What Counts as AI Adoption in SMEs? Construct Validity and Organizational Mechanisms

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Abstract

Reviews of artificial intelligence (AI) adoption in small and medium-sized enterprises (SMEs) may combine studies that do not verify the technology, the firm or the use. This study audits a pre-selected corpus of 30 candidate case reports from a February 2025 Web of Science and Scopus search. Three sequential gates test for qualifying AI, verifiable SME status and use in real work. Twelve reports pass the baseline definition, and 18 fail at their first unmet gate. Strict and permissive AI definitions retain 11 and 16 reports, respectively. The audit therefore yields a reusable decision tree and a screening checklist. The retained reports are then read against organizational theory. Four theory-derived propositions are compatible with these reports to different degrees. A conceptual proposition on employee-initiated generative AI and a rival explanation are offered for future testing. Construct validity therefore changes what counts as evidence of AI adoption in SMEs.

Keywords: *artificial intelligence; SMEs; AI adoption; construct validity; organizational mechanisms.*

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1. Introduction

Studies of artificial intelligence (AI) adoption apply this label to machine learning, but also to automation, business intelligence, optimization, robotics and data infrastructure. A review of AI adoption in small and medium-sized enterprises (SMEs) must therefore verify three elements. These elements are a qualifying AI component, a firm that meets an SME definition and use of the system in real work.

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An AI system infers from inputs how to generate predictions, content, recommendations or actions (OECD, 2024). In this study, learned models qualify, as does a separable knowledge-based component, whereas data capture and descriptive analytics do not. The European definition of an SME requires fewer than 250 employees and either an annual turnover of at most EUR 50 million or a balance-sheet total of at most EUR 43 million (European Commission, 2003). The same definition adds the data of partner and linked enterprises (European Commission, 2003). Case reports may not provide all these data, so this audit applies an operational approximation of the definition (Section 3.2). Adoption, finally, requires a pilot, deployment or other episode of real work use.

Explanation poses a second challenge. In context-intervention-mechanism-outcome (CIMO) logic, a mechanism is the change in actors' reasoning or resources that links an intervention to an outcome (Pawson & Tilley, 1997; Denyer et al., 2008; Hedström & Ylikoski, 2010). Grouping context, intervention and outcome codes therefore yields configurations rather than mechanisms.

Generative AI adds a third challenge. Recent evidence points to off-the-shelf and sometimes concealed AI use at work (OECD, 2026; Crane et al., 2025). Employee-initiated use may therefore follow a different sequence than planned roll-outs.

These challenges lead to two research questions. The first question (RQ1) asks how the eligible evidence changes when qualifying AI, verifiable SME status and real work use are applied as sequential criteria. The second question (RQ2) asks which organizational mechanisms can be proposed from the retained evidence.

The study audits a pre-selected corpus of 30 case reports rather than the full literature. It contributes a reusable construct audit and a set of theory-derived propositions for future research.

2. Literature review and theoretical framing

2.1. What existing reviews establish – and leave unresolved

Recent reviews of AI adoption in SMEs answer different questions. They map implementation challenges (Oldemeyer et al., 2025), adoption conditions (Schwaeke et al., 2025) and technologies by business function (Le Dinh et al., 2025). Other reviews compare SMEs with large firms (Ayinaddis, 2025) or derive guidance from the technology-organization-environment and diffusion-of-innovations frameworks (Sánchez et al., 2025). None of these reviews tests at report level whether each study contains qualifying AI, a verified SME and real work use.

Such a test may matter because the AI label is broad. AI may act as a high-status innovation label that draws adjacent analytics and automation into search results (Abrahamson, 1991). A Scopus search for artificial intelligence, limited to business and management, identified 4,763 papers published between 2020 and 2023 (Vidu, 2024). In this corpus, author keywords such as big data, data analytics,

automation and Industry 4.0 formed a distinct thematic cluster (Vidu, 2024). Studies labeled as AI may therefore include technologies outside an AI definition.

