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Artificial intelligence applications and
manufacturing innovation outcomes: An
exploratory qualitative multiple-case study
using grounded-theory codingZhiping Jiang¹, Li Fu^{2*}, and Xinguo Jiang³¹School of Business Administration, Liaoning Finance and Trade College, Huludao, Liaoning, China²Jiangxi Qiangyu New Energy Co., Ltd., Wanzai, Jiangxi, China³Beijing Taisheng Tongying Technology Co., Ltd., Beijing, China

Abstract

Artificial intelligence (AI) is increasingly embedded in manufacturing activities, but adoption alone does not explain how AI is associated with innovation outcomes. This exploratory qualitative multiple-case study draws on semi-structured interviews with 15 managerial and technical participants from four manufacturing firms and one AI technology provider, four site visits, and supplementary organizational and public materials collected from July 2022 to October 2025. Grounded-theory coding techniques yielded 14 subcategories within 7 main categories. The analysis was made transparent through explicit coding steps, source-to-category tables, an illustrative end-to-end audit trail, comparison across available source types, examination of negative evidence, and a reserved-material category-sufficiency check. The available record does not support claims of iterative theoretical sampling, independent coding, inter-coder agreement, or theoretical saturation across contexts. The resulting qualitative framework links task characteristics and AI affordances to perceived task-technology fit and organizational embedding of AI; participants' accounts further relate embedded AI use to dynamic-capability processes, innovation-network embeddedness, and exploitative and exploratory innovation. The framework offers context-bound interpretive propositions rather than causal or population-wide claims.

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1. Introduction

1.1. Research background and problem statement

Artificial intelligence (AI) technologies can support manufacturing activities ranging from quality monitoring and process optimization to knowledge search and collaborative problem solving. Adoption, however, is not equivalent to effective organizational use. The value of an AI application depends on whether its functions address task requirements, can be incorporated into established workflows, and support organizational processes

related to internal capability development and external collaboration. AI-enabled innovation is therefore an organizational as well as a technological process.

Manufacturing provides a relevant setting because innovation tasks often involve uncertainty, iterative experimentation, cross-functional coordination, and interorganizational knowledge exchange. In the available cases, participants assessed AI against concrete work problems and implementation burdens rather than as a general-purpose investment. This context motivates attention to task–technology fit, organizational embedding, and differentiated innovation outcomes.

Prior research addresses AI adoption, innovation management, industrial innovation, and organizational performance through diverse constructs, levels of analysis, technologies, and settings. A focused gap remains: task–technology fit, internal dynamic-capability processes, innovation-network embeddedness, and exploitative and exploratory innovation are often examined separately. This study provides process-level qualitative evidence of how manufacturing participants connect these elements during AI implementation, without suggesting that prior research has ignored any single mechanism.

Against this background, the study addresses two related research questions (RQs):

- (i) RQ1: How do manufacturing participants describe the alignment and organizational embedding of AI in innovation-related work?
- (ii) RQ2: How do participants relate the organizational embedding of AI to internal dynamic-capability processes, innovation-network embeddedness, and exploitative and exploratory innovation?

The RQs guide an exploratory qualitative interpretation; they are not causal tests or statistically testable hypotheses.

The study's incremental contribution is the level-sensitive alignment of constructs. It distinguishes perceived task–technology fit from organizational embedding, focal-firm dynamic-capability processes from innovation-network embeddedness, and exploitative from exploratory innovation. The resulting framework is a bounded qualitative interpretation rather than a new causal theory or an estimate of effect size.

The framework is intended primarily as an analytical vocabulary for interpreting implementation processes. Its managerial implications are developed separately in Section 4.6.

Empirically, the article reports an exploratory, qualitative, multiple-case study based on interviews, field observations, documentary material, and grounded-

theory coding. The propositions provide an interpretive framework; they are not statistically tested hypotheses or a quantitative model.

1.2. Key concepts and analytical scope

Exploitative innovation involves incremental improvement of existing products, processes, services, and routines. Exploratory innovation involves experimentation, new knowledge development, engagement with emerging technologies, and movement beyond established product or technological domains. Organizational ambidexterity research treats these as distinct learning orientations that may complement one another but may also compete for attention and resources. This study therefore examines how participants associate AI-supported activities with each innovation type, rather than assuming that AI improves both uniformly.

Organizational embedding of AI refers to the iterative incorporation of AI-enabled functions into manufacturing-related activities, including research and development, production, sales, and interorganizational collaboration. The analysis distinguishes autonomous AI affordances, such as automated sensing, analysis, decision support, and coordination, from interactive AI affordances, such as natural-language communication, customized responses, and learning from user feedback. An affordance contributes to activity only when organizational actors perceive it as relevant to a task and incorporate it into work practices.

