



An Integrated RBV-KBV Conceptual Framework for Generative AI Adoption in Small Manufacturing Enterprises

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Abstract

Small manufacturing enterprises remain economically important but continue to face recurring operational constraints in planning, scheduling, quality control, maintenance, and process-data use. Generative artificial intelligence offers increasingly accessible support for these bounded operational tasks, yet adoption remains uneven because many firms lack a coherent basis for linking digital opportunity to internal resources, organizational knowledge, and measurable operational improvement. This study develops a conceptual framework that integrates the resource-based view and the knowledge-based view to explain generative artificial intelligence adoption in small manufacturing enterprises. Using an evidence-grounded theory-development approach, the study builds a staged framework that separates foundational conditions, perceived operational AI opportunity, organizational translation mechanisms, and performance outcomes. The framework theorizes internal resources and knowledge assets as foundational antecedents, perceived generative artificial intelligence potential in operational functions as the adoption bridge, knowledge integration and dynamic capability as organizing mechanisms, and performance improvement as the downstream consequence. It further explains how conceptual clarity can support later empirical reduction without losing the richer logic needed for practical implementation. The study also clarifies how the framework can guide applied information-system design through data-readiness assessment, bounded decision-support use cases, human-in-the-loop verification, and operational KPI monitoring. The resulting architecture strengthens theoretical explanation and operational design logic for generative artificial intelligence adoption in constrained manufacturing environments, while preserving clear boundaries for subsequent validation and applied deployment.

Keywords: conceptual framework; generative artificial intelligence; knowledge-based view; manufacturing information systems; resource-based view

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1. Introduction

Small manufacturing enterprises often operate with limited resources while facing recurring operational bottlenecks in quality management, maintenance, production scheduling, and process-data use. These constraints matter because they limit stable performance and reduce the ability of small firms to convert daily operational effort into sustained business outcomes. Recent digital-maturity evidence shows that many small manufacturing enterprises remain at an early stage of transformation, which makes generic digitalization advice insufficient for this context [1].

This operational framing is important because small manufacturers rarely experience AI adoption as a single

strategic decision. In practice, adoption is filtered through narrow production routines, uneven documentation, limited managerial attention, and the need to protect continuity in daily operations. A useful framework must therefore begin from the work problems that managers and operators actually recognize, not from broad assumptions that all digital technologies follow the same adoption pathway.

Generative artificial intelligence is increasingly accessible through cloud-based interfaces, prompt-based assistants, and user-oriented digital services. However, accessibility does not remove implementation constraints. Evidence on machine-learning implementation in SMEs shows that willingness to invest is not enough when data quality

and implementation readiness remain weak [2]. Research on AI adoption intention also shows that top-management support and employee capability can matter more than purely technological perceptions [3]. The adoption problem in small manufacturing enterprises is therefore not simply whether AI tools exist, but whether firms can identify where AI fits their internal resources, knowledge base, and operational routines.

The distinction between access and fit is central to the research problem. A small firm may be able to open an AI service quickly, but still lack clean records, stable digital routines, or employees who can judge whether an AI-generated recommendation is operationally valid. Conversely, a firm with strong process know-how may not benefit from AI if that knowledge remains informal and disconnected from usable data. The adoption problem is therefore both technical and organizational.

Applied studies already show why this issue belongs within computer science applications and manufacturing information systems. AI has been linked to supply-chain resilience in manufacturing SMEs [4], big-data-driven operational continuity [5], digital strategy decision support [6], demand forecasting and inventory management [7], low-cost quality-control automation [8], and AI-based digital-twin decision support in an SME setting [9]. These studies demonstrate that AI can support concrete operational functions, but they remain distributed across use cases. They do not yet provide an integrated explanation of how small manufacturers should connect internal readiness, operational AI opportunity, organizational learning, and performance improvement.

This fragmentation creates a design problem for later systems development. Decision-support tools, readiness dashboards, or AI-assisted operational modules require a stable explanation of which firm conditions should be assessed first, which operational functions should be prioritized, and how performance should be monitored after deployment. Without such a conceptual bridge, applied AI systems risk becoming technically plausible but organizationally weak.