Measures of AI use raise a similar problem. Novice use of embedded tools differs from broader, customized use (OECD, 2025). The 2026 OECD survey suggests that uptake can coexist with shallow integration, although its sample is not representative (OECD, 2026). In a sample of 285 Romanian SMEs, only 18.6% of firms had implemented AI solutions (Filip et al., 2026). In the same sample, AI use predicted neither perceived relative advantage nor business performance (Filip et al., 2026). Reported use may therefore differ from integration into real work.

2.2. Smallness and generative mechanisms

Smallness may shape how such integration unfolds. Small-business research treats resource poverty and owner-manager centrality as structural conditions (Welsh & White, 1981; Cragg & King, 1993; Thong, 1999). Scarce slack may concentrate attention or produce rushed commitment, while concentrated authority may speed alignment but magnify owner-manager error. Smallness may therefore act as a causal condition rather than a descriptor.

Causal conditions require a mechanism-based account. Critical realism separates an observed regularity from the process that produces it (Bhaskar, 1998). Theory, temporal traces and rival explanations support the inference of such processes (Hedström & Ylikoski, 2010). Four theories supply processes of deliberate adoption, namely attention allocation (Ocasio, 1997), absorptive capacity (Cohen & Levinthal, 1990), routine enactment (Feldman & Pentland, 2003) and resource orchestration (Sirmon et al., 2011; Peretz-Andersson et al., 2024). Job crafting and shadow user innovation inform employee-initiated use (Wrzesniewski & Dutton, 2001; Liu et al., 2025; Waters-Lynch et al., 2025).

3. Methods

3.1. Audit design and corpus

This study is a methodological audit of a pre-selected corpus, not a new review of the full literature. The corpus comes from a February 2025 search of Web of Science and Scopus with SME, AI-proxy and case-study blocks (Appendix A). The search followed the PRISMA 2020 statement for reporting systematic reviews (Page et al., 2021). It returned 1,700 records, of which 1,679 remained after deduplication. Of the 137 full texts sought, 132 were assessed and 30 were retained under the original review criteria.

These 30 candidate reports form the denominator of the audit (C01–C30, Appendix B). The other 102 full-text exclusions could not be reconstructed, because the earlier review kept neither complete extraction rows nor reason-specific decisions. A background source on cobot decisions also sits outside the denominator (Sullivan et al., 2024).

3.2. Construct Definitions and Boundary Variants

Eligibility was assessed through three gates in a fixed order. Gate 1 required a focal artifact with learned inference or a separable knowledge-based component. Gate 2 required a headcount below 250, financial data within the European thresholds or an explicit SME classification under a stated rule. Gate 2 did not assess partner or linked enterprises. Gate 2 therefore approximates the European definition rather than applying it in full. Gate 3 required a pilot, deployment or other episode in which people used the output in real work. A cobot deployment that remains a simulation therefore fails Gate 3 (Raza et al., 2021). Formal authorization was not required, because it describes the mode of adoption rather than its occurrence.