1.3. Literature review and theoretical framing

1.3.1. Artificial intelligence and innovation outcomes

Artificial intelligence should not be treated as a homogeneous input with a uniformly positive influence on innovation. Firm-level and innovation-management research links AI use to product and process innovation while documenting variation in the breadth and organizational pattern of implementation (Füller *et al.*, 2022; Rammer *et al.*, 2022). Research on AI in research and development also distinguishes automation from augmentation, and exploratory from exploitative activities (Johnson *et al.*, 2022). Together, these studies motivate a contingent implementation perspective.

1.3.2. Organizational ambidexterity

The exploration–exploitation distinction provides the theoretical basis for defining the study's outcomes. Exploitation involves refinement, efficiency, implementation, and the extension of existing knowledge, whereas exploration emphasizes search, experimentation, variation, and the generation of new knowledge (March, 1991). Because the two modes compete for scarce resources

and require partly different arrangements, organizational ambidexterity refers to the capacity to pursue both rather than to either outcome in isolation (Benner & Tushman, 2003; O'Reilly & Tushman, 2013). The outcomes are therefore examined separately, and evidence concerning either outcome alone is not interpreted as proof of ambidexterity.

1.3.3. Task–technology fit

Task–technology fit is the perceived correspondence between technological functionality and task requirements. Technology supports performance when it is used and well matched to the task it serves (Goodhue & Thompson, 1995). Fit is relational: greater investment or more advanced functionality does not necessarily create better fit. Autonomous and interactive affordances are situated possibilities for action arising from the relationship among the AI artifact, organizational actors, and tasks, rather than fixed properties of the technology (Volkoff & Strong, 2013). In this framework, task–technology fit precedes, but does not subsume, organizational embedding, dynamic-capability processes, or innovation-network embeddedness.

1.3.4. Dynamic-capability processes

Dynamic capability theory explains how firms integrate, build, and reconfigure competences in changing environments (Teece *et al.*, 1997). Its commonly used microfoundations are sensing opportunities and threats, seizing selected opportunities, and transforming or reconfiguring the resource base (Teece, 2007). The inductive categories of need sensing, opportunity seizing, and resource reconfiguration are interpreted through these processes and are distinguished from ordinary operational capabilities and innovation outcomes (Winter, 2003). Innovation resilience is retained as an inductively observed coping and adaptation process, not as a canonical fourth dynamic capability (Duchek, 2020).

1.3.5. Innovation-network embeddedness

This perspective complements dynamic-capability theory by explaining access to and coordination of resources beyond the focal firm. Economic action is embedded in ongoing social relationships (Granovetter, 1985), and alliance opportunities and outcomes are shaped by broader networks (Gulati, 1998). Structural embeddedness concerns direct and indirect ties and network position; relational embeddedness concerns the quality of particular relationships, including trust, reciprocity, and commitment. Such ties may facilitate knowledge access and innovation, although redundant or excessive embeddedness may also restrict novelty (Ahuja, 2000; Uzzi, 1997). In the present

cases, AI-supported partner identification, information synthesis, and coordination are interpreted as perceived processes.

1.3.6. Theoretical integration and research gap

The theories used here serve distinct analytical roles: task–technology fit addresses perceived task–function correspondence; affordance theory addresses situated possibilities for action; dynamic-capability theory interprets focal-firm processes; innovation-network embeddedness interprets interorganizational access and coordination; and organizational ambidexterity distinguishes exploitative and exploratory innovation. The gap is therefore not the absence of these constructs, but their level-sensitive alignment in accounts of AI implementation. Organizational embedding serves as the conceptual bridge between perceived fit and later organizational processes, while internal processes, external relationships, and innovation types remain analytically distinct. Environmental dynamism, digital culture, region, ownership, and industry technology intensity are future research conditions, not tested elements of this study.

1.3.7. Technical implementation and responsible-AI boundary conditions

Recent technical studies identify conditions that organizational research should measure rather than assume. Work on low-cost multisensory robotics highlights sensor, cost, and deployment constraints (Mittal *et al.*, 2023), whereas research on dermatological AI shows how unrepresentative training data can undermine model validity and subgroup transferability (Ruga *et al.*, 2025). These studies do not test the organizational processes examined here; they identify implementation resources and data representativeness as boundary conditions for future multi-source manufacturing research.