Recent synthesis-oriented work strengthens this gap. Digital transformation research links SME transformation to sustainable competitive advantage [10], while AI-guided synthesis connects AI to business-model innovation and competitive advantage in SMEs [11]. A recent generative AI adoption study further shows that SME leaders must balance aspiration, motivation, and resource allocation under organizational constraints [12]. These studies clarify that AI adoption is not a one-step technology event. It is a capability-building process that depends on how firms interpret, organize, and apply their available resources and knowledge.

The same conclusion appears in adjacent capability and maturity research. Dynamic-capability perspectives explain digital transformation as an adaptive process

[13], emerging-market SME research highlights resource-adaptive digital barriers [14], and Industry 4.0 studies on micro and small enterprises emphasize implementation constraints [15]. Manufacturing-focused maturity models and assessment studies further show that SMEs need staged readiness evaluation rather than broad technology enthusiasm [16-19]. These studies provide useful diagnostics, but readiness scores and maturity labels do not fully explain how small firms convert internal conditions into AI-enabled operational value.

Adoption models provide another partial explanation. Industry 4.0 adoption and sustainability research identifies organizational and technological determinants of adoption [20], while TOE-based e-commerce adoption research shows how technology adoption can influence SME marketing performance [21]. Such models are useful for explaining adoption likelihood, yet they often stop short of explaining how internal resources and knowledge assets become a staged operational capability. This leaves an unresolved gap at the point where resource conditions, knowledge conditions, operational AI opportunity, and performance translation should be connected in one coherent architecture.

This study treats that unresolved gap as a translation problem. It asks how internal resources and knowledge assets make AI opportunity visible, how that perceived opportunity becomes organizationally usable, and why performance improvement should be interpreted as the result of a conversion process rather than as a direct consequence of tool exposure. This framing also prevents the framework from overstating generative AI as an automatic productivity solution.

This study addresses that gap by developing an integrated RBV-KBV conceptual framework for generative AI adoption in small manufacturing enterprises. The resource-based view explains why internal resources such as financial support, technological infrastructure, and human capability matter. The knowledge-based view explains why explicit records, tacit know-how, knowledge sharing, and absorptive capacity matter. The framework integrates these two views because small firms need both resource availability and usable knowledge before generative AI can support operational work.

The study addresses two research questions. RQ1: How do internal resource and knowledge conditions shape perceived generative AI opportunity in small manufacturing operations? RQ2: Through what organizational mechanisms does perceived AI opportunity translate into performance improvement? The study contributes by reframing adoption as staged capability formation, separating foundational stocks from translation processes, and providing a framework that can later guide empirical testing and applied information-system design.

The intended contribution is therefore both conceptual and application-facing. Conceptually, the framework clarifies why RBV and KBV should not be treated as parallel labels, but as complementary explanations of what firms can mobilize and what firms can meaningfully use. For applied information systems, the framework identifies the logic that can later inform readiness assessment, use-case selection, workflow design, human verification, and KPI-based monitoring.

2. Methods

This study uses an evidence-grounded theory-development method because the purpose is to construct a conceptual framework rather than to estimate causal coefficients. The method is appropriate because the present stage must clarify the conceptual architecture before later empirical simplification. Adjacent studies on digital capability and business performance [22], AI capabilities and organizational agility [23], digital-twin systematization in manufacturing [24], and generative AI use in SME financial management [25] show that AI-related value is often mediated by organizational capability, workflow fit, and task relevance. These studies support the need for a framework-building method rather than immediate statistical reduction.

This methodological choice is also appropriate because the study does not introduce a new algorithm, survey result, or software prototype. Its output is a conceptual artifact that organizes a fragmented evidence base into a structure that can later be tested or implemented. The methodological standard is therefore procedural transparency: the evidence boundary, theoretical integration, construct separation, and propositions must remain traceable.

The methodological workflow has five stages. First, the study fixes the evidence boundary by using the prior literature synthesis and recent adjacent studies as the basis for conceptual development. Second, it isolates the unresolved explanatory gap: small manufacturers need a framework that connects internal resources, internal knowledge, operational AI opportunity, and performance outcomes. Third, it reframes generative AI adoption as an internal capability-development problem rather than as simple technology uptake. Fourth, it integrates RBV and KBV with knowledge integration and dynamic capability logic. Fifth, it formalizes the framework into construct roles, boundary conditions, and testable propositions.