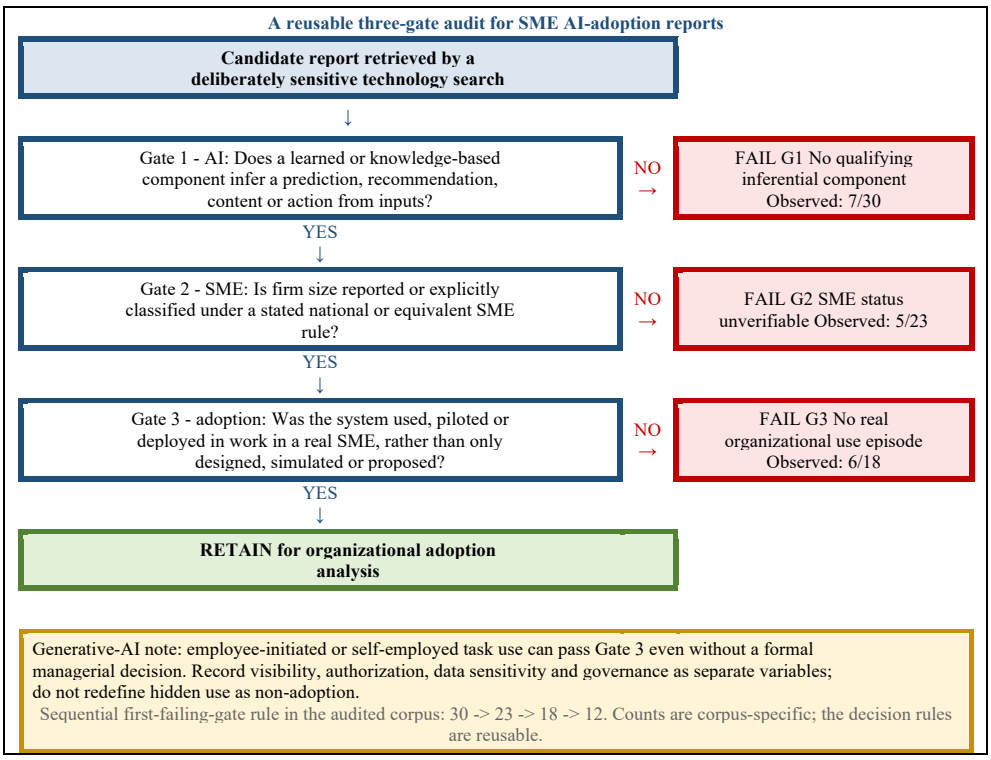


Fig. 1. A Reusable three-gate decision tree for SME AI-adoption reviews
Source: Authors' elaboration

The AI boundary was then varied. The strict rule counts only systems trained or estimated from data. The permissive rule admits any implemented artifact that produces a prescription or optimized plan. Gates 2 and 3 are reapplied in every variant, so a broader AI definition cannot turn an unverified firm or a demonstration into an adoption case.

Each report was assigned to the first gate it failed (Fig. 1). This rule makes totals additive and removes the subjective choice of a primary exclusion reason. Gate 2 and Gate 3 counts are therefore conditional on passing the earlier gates.

3.3. Unit of analysis, extraction, and evidence adequacy

The unit of analysis is the report, so a report covering two small organizations counts once (Lu et al., 2021). Extraction recorded sector, the AI component, SME evidence, the work-use episode, outcomes, process detail and any temporal or actor-reasoning trace.

The mixed designs do not allow a single bias score. Appendix B therefore follows the criterion-level logic of the Mixed Methods Appraisal Tool (MMAT) (Hong et al., 2018). It records eligibility (Q1–Q3), context and process detail (Q4), outcome evidence (Q5) and a temporal or actor-reasoning trace (Q6). A report is process-rich when Q4 and Q6 are both met.

One reviewer coded all gates and appraisal criteria, and Appendix B records each decision for independent recoding.

3.4. Theory construction and use of cases

The theories in Section 2.2 were translated into design propositions (DP), each with a refutation condition. DP1–DP4 derive from the four theories of deliberate adoption. DP5 derives from job crafting and shadow user innovation. A rival proposition (RP1) describes a failure path.

The retained reports were then read for compatibility with each proposition. Four reports contain actor or temporal traces (Groene & Zakharov, 2024; Konur et al., 2021; Lu et al., 2021; Sabah Salih et al., 2023). The other eight reports show only configurations of problem, intervention and outcome. The reports can therefore support the plausibility of the propositions, but they cannot demonstrate the mechanisms.

4. Results

4.1. Sequential attrition and boundary sensitivity

Under the baseline AI definition, the audit retains 12 of the 30 candidate reports. Gate 1 removes seven reports whose artifacts are infrastructure, fixed optimization, configurators or simulations. Gate 2 removes five reports with unverified SME status. Gate 3 removes six reports without a work-use episode.

This result does not depend on one AI definition. Under the strict rule, one rule-based report moves to Gate 1 (Choy et al., 2017), and 11 reports remain. The permissive rule also admits configuration, manufacturing execution, system selection and scheduling artifacts (Forza & Salvador, 2002; Pfeifer, 2021; Zeng et al., 2017; Zhong et al., 2013). Under this rule, 16 reports remain, and 14 of the

30 candidates still fail at least one criterion. Construct verification therefore changes the evidence base under every tested definition.

