Identifiers INT-01 to INT-09 are used throughout.

3.3 Data Collection

Data were collected through in-depth expert interviews conducted between June 2022 and October 2025. The interview guide was developed using the three-stage rigour framework of Kallio et al. (2016): theoretical grounding from the literature review, item formulation along the enablement dimensions (strategy, finance, human resources, processes, technology, data), and validation through a pilot interview (INT-01). As the pilot produced no substantive revisions, its data were retained in the main analysis (Castillo-Montoya, 2016). Interviews lasted 35 to 75 minutes (mean approximately 60) and were audio-recorded with consent. Transcripts were returned to experts for member verification and analysed in the original Lithuanian to preserve nuance; quotations reported here are the author's translation.

3.4 Analysis

Thematic analysis followed the six-phase procedure of Braun and Clarke (2006) and was conducted in MAXQDA. Coding combined deductive codes derived from the theoretical dimensions with inductive codes that emerged from the data. After iterative refinement, the final coding frame contained 725 segments, 106 codes and eight categories organised into seven themes: five deductive themes corresponding to the core enablement dimensions and two emergent themes capturing barriers and enabling catalysts. Inter-thematic relations were examined through segment-level code co-occurrence counts, which made it possible to move beyond theme-by-theme description and identify which dimensions are tightly coupled in practice.

Data saturation was assessed along three dimensions: new-code emergence, category coverage, and thematic convergence (Guest, Bunce and Johnson, 2006; Saunders et al., 2018). The first interview generated 43 baseline codes; the rate of new code generation fell below 6% by the fifth interview and below 3% by the sixth. The eighth interview added only one new code (2%), and the ninth added none. All eight coding categories appeared in at least seven interviews, with five categories reaching 9/9 coverage. No new themes emerged in the final three interviews. Sample adequacy is thus supported empirically and by the information-power criterion of Saunders et al. (2018).

Trustworthiness was addressed along the four criteria established in the qualitative methodology literature (Creswell and Poth, 2018): credibility, transferability, dependability and confirmability. Credibility was supported by member checks with three experts who reviewed the interpretation of their interviews; by analytic memos that documented coding decisions; and by peer debriefing with two doctoral colleagues. Transferability is supported by thick description of the SME context and of each expert's background. Dependability and confirmability are supported by an audit trail that includes the coding frame, memos and co-occurrence outputs, archived in the project repository.

The four divergences presented in the next section were identified by comparing the emergent thematic structure and the co-occurrence link pattern with the theoretical model that guided the interview guide. A divergence was flagged when the empirical pattern was stable across interviews and could not be accommodated by the original theoretical framing without distortion.

4. Findings

Seven themes emerged: strategic AI vision, financial pragmatism, human resources, process transformation, technological environment, barriers and enabling catalysts. This section presents four divergences between theory and empirical data that cut across themes (Table 1). Two framing findings anchor the analysis: the most frequent code is SME managers' lack of knowledge about AI capabilities (33 segments, all nine interviews); and the strategic dimension has the strongest links with every other dimension, the single strongest being strategy–catalysts (135 co-occurrences). AI enablement in SMEs is organised around knowledge and strategy rather than technology.

Table 1: Four theory–empirical divergences in AI enablement in SMEs.

Dimension	Theoretical assumption	Empirical finding (SMEs)
Strategy	Formal document preceding adoption	Dynamic process co-produced with consultants
Primary barrier	Technological complexity and cost	Manager knowledge and perception gaps
Innovation culture	Distinct organisational dimension	Embedded facet of human-resource dynamics
Dynamic capabilities	Internal organisational functions	Realised relationally through external partnership

4.1 Strategy as a Dynamic Process, not a Formal Document

In the SME context, strategy as a formal artefact does not exist. Experts were consistent: “in general, I have never seen a strategy, let alone one dedicated to artificial intelligence” (INT-07). The absence of a document does not mean the absence of strategic thinking, but that it takes a different form. One expert estimated “one in ten businesses has a vision” (INT-09); the other nine have operational priorities they revise continuously as their environment changes.