At each stage, the study applies a conservative interpretation rule. A construct is not retained merely because it is frequently mentioned in the literature. It is retained only when it performs a necessary role in the adoption sequence. This rule is important because AI adoption studies often accumulate many determinants, but a long determinant list does not automatically produce a usable framework. The present method therefore prioritizes explanatory necessity over construct quantity.

Figure 1 summarizes the five-step evidence-grounded theory-development workflow used to construct the framework.

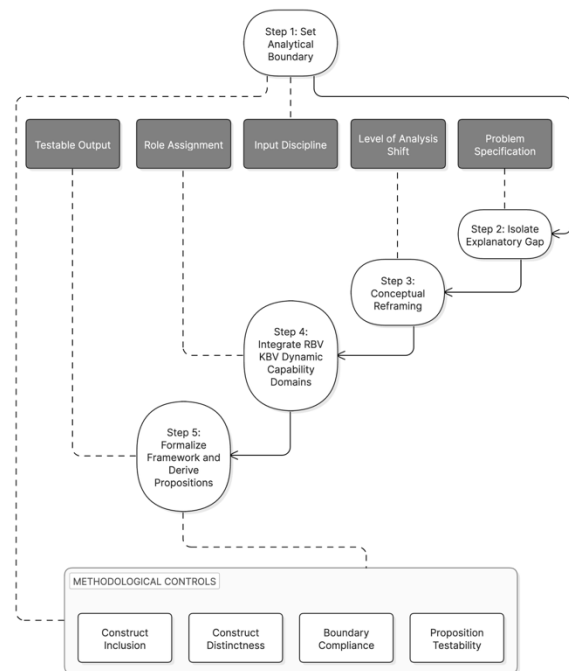


Figure 1. The five-step evidence-grounded theory-development workflow.

The workflow moves from evidence boundary setting to gap isolation, conceptual reframing, theoretical integration, and proposition formalization. The study applies three conceptual validity rules. The construct inclusion rule retains a construct only when it is supported by the evidence base and has a clear role in the framework. The construct distinctness rule requires each construct to perform a non-overlapping explanatory function. The proposition testability rule requires each proposition to be directional and suitable for later empirical operationalization. These rules prevent the framework from becoming a broad inventory of adoption factors.

These validity rules also support replicability. Each construct decision is linked to a specific layer and function, so the basis for accepting, revising, or rejecting a construct remains visible. This is important for a conceptual study because rigor cannot come from statistical diagnostics at this stage. It must come from clear boundaries, explicit decision rules, and coherent movement from evidence to framework.

The study is bounded to small manufacturing enterprises and decision-support-oriented generative AI applications. It does not claim immediate generalizability to large enterprises, non-manufacturing sectors, safety-critical autonomous systems, or contexts where AI is deployed without human oversight. Knowledge-management research in SMEs supports the inclusion of explicit and tacit knowledge as important organizational conditions [26], while AI and knowledge-management research in emerging-

economy SMEs supports the relevance of knowledge processes for AI-enabled entrepreneurship [27]. Dynamic-capability research further supports the inclusion of adaptive capability in AI-related risk reduction [28], and Indonesian SME evidence shows that digital capability can contribute to adaptive capability under disruption [29]. These studies justify the framework boundary while keeping the conceptual structure tied to resource, knowledge, and capability mechanisms.

The boundary conditions also define what the framework does not claim. It does not treat generative AI as an autonomous substitute for managerial judgment, and it does not assume that every small manufacturer should pursue the same AI pathway. Instead, it treats AI as a decision-support resource whose value depends on data readiness, task fit, employee interpretation, and routine adaptation. This boundary keeps the study aligned with a realistic information-system implementation context.

3. Results and Discussions

3.1. Design Requirements for the Working Framework

The first result of this study is the specification of design requirements for a working conceptual framework. The framework must explain more than the relevance of RBV and KBV. It must show how a small manufacturing enterprise can move from internal conditions to operationally meaningful AI use and then to performance improvement. Empirical evidence from SME performance research using SEM-ANN indicates that AI-related performance effects are easier to interpret when organizational and technological conditions are considered together [30]. This supports a layered framework rather than a direct tool-to-performance model.

The first design implication is that the framework must preserve a sequence. If resource readiness, knowledge assets, AI opportunity, and performance are placed in one undifferentiated model, the framework cannot explain why some firms experiment with AI but fail to obtain operational gains. A sequenced framework is needed to show where adoption can stall: at the resource base, at the knowledge base, at use-case recognition, at organizational integration, or at outcome monitoring.