4.2. From local audit to reusable instrument

These results show that eligibility must precede description. Pooling drivers or barriers across all 30 reports would mix qualifying AI with adjacent infrastructure and verified SMEs with unspecified firms. The 12 retained reports remain heterogeneous, but each contains the three required elements.

Table 1 turns this logic into a reusable checklist. It links common search signals to the evidence to capture, the controlling gate and the variables coded after eligibility. The checklist therefore verifies the construct instead of accepting the labels used by authors.

The 18-of-30 result belongs to this corpus and is not a prevalence estimate. It supports the portable proposition that broad technology searches may overstate usable evidence. Other teams can test this proposition on other corpora.

Table 1. Construct-Validity Screening and Reporting Checklist

Search signal	Evidence passage to capture	Gate rule	Code after eligibility
AI, ML, neural network, GenAI	Named component, inputs, inferential operation and output used in the case	Pass G1 only when the component performs learned or knowledge-based inference	Model family; task; human role
RFID, IoT, ERP, MES, cloud, robot	A separable component beyond sensing, connectivity or transaction processing	Infrastructure alone stops at G1	Infrastructure; integration; data source
Algorithm, optimization, MCDM, fuzzy, simulation, configurator	How the artifact derives a prescription and whether it learns or represents knowledge	Apply the declared AI boundary and report sensitivity	Optimization coupling; boundary variant
SME, small firm, SME-ready	Employee/financial evidence or explicit classification under a stated rule	Suitability language alone stops at G2	Size band; national definition
Case, pilot, prototype, accuracy	Who used the output, at what work point and during which real episode	Technical demonstration alone stops at G3	Scope; duration; user; outcome
ChatGPT, copilot, LLM, AI agent	Qualifying task use in a verified SME, including employee-initiated use	Formal authorization is not required for G3	Visibility; permission; data sensitivity; governance

Source: Authors' elaboration.

4.3. Theory-derived propositions

The following propositions are theoretical. DP1–DP4 are compatible with the retained reports to different degrees, and Table 2 shows which reports support each proposition. DP5 is a conceptual extension for future research. RP1 is a rival explanation that requires empirical testing.

Table 2. Retained reports, AI components and compatible propositions

Report	Sector	AI component	Evidential role	DPs
Choy et al. (2017)	Manufacturing	Rule-based storage assignment	Configuration	DP3
Groene & Zakharov (2024)	Food manufacturing	ML sales forecasting	Process-rich	DP1, DP2
J. Lee et al. (2025)	Manufacturing	ML-supported decision framework	Configuration	DP3, DP4
J.Y. Lee et al. (2017)	Manufacturing	Big-data analytics platform	Configuration	DP3, DP4
Kiefer et al. (2022)	Manufacturing	Gradient-boosting demand forecasting	Configuration	DP2
Komori-Zevallos et al. (2023)	Food manufacturing	ML demand forecasting	Configuration	DP3
Konur et al. (2021)	Food manufacturing	ML prediction and intelligent control	Process-rich	DP1, DP3, DP4
Lu et al. (2021)	Multi-sector (manufacturing and charity)	Data-science customer analytics	Process-rich	DP2, DP4
Chiu & Huang (2023)	Manufacturing	Hybrid ML quality prediction	Configuration	DP2
Sabah Salih et al. (2023)	Distribution	AI-enabled inventory management	Process-rich	DP2, DP3
Teerasoponpong & Sopadang (2021)	Food manufacturing	ANN–GA capacity planning	Configuration	DP3, DP4
Urban et al. (2024)	Manufacturing	ML production-time estimation	Configuration	DP3 (boundary case)

Source: Authors' elaboration based on the construct audit (Appendix B).

4.3.1. Problem-pressure mobilization

A measurable process problem may trigger adoption. In two retained cases, adoption started from a sales-forecasting problem (Groene & Zakharov, 2024) or from production constraints (Konur et al., 2021). Where authority is concentrated,

such a problem may reorder the agenda and legitimate resources for a bounded intervention (Ocasio, 1997).