What the interviews describe is a process in which strategy is co-produced with external consultants and refined through small implementation steps. The consultant typically begins not with AI but with a business problem: “often the consultation does not start with artificial intelligence. The company comes with some other problem that could be solved through digitalisation. Then, over time, this intertwines with artificial intelligence” (INT-02). Over the course of several engagements, a de facto AI strategy crystallises out of a sequence of concrete decisions, each of which is small enough to fit the firm's resource envelope but cumulatively reshapes the way the business operates.

The co-occurrence data reinforce this picture. The strategic dimension has the strongest link with catalysts (135 co-occurrences), followed by processes (123) and human resources (94). Strategy and catalysts are effectively discussed together: when experts describe how a firm acquires an AI strategy, they describe the same situations in which external partnership, incremental experimentation and targeted learning take place. This finding is a direct challenge to frameworks that treat strategy as an antecedent of adoption. In SMEs, strategy is not a precondition but a by-product of partnership-enabled action.

4.2 The Primary Barrier is Knowledge, not Technology

TOE and DOI frameworks assume technological characteristics (complexity, compatibility, cost) are the first hurdle. The data tell a different story. Technology barriers account for only 9 segments across 5 of 9 interviews, whereas knowledge-related barriers account for 27 segments across 7 interviews and, combined with human-resource codes, dominate the landscape. The most frequent code in the dataset, present in every interview, is SME managers' lack of knowledge about AI capabilities.

Experts framed their work as fundamentally educational. One stated: “we really have to educate them, because they do not fully understand what, how and where” (INT-04). Another described the asymmetry between expectation and understanding: “even a clear understanding of what exactly artificial intelligence can offer to my company is really lacking” (INT-02). A paradox runs through the interviews. SME managers have been exposed to popular media narratives that present AI as almost omnipotent, which produces unrealistic expectations: “they think that you will do everything at once, and it will all happen without them having to do anything” (INT-05). Yet the same managers know almost nothing about what AI cannot do, which makes them unable to evaluate proposals or decide where to start.

Technology, in the experts' accounts, is rarely the binding constraint. Cloud services, generative AI assistants and low-cost APIs are widely accessible. The obstacle is that managers do not know which problem to solve, what questions to ask the technology or how to recognise a useful output. The relevant policy question therefore shifts from “how do we make the technology cheaper?” to “how do we close the knowledge gap that prevents SMEs from using what is already available?”

4.3 Innovation Culture is Part of Human Resources, not a Separate Dimension

AI readiness frameworks treat innovation culture as a distinct organisational property, measured by openness to change, tolerance of failure and willingness to experiment. In the interviews, culture in this abstract sense did not surface as a separate construct. Experts described instead human dynamics embedded in the owner-employee relationship. Resistance was individual rather than organisational: “systems are inert, they change slowly. Right now the bigger resistance comes from people themselves, not from the technology” (INT-06). Innovation typically originated with a specific person rather than a cultural programme: “there is often that one employee who is curious, who is interested, and who ignites the enthusiasm in the company” (INT-09).

The theme labelled “human resources” absorbed 106 segments across all nine interviews and included five sub-topics: manager knowledge gaps, willingness to learn, employee attitudes, bottom-up initiatives and innovation culture. Empirically, these sub-topics are too entangled to separate. A bottom-up initiative by a motivated employee is simultaneously an act of learning and of cultural change; a manager who invests twenty minutes a day in generative AI is simultaneously a strategic actor and a cultural signal for the rest of the team. In a firm of ten or twenty people, culture is not a backdrop against which behaviour takes place; it is the behaviour itself.

This finding carries a measurement implication. Items used to measure innovation culture in large-firm surveys (formal innovation programmes, tolerance for failure, dedicated innovation units) do not correspond to anything present in an SME. What matters instead is whether the manager learns, whether specific employees experiment and whether those experiments are allowed to propagate.