Four requirements follow from this logic. First, the framework must remain rooted in internal firm conditions because small manufacturers often face resource and capability constraints. Second, it must remain operationally grounded because AI adoption becomes meaningful only when linked to bounded work domains such as scheduling, quality control, customer response, planning, or maintenance support. Third, it must remain actionable for later empirical testing and system design. Fourth, it must preserve enough theoretical structure to distinguish what enables AI use from what translates AI use into value.

The second design implication is that the framework must remain parsimonious enough for later empirical work. A conceptually rich framework is useful only if it can be reduced into measurable constructs without losing its central logic. For that reason, the framework distinguishes the full conceptual architecture from the later survey model. The full architecture explains the mechanism, while the reduced model can test the most measurable relationships.

This design orientation is consistent with broader implementation research. Studies on digital transformation and Industry 4.0 in SME supply chains emphasize staged capability building [31]. CPS architecture guidelines show the importance of implementation structure in SME settings [32]. Additive-manufacturing research highlights the role of maturity and knowledge networks [33]. Manufacturing innovation research emphasizes innovation capability in Industry 4.0 contexts [34]. Human-centered Industry 4.0 adoption research also shows that external competence support and organizational readiness shape SME adoption pathways [35]. Together, these studies support a framework that is staged, operational, and capability-oriented.

3.2. Proposed RBV-KBV Conceptual Framework

The central result of this study is the proposed RBV-KBV conceptual framework shown in Figure 2. The framework contains four linked layers: foundational conditions, operational AI opportunity, organizational translation mechanisms, and performance improvement. Its main contribution is the separation of resource and knowledge stocks from the processes that convert AI opportunity into operational value.

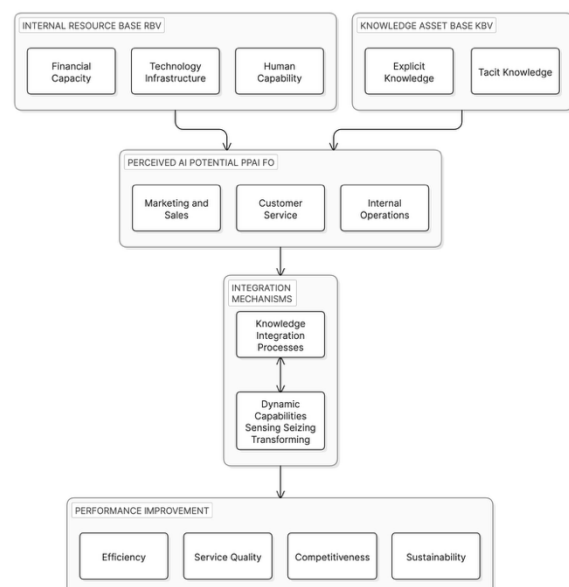


Figure 2. Proposed RBV-KBV conceptual framework for generative AI adoption in small manufacturing enterprises

Foundational resource and knowledge conditions shape perceived operational AI opportunity, which is translated into performance outcomes through

knowledge integration and dynamic capability mechanisms.

The first layer is the foundational condition layer. It contains internal resources and knowledge assets. Internal resources include financial capacity, technological infrastructure, managerial support, and human capability. Knowledge assets include documented records, structured data, standard operating procedures, customer knowledge, process know-how, and informal experiential knowledge. The framework keeps these domains separate because resources describe what the firm can mobilize, while knowledge assets describe what the firm knows and can interpret.

This first layer is deliberately positioned as an antecedent layer rather than as a direct performance driver. Financial capacity may allow a firm to pay for AI access, but it does not guarantee that the firm will choose the right operational task. Technological infrastructure may allow data capture, but it does not guarantee that data are meaningful. Human capability may support experimentation, but it does not automatically create shared routines. The framework therefore treats resources and knowledge as enabling conditions that require later translation.

The second layer is the operational AI opportunity layer. This layer is represented by perceived generative AI potential in operational functions. It is not the same as general adoption intention. It captures whether the firm sees AI as practically useful for specific work domains such as sales support, customer-service support, production planning, scheduling, documentation, quality analysis, or maintenance-related knowledge organization.