DP1. In an SME facing a salient, measurable process problem and scarce slack (C), a time-limited AI pilot with a baseline, an accountable owner and a stop/scale rule (I) activates problem-pressure mobilization, whereby attention concentrates and temporary resource reallocation becomes legitimate (M), producing gains in reliability, time, quality or cost (O).

DP1 is refuted if comparable gains occur without shifts in attention or resource commitment.

4.3.2. Trust-building through bounded experimentation

Early acceptance may reflect learning or deference to a supplier. Reversible experiments may separate the two, because they expose outputs to revision before commitment becomes costly. Absorptive capacity depends on prior related knowledge (Cohen & Levinthal, 1990). Three retained reports trace managers or users converting external analytics into local knowledge (Groene & Zakharov, 2024; Lu et al., 2021; Sabah Salih et al., 2023). Two further reports are consistent with this logic (Kiefer et al., 2022; Chiu & Huang, 2023).

DP2. In an SME with limited AI experience, uncertain benefits and access to a credible partner (C), a reversible co-design experiment with training, human validation and rapid feedback (I) activates experiential learning and calibrated trust (M), producing an informed stop/adapt/scale decision and reusable internal capability (O).

DP2 does not hold if training leaves error calibration unchanged while scaling proceeds for unrelated reasons.

4.3.3. Data-to-routine embedding

Organizational value may arise from repeated enactment rather than from the artifact itself (Feldman & Pentland, 2003). Embedding may fail when data relationships are too weak, as in rejected lead-time models (Urban et al., 2024). Seven retained reports show outputs entering a recurring decision, although not all document the enactment process (Choy et al., 2017; J.Y. Lee et al., 2017; Teerasoponpong & Sopadang, 2021; Konur et al., 2021; Komori-Zevallos et al., 2023; Sabah Salih et al., 2023; J. Lee et al., 2025).

DP3. In an SME with a repetitive, data-generating process and a consequential recurring decision (C), integration of AI output at the decision point, assigned data ownership, human override and exception review (I) activates data-to-routine embedding, whereby tacit judgment is codified and evidence-based rules are repeatedly enacted and revised (M), producing sustained gains in consistency, quality, cycle time or cost (O).

DP3 is refuted if gains persist while staff bypass the output, or if repeated use brings no gain in process stability.

4.3.4. Owner-manager resource orchestration

Scaling may expose dependencies hidden by a pilot, such as data ownership, staff time and partner contracts. Resource orchestration stresses structuring, bundling and leveraging resources rather than holding them (Sirmon et al., 2011; Peretz-Andersson et al., 2024). Five retained reports show managerial, technical or partner alignment around AI-enabled work (J.Y. Lee et al., 2017; Konur et al., 2021; Lu et al., 2021; Teerasoponpong & Sopadang, 2021; J. Lee et al., 2025).

DP4. In an SME where AI value spans functions or external partners and decision authority is concentrated (C), an owner-led portfolio of use cases with staged funding, named data responsibilities and partner governance (I) activates resource orchestration, whereby scarce internal and external resources are aligned and recombined (M), producing cross-process capability and coherent outcomes (O).

DP4 is refuted if capability emerges without owner-led alignment, or if orchestration predicts only dependence and lock-in.

4.3.5. User-initiated affordance discovery and revelation

DP5 is not derived from the retained reports, because the search did not include generative-AI terms. It is a conceptual extension based on the gate logic and adjacent theory. A worker may discover an affordance when an accessible tool meets an unmet task need. Job crafting may then alter the task before formal approval (Wrzesniewski & Dutton, 2001; Liu et al., 2025). Concealment may keep this evidence private, a dynamic described as shadow user innovation (Waters-Lynch et al., 2025).

DP5. In an SME where off-the-shelf generative AI meets an unmet task need and local discretion, but no formal AI initiative exists (C), employee experimentation combined with a sanctioned sandbox and a non-punitive disclosure channel (I) activates affordance discovery and revelation, whereby private task evidence becomes legitimate organizational knowledge (M), producing a governed task routine, shared learning and selective scaling (O).