4.4 Partnership as the Central Enablement Mechanism

Partnership with external IT consultants is the central mechanism by which AI enablement happens in SMEs. The catalyst theme, which captures this partnership, accounts for 112 segments across all nine interviews, of which 51 concern the consultant relationship. Its co-occurrence link with strategy (135 segments) is the strongest in the entire matrix. Experts described their role not as product suppliers but as long-term partners: “my goal is to be with them, a partner on this evolution path” (INT-09).

The data support a three-tier model of partnership (Figure 2). The first tier is consulting and training, in which the consultant provides structured exposure to AI capabilities and teaches the manager and employees to use basic tools. One expert described this work as largely educational: “a large part of the work is education, planning and explaining what is possible with current technology” (INT-09). The second tier is joint planning, in which the consultant and the SME co-design specific use cases, prioritise them against the firm's resources and agree on an implementation sequence. The third tier is long-term support, in which the consultant remains available as the firm experiments and gradually builds competence. The tiers are overlapping modes rather than sequential stages.

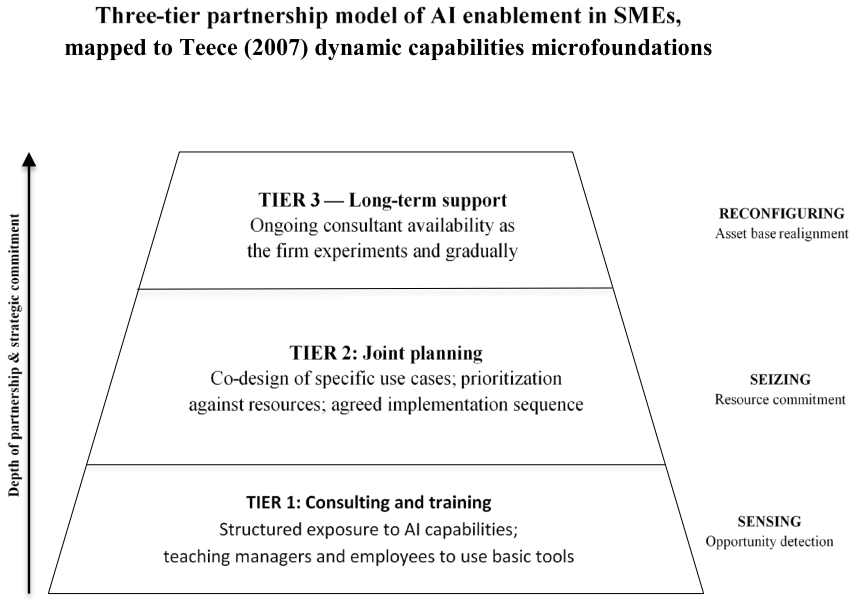


Figure 2: Three-tier partnership model of AI enablement in SMEs, mapped to Teece (2007) dynamic capabilities microfoundations

This partnership mechanism refines the dynamic capabilities view for SMEs: sensing is performed by the consultant, seizing is a joint act in which the consultant commits expertise and the firm commits managerial attention and budget, and reconfiguring occurs as processes and roles adjust to new tools with ongoing consultant support. Dynamic capabilities, in other words, are realised relationally rather than internally. This also explains why strategy rather than technology has the strongest position in the co-occurrence matrix: partnership produces strategy as a by-product of repeated engagement, and strategy in turn shapes which technologies are adopted.