The operational AI opportunity layer is the bridge between readiness and action. It keeps the framework from assuming that all AI exposure is equally useful. For example, a firm may perceive strong AI potential for summarizing customer complaints but weak potential for production scheduling if its scheduling records are incomplete. Another firm may see AI potential in quality documentation before it is ready for predictive maintenance. This layer allows the framework to represent such task-level differences.

The third layer is the organizational translation layer. This layer contains knowledge integration and dynamic capability. Knowledge integration explains how firms combine explicit records, tacit know-how, external information, and AI outputs into usable decisions and routines. Dynamic capability explains how firms sense operational opportunities, seize them through bounded AI use cases, and transform routines so that AI support becomes repeatable rather than episodic. Research on big data and dynamic capabilities [36], dynamic managerial capability portfolios [37], AI-enabled dynamic capabilities [38], institutional stewardship for AI-enabled transformation [39], innovation capability and sustainability [40], and failure-based SME growth

[41] supports this process-oriented view of capability formation.

The fourth layer is the outcome layer. It represents performance improvement in operationally grounded terms, including efficiency, service quality, scheduling reliability, defect reduction, response consistency, competitiveness, sustainability, and continuity of operations. The framework does not claim that tool access directly produces these outcomes. It argues that performance improvement emerges when internal conditions make AI use feasible and when firms translate that opportunity through knowledge integration and routine adaptation.

This outcome definition is intentionally broader than a single financial metric but narrower than a vague claim of business success. In small manufacturing enterprises, early AI value may appear as shorter response time, more consistent documentation, clearer production notes, better prioritization of maintenance issues, or improved visibility of recurring defects. These intermediate improvements matter because they are closer to the operational processes that generative AI can realistically support before broader performance effects are observable.

3.3. Construct Roles and Causal Logic

The proposed framework assigns a distinct role to each construct. Internal resources provide the material and organizational capacity required for experimentation. Knowledge assets provide the contextual base required to interpret AI outputs. Perceived AI potential identifies where AI appears useful in concrete operational functions. Knowledge integration explains how AI-related information is connected to firm-specific judgment. Dynamic capability explains how the firm adapts routines around promising AI-supported actions. Performance improvement is the downstream consequence of this conversion process.

The most important distinction is between knowledge assets and knowledge integration. Knowledge assets refer to what the firm already possesses, including documents, records, customer knowledge, employee experience, and process understanding. Knowledge integration refers to what the firm can do with those assets when AI outputs enter the workflow. This distinction prevents the model from assuming that knowledge automatically becomes useful once AI is introduced. Knowledge must be shared, interpreted, checked, and embedded in decisions.

This construct separation matters because failure can occur at different points in the process. A firm may have sufficient technological access but poor process documentation. Another firm may have strong tacit know-how but limited data infrastructure. A third firm may perceive AI as useful but fail to embed its outputs into routines. By separating resources, knowledge assets, perceived opportunity, knowledge integration, dynamic capability, and performance outcomes, the framework makes these failure points visible.

The separation also improves later measurement. Internal resources can be measured through infrastructure, budget, and human capability indicators. Knowledge assets can be measured through documentation, data availability, and accumulated operational know-how. Perceived AI potential can be measured at the task level. Knowledge integration and dynamic capability can be examined as mechanisms that explain whether perceived opportunity becomes organized action. Performance improvement can then be assessed through operational outcomes rather than broad statements of adoption success.

The causal logic is staged. Stronger internal resources and stronger knowledge assets are expected to increase perceived generative AI potential in operational functions. Perceived AI potential then becomes performance-relevant only when the firm integrates knowledge and adapts routines. This logic is consistent with recent SME-focused AI evidence showing mediated relationships between AI chatbot adoption and sustainable manufacturing supply-chain performance [42], staged movement toward AI-twin and AI-triple configurations in European SMEs [43], TOE-DOI findings on AI adoption drivers and challenges [44], and evidence that generative AI contributes to SME resilience when embedded in coping, interpretation, and decision routines [45].

The framework yields nine propositions. P1: Stronger internal resources are positively associated with perceived generative AI potential in operational functions within small manufacturing enterprises. P2: Stronger internal knowledge assets are positively associated with perceived generative AI potential in operational functions. P3: The joint presence of stronger internal resources and stronger knowledge assets has a stronger positive association with perceived AI potential than either domain alone. P4: Higher perceived AI potential is positively associated with stronger knowledge integration. P5: Higher perceived AI potential is positively associated with stronger dynamic capability activation. P6: Knowledge integration mediates the relationship between perceived AI potential and performance improvement. P7: Dynamic capability mediates the relationship between perceived AI potential and performance improvement. P8: The positive relationship between perceived AI potential and performance improvement is stronger when knowledge integration and dynamic capability are jointly high. P9: A later empirical model may test a parsimonious subset of the framework while interpreting the results within the richer conceptual architecture.