DP5 fails if safer disclosure channels do not increase revelation, or if revealed practices change neither learning nor governance.

4.3.6. Negative rival: premature commitment and capability erosion

Success-selected cases may hide failure. Under severe pressure, an SME may accept a vendor's framing, centralize around one tool and skip user learning. Apparent orchestration may then turn into dependence and capability erosion.

RP1. In an SME under acute performance pressure, with weak AI knowledge and high supplier dependence (C), rapid commitment to a bundled

proprietary solution without reversible trials, user challenge or exit rights (I) activates overload-driven deference and dependency (M), producing ceremonial use, lock-in and erosion of internal capability despite technical installation (O).

RP1 is refuted if rapid bundled commitment yields durable use and transferable capability without higher switching costs.

5. Discussion

5.1. Contributions and research agenda

The first contribution concerns construct validity. In this corpus, 18 of 30 candidate reports fail before synthesis. Construct verification is therefore a substantive result rather than a preliminary step. The ordered gates and Table 1 make this verification reusable.

The second contribution is a set of testable propositions. DP1–DP4 may explain why similar initiatives diverge, as some learn and scale while others stall or create supplier dependence. These propositions also treat smallness as a causal condition rather than a descriptor.

These results qualify the factor lists of earlier reviews. These reviews identified finance, skills, data readiness, management support and ecosystem ties as adoption factors (Oldemeyer et al., 2025; Schwaeke et al., 2025; Le Dinh et al., 2025; Ayinaddis, 2025; Sánchez et al., 2025). In the present corpus, 18 of 30 candidate reports could not support such factors as evidence of AI adoption in SMEs. Factor lists built without report-level verification may therefore mix AI adoption with adjacent digitalization. Survey evidence from 285 Romanian SMEs may point in the same direction, because firm-level AI use did not predict business performance (Filip et al., 2026).

The gates also imply a reporting standard for future reviews. Each included study could report its AI component, its SME evidence and its work-use episode. Such reporting would make reviews with different AI definitions comparable. It would also support cross-country comparison, because national SME rules may differ from the European definition.

These contributions require further testing. A replication should re-screen all 132 full texts and update the search after February 2025. At least two reviewers should report agreement for each gate and keep the source passage for every decision.

Testing the propositions requires temporal data, such as budgets for DP1, error calibration for DP2, overrides for DP3, contracts for DP4 and disclosure for DP5. RP1 requires matched failures. Configurational designs can test combinations of conditions (Ragin, 2008). Process research can test sequence and feedback (Van de Ven & Poole, 1995; Langley, 1999).

5.2. Practical implications and limitations

For managers, the propositions suggest diagnosing the organizational bottleneck before choosing an AI tool. A pilot may start with a baseline and a stop/scale threshold. Successful outputs may then be placed at a named work point with clear data ownership.

For bottom-up generative AI, a blanket ban may encourage concealment. A sanctioned sandbox and a non-punitive disclosure route may help managers identify useful practices.

The study has five limitations. First, the audit starts from 30 pre-selected reports, so the 18-of-30 result is not a prevalence estimate. Second, one reviewer coded all decisions, and Appendix B reports the decisions without the supporting source passages. Third, Gate 2 approximates the European SME definition and does not assess ownership links. Fourth, ten of the 12 retained reports concern production, and only four contain process traces. Fifth, DP5 is not grounded in the retained reports.

6. Conclusions

Case definition determines what a review can explain. Three gates in a fixed order reduce 30 candidate reports to 12, and alternative AI definitions retain between 11 and 16. A qualifying report must therefore document an inferential AI component, a firm within an SME rule and use in a real work episode. On this verified base, the study proposes four mechanisms of deliberate adoption, one conceptual mechanism of employee-initiated use and one rival failure path. These propositions may explain why AI becomes a capability in some SMEs but a stalled pilot or a source of dependency in others. Their causal force remains to be tested.