5. Discussion

5.1 Refining Dynamic Capabilities for SMEs

The findings refine Teece's (2007) dynamic capabilities framework for SMEs. In large firms, sensing, seizing and reconfiguring are distributed across internal functions; in SMEs they do not disappear but migrate into the relationship between the owner-manager and a small number of trusted external partners. This is consistent with recent work reframing AI adoption in SMEs as a managerial-capability phenomenon realised through leadership and external collaboration rather than internal departments (Hossain, Fernando and Akter, 2025;

Simón, Revilla and Sáenz, 2024). SMEs therefore do not lack dynamic capabilities; they realise them through a different institutional arrangement. Survey items asking whether a firm has a dedicated function for identifying new technologies will mechanically return low scores even in SMEs that sense and seize effectively through consultants; items probing the quality of external partnerships and willingness to act on consultant input capture the same construct with less bias.

5.2 Implications for AI Adoption Models

The four divergences, taken together, point towards a partnership-oriented, knowledge-first, incremental model of AI enablement in SMEs. This model differs from technology-centric frameworks in three respects. First, it places knowledge gaps, rather than technological barriers, at the centre of the adoption problem, a pattern also reported in the most recent SME systematic reviews (Schwaeke et al., 2025; Oldemeyer, Jede and Teuteberg, 2025). Second, it treats strategy as an outcome of engagement rather than a precondition for it. Third, it treats external partnerships as constitutive of the firm's AI capability, not as auxiliary inputs. These shifts qualify rather than invalidate existing frameworks. The TOE framework remains useful where its assumptions hold (Badghish and Soomro, 2024); in SMEs it requires substantial adaptation, and the items most commonly used to operationalise it need to be reconsidered (Arroyabe et al., 2024; Soomro et al., 2025).

5.3 Practical Implications

For SME managers, the findings suggest engaging consultants earlier rather than later, and treating the initial engagement as an investment in learning rather than in a specific tool. The value of the first engagement often lies less in the deliverable than in the map of possibilities it produces (Acimovic, 2024). For IT consultants, the three-tier partnership model offers a useful self-diagnostic: engagements that stop at the first tier risk leaving the client with fragile capability, while engagements that include planning and long-term support are more likely to produce sustained adoption. For policymakers, the findings argue for programmes that fund partnerships and learning, not only technology grants (OECD, 2025).

6. Conclusions, Limitations and Future Research

This paper has argued that AI enablement in SMEs is organised around knowledge and partnership rather than technology, and that existing frameworks derived from large-firm contexts miss important features of SME reality. Four empirical-theoretical divergences were identified: strategy as a dynamic process rather than a document; knowledge as the primary barrier rather than technology; innovation culture as a facet of human resources rather than a separate dimension; and partnership as the central enablement mechanism rather than an auxiliary input. Together these findings support a partnership-based refinement of dynamic capabilities theory for smaller firms.

The study has several limitations. The sample is small (nine experts) and drawn from a single national context (Lithuania), which limits statistical generalisation but is appropriate for a qualitative phase. The perspective is that of experts observing SMEs from the outside rather than owners themselves, a deliberate choice mitigated by member checks and triangulation with the forthcoming quantitative phase.

The next step is the quantitative phase, in which a survey of Lithuanian SME managers tests the refined model on a larger sample. Particular attention will be paid to the partnership construct, which is under-represented in existing AI adoption instruments, and to the collapse of innovation culture into human resources. Comparative work in other national contexts, and in sectors with different consultant ecosystems, would further test the boundary conditions of the partnership-based view.

Ethics Declaration: The qualitative data reported in this paper were collected between 2022 and 2025, prior to the introduction of the current institutional research ethics review procedure at Vilnius University Šiauliai Academy. All experts participated voluntarily, were informed of the study's purpose and intended publication, and provided consent for the use of anonymised excerpts from their interviews; identifying information has been removed and experts are referred to only by the codes INT-01 to INT-09. The quantitative phase of the wider doctoral study received formal ethics approval from the Vilnius University Šiauliai Academy ethics committee.

The author used the large language model Claude (Anthropic) to assist with translation of Lithuanian source materials into English and to polish scientific English language during manuscript preparation. The tool was used iteratively under direct human oversight. All scholarly content, analysis, interpretation and conclusions are the work and responsibility of the author.

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