These propositions function as conceptual claims prepared for later testing, not as empirically confirmed effects. Their value lies in making the framework testable while keeping the study within its appropriate methodological boundary. They also make the implied mediation logic explicit. The framework does not merely ask whether AI adoption is associated with

performance. It asks whether internal resources and knowledge assets first shape perceived operational AI potential, and whether that potential requires knowledge integration and dynamic capability before performance improvement becomes plausible.

3.4. Conceptual-to-Empirical and Implementation Translation

The framework is intentionally richer than the later empirical model because conceptual development and empirical testing perform different tasks. The conceptual framework preserves the full explanatory logic. The later empirical model can simplify this logic into measurable paths. Applied system development can then translate validated relationships into bounded AI-enabled decision-support tools. Figure 3 clarifies this staged handoff.

The conceptual stage develops the full RBV-KBV framework, the empirical stage tests a parsimonious model, and the implementation stage translates validated relationships into bounded AI-enabled decision-support tools.

As shown in Figure 3, the conceptual stage has two functions. It integrates the theoretical lens and fixes the construct boundaries. This prevents the framework from confusing foundational conditions with organizing mechanisms. The empirical stage then reduces the framework into measurable relationships that can be tested with survey or field data. This reduction should preserve the core path from internal resources and knowledge assets to perceived AI potential and performance improvement, while using knowledge integration and dynamic capability as mediating or explanatory mechanisms where data allow. The implementation stage translates the validated model into operational tools, such as readiness profiles, use-case recommendation logic, KPI monitoring, and human-in-the-loop decision-support workflows.

Figure 3 also shows why the construct rules are necessary. Traceability is needed so that each empirical indicator can be linked back to a conceptual layer. Measurement validity is needed so that resources, knowledge assets, perceived AI potential, and performance improvement are not collapsed into one broad adoption score. Boundary stability is needed so that the framework remains specific to small manufacturing enterprises and decision-support-oriented AI applications. These rules make the framework usable for later empirical testing without turning it into a generic technology-adoption checklist.

The staged translation also reduces implementation risk. If the conceptual stage is skipped, system developers may build features around broad AI enthusiasm rather than validated operational needs. If the empirical stage is skipped, the framework may remain persuasive but untested. If the implementation stage is disconnected from the prior stages, the resulting artifact may not reflect the firm conditions that the model identifies as important. Figure 3 therefore

functions as a roadmap for maintaining continuity between theory development, measurement, and applied system design.

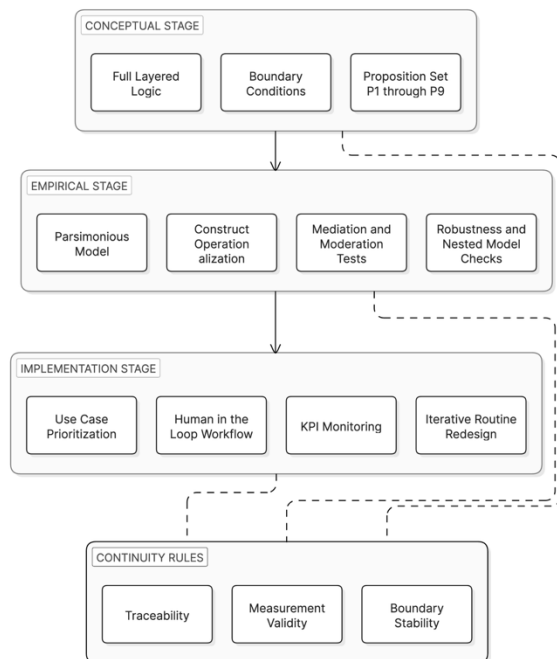


Figure 3. Conceptual-to-empirical stages.

3.5. Implications for Systems Design and Practice

For systems design, the framework implies that small manufacturers should not begin with broad AI adoption claims. They should begin with a bounded operational bottleneck and ask whether the firm has enough resources, data, process knowledge, and human capability to use AI safely and productively. This logic supports incremental deployment rather than broad automation.