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Appendix A. Executed Search and Prospective Replication Terms

The first three blocks reproduce the February 2025 search and were combined with AND. The prospective GenAI block contributed no records and can be added to the AI block with OR in a replication. The literal term machine version is kept because it appeared in the executed query.

SME block (executed): SME* OR "small and medium enterpris*" OR "small and medium-sized enterprises" OR "small and medium businesses" OR "small and medium-sized businesses" OR "small and medium companies" OR "small and medium sized companies" OR "micro small and medium enterprises" OR "micro small and medium sized enterprises" OR MSME OR "micro enterpris*" OR "micro-sized enterpris*" OR "micro compan*" OR "micro-sized compan*" OR "micro business*" OR "micro sized business*" OR "micro firm*"

AI-proxy block (executed): "artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR AI OR "natural language processing" OR "data mining" OR "big data" OR robot OR chatbot OR "machine intelligence" OR "reinforcement learning" OR "deep mining" OR "data science" OR "support vector machine" OR algorithm OR "machine version" OR "training data" OR dataset

Study-design block (executed): "qualitative study" OR "qualitative paper" OR "case study"

GenAI block (prospective): "generative AI" OR GenAI OR "large language model*" OR LLM* OR "foundation model*" OR GPT OR ChatGPT OR copilot OR "AI agent*" OR "agentic AI"

Appendix B. Construct Audit and Appraisal of the 30 Candidate Reports

Table A1. Sequential Gate Decisions and Appraisal of the Retained Reports

ID	Report	Outcome	Q4	Q5	Q6
C01	Aydın & Altun (2024)	Excl. G2	–	–	–
C02	Choy et al. (2017)	Retained	P	Y	N
C03	Cid-López et al. (2018)	Excl. G3	–	–	–
C04	Forza & Salvador (2002)	Excl. G1	–	–	–
C05	Groene & Zakharov (2024)	Retained	Y	Y	Y
C06	J. Lee et al. (2025)	Retained	P	Y	N
C07	J.Y. Lee et al. (2017)	Retained	P	Y	N
C08	K. Lee et al. (2017)	Excl. G1	–	–	–
C09	Kannan et al. (2022)	Excl. G2	–	–	–
C10	Kiefer et al. (2022)	Retained	Y	P	N
C11	Komori-Zevallos et al. (2023)	Retained	P	P	N
C12	Konur et al. (2021)	Retained	Y	Y	Y
C13	Lepore et al. (2023)	Excl. G3	–	–	–
C14	Lopez-de-Teruel et al. (2017)	Excl. G3	–	–	–
C15	Lu et al. (2021)	Retained	Y	P	Y
C16	Chiu & Huang (2023)	Retained	P	Y	N
C17	Natanael & Sutanto (2022)	Excl. G2	–	–	–
C18	Oni-Orisan (2024)	Excl. G3	–	–	–
C19	Pfeifer (2021)	Excl. G1	–	–	–
C20	Raza et al. (2021)	Excl. G3	–	–	–
C21	Risco-Ramos et al. (2022)	Excl. G2	–	–	–
C22	Sabah Salih et al. (2023)	Retained	Y	Y	Y
C23	Saqlain et al. (2019)	Excl. G1	–	–	–
C24	Teerasoponpong & Sopadang (2021)	Retained	P	Y	N
C25	Urban et al. (2024)	Retained	P	P	N
C26	Wen et al. (2023)	Excl. G2	–	–	–
C27	Yan (2017)	Excl. G1	–	–	–
C28	Zeng et al. (2017)	Excl. G1	–	–	–
C29	Zheng et al. (2023)	Excl. G3	–	–	–
C30	Zhong et al. (2013)	Excl. G1	–	–	–

Note. Excl. G1–G3 = first failed gate (Gate 1, qualifying AI; Gate 2, verifiable SME status; Gate 3, organizational work use). Q1–Q3 are Y for every retained report. Q4 = context/process description; Q5 = outcome evidence beyond model accuracy; Q6 = temporal or actor-reasoning trace; Y/P/N = yes/partial/no. Table 2 gives the sector and evidential role of the retained reports.

Source: Authors' elaboration.