A practical implementation pathway can follow the same sequence as the framework. A firm can first assess whether the relevant records, employees, and digital tools are available. It can then select one use case where AI support is expected to reduce coordination effort or improve decision quality. After that, it can design a human-in-the-loop process that checks AI outputs against local knowledge. Only after the workflow becomes stable should the firm expand AI use to adjacent functions.

The framework also suggests four design principles. First, use-case selection should be tied to one operational problem, such as production planning, customer-response consistency, defect documentation, or maintenance knowledge organization. Second, AI outputs should remain subject to human verification when quality, safety, or customer commitments are involved. Third, performance should be monitored with task-level KPIs before the firm scales AI use across functions. Fourth, routines should be reconfigured when performance drift, poor output quality, or weak user adoption appears.

These principles are particularly relevant for small manufacturing information systems because many small firms cannot absorb complex enterprise-wide transformation at once. A readiness module can record the resource and knowledge conditions. A use-case module can map AI opportunities to operational functions. A workflow module can assign human verification responsibilities. A monitoring module can track whether the AI-supported task improves speed, consistency, quality, or continuity. This translation shows how the framework can inform later software design without becoming a premature prototype.

Recent sustainability and practice-oriented studies reinforce this implementation logic. Green-AI research links AI adoption to investment and leadership conditions [46], while AI adoption and green HRM research connects employee behavior and organizational culture to sustainability outcomes [47]. Digital transformation research in coastal SMEs shows that contextual transformation models remain important for competitiveness [48], and AI-enabled demand-forecasting research highlights the role of technological capability in supply-chain performance [49]. Knowledge-oriented leadership research further shows that knowledge processes and AI-related capability can jointly shape innovation outcomes [50]. Evidence from Indonesian MSMEs and startups highlights human-resource challenges in the digital economy [51], while productivity research in small teams suggests that AI value often becomes visible first in narrow, repetitive, and quality-definable tasks [52]. These findings support the framework's practical recommendation: small manufacturers should align AI use with specific resource and knowledge conditions before scaling toward broader transformation.

The overall discussion therefore answers both research questions. For RQ1, internal resources and knowledge assets shape perceived AI opportunity by making operational use cases visible, feasible, and interpretable. For RQ2, perceived AI opportunity is translated into performance improvement through knowledge integration and dynamic capability. The framework's value lies in making this staged logic explicit and usable for empirical testing and applied information-system development.

The framework also clarifies the study's limits. It does not prove that generative AI improves performance in all small manufacturing enterprises, and it does not claim that the full conceptual structure should be estimated without simplification. Its contribution is to define a coherent architecture that can guide later measurement, comparison, and implementation. This limitation is important because conceptual usefulness depends on disciplined scope. The framework is strongest when used to organize bounded AI adoption in small manufacturing contexts, not when generalized to every firm size, sector, or autonomous AI application.

4. Conclusions

This study develops an integrated RBV-KBV conceptual framework for generative AI adoption in small manufacturing enterprises. The framework argues that AI value is not produced by access to tools alone. It emerges when internal resources and knowledge assets make AI use feasible in concrete operational functions and when firms translate that opportunity through knowledge integration and dynamic capability processes.

The study contributes in three ways. First, it reframes generative AI adoption as staged capability formation rather than binary technology uptake. Second, it separates foundational conditions, operational AI opportunity, organizational translation mechanisms, and performance outcomes. Third, it links conceptual theory to applied information-system design by showing how the framework can inform readiness assessment, bounded decision-support use cases, human-in-the-loop verification, and KPI-based monitoring.

The framework is a working conceptual artifact. It does not claim empirical validation at this stage. Its value is to provide a disciplined basis for the next research stage, where the richer architecture can be reduced into measurable relationships without losing the logic that explains why adoption succeeds or fails. Future research should test the proposed relationships with transparent measurement models, explicit validity checks, and multi-context comparison.

For practice, the framework suggests that small manufacturers should begin with bounded operational problems, strengthen the resource and knowledge conditions required for AI use, and evaluate performance at the task level before expanding implementation. This sequence is intentionally modest. It protects small firms from treating generative AI as a broad automation shortcut and instead positions AI as a decision-support capability that must be aligned with local data, routines, and human judgment.

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