1.4. Theoretical integration and analytical boundaries

The framework assigns a limited role to each theoretical perspective. Task–technology fit addresses perceived task–function correspondence; dynamic-capability theory interprets internal organizational processes; innovation-network embeddedness interprets external relationships; and organizational ambidexterity distinguishes innovation types. Organizational embedding connects these domains analytically without collapsing them into a single construct. The arrangement is a qualitative heuristic, not a fixed temporal sequence or a mediation model.

1.5. Theory-linked qualitative propositions

The central theoretical message is straightforward: task–

technology fit concerns the relevance of AI functionality to a task; organizational embedding concerns its incorporation into work; dynamic-capability processes and innovation-network embeddedness describe related internal and external organizational processes; and organizational ambidexterity distinguishes innovation types. The following five propositions express interpretive associations, not independent causal hypotheses or estimated effects.

- Rationale for Proposition 1: Task–technology fit implies that relevance depends on correspondence between task requirements and technological functionality rather than on technology intensity alone (Goodhue & Thompson, 1995). Affordance theory and prior task-fit research further support examining task demands and situated possibilities for action (Hua *et al.*, 2023; Volkoff & Strong, 2013).
- Proposition 1: Participants' accounts indicate that organizational embedding of AI is discussed, with task requirements—particularly complexity and interdependence—perceived as aligned with AI affordances for autonomous information processing and interactive support.
- Rationale for Proposition 2: Perceived fit does not automatically lead to a technology's adoption in the organization. Affordances are realized through situated changes in user practices and workflows, making appropriation and embedding analytically distinct from the initial fit (Felicetti *et al.*, 2024; Volkoff & Strong, 2013).
- Proposition 2: Participants' accounts indicate that perceived task–technology fit can be sustained through iterative adjustment of AI functions, user practices, and workflows, rather than through technology deployment alone.
- Rationale for Proposition 3: Dynamic-capability theory locates sensing, opportunity seizing, and resource reconfiguration in organizational action rather than in the technology itself (Teece, 2007; Teece *et al.*, 1997; Winter, 2003). Innovation resilience is treated as an inductively observed adaptive process, not as a new canonical dynamic-capability dimension (Duchek, 2020).
- Proposition 3: Embedded AI use may be associated with exploitative and exploratory innovation through need sensing, opportunity seizing, resource reconfiguration, and innovation resilience within the focal firm.
- Rationale for Proposition 4: Network research distinguishes access arising from network structure from the quality of particular relationships (Granovetter, 1985; Gulati, 1998). AI-supported

search or coordination may operate within these relationships, but the proposition does not imply that AI creates trust or that greater embeddedness is always beneficial (Ahuja, 2000; Drechsler *et al.*, 2025; Uzzi, 1997).

- Proposition 4: Embedded AI use may be associated with exploitative and exploratory innovation through structural and relational innovation-network embeddedness.
- Rationale for Proposition 5: Dynamic-capability processes and innovation-network embeddedness concern different levels of action—the focal firm and its interorganizational relationships. Their potential complementarity is an abductive synthesis of the case accounts, not a tested interaction or mediation effect.
- Proposition 5: Participants' accounts associate embedded AI use and differentiated innovation outcomes with analytically distinct, potentially complementary dynamic-capability processes and innovation-network embeddedness; their relative importance requires future research.

2. Methodology

2.1. Research design

This article reports an exploratory, qualitative, multiple-case study that uses open, axial, and selective grounded-theory coding techniques (Eisenhardt, 1989; Strauss & Corbin, 1998). It is not presented as a classical grounded-theory design because the reportable record does not establish iterative theoretical sampling or theoretical saturation. The study addresses two “how” RQs by tracing implementation accounts from meaning-bearing passages to concepts, subcategories, main categories, and a qualitative process framework. Each organization is treated as a contextual case, and particular AI initiatives provide embedded empirical episodes. Interview statements are qualitative evidence rather than independent statistical observations. Figure 1 summarizes the research design.

2.2. Case selection, data sources, and sample boundaries

2.2.1. Case-set logic and status

The available case set comprised four manufacturing firms in home appliances, advanced equipment, new materials, and papermaking, as well as one AI technology provider. The inclusion of manufacturing users and a technology supplier provides contrast in actor position and sector context. Because the surviving record did not preserve a sequential case-selection, recruitment, or stopping trail, the set was characterized as a bounded, analytically relevant case set rather than a theoretical



Figure 1. Qualitative multiple-case-study research process
Abbreviation: AI: Artificial intelligence.

sample. It supports comparison of category patterns in the available settings, not statistical representation, population coverage, or subgroup inference. Firm size, ownership, location, technology intensity, and AI maturity were not systematically reported.

2.2.2. Participant and source composition

The 15 participants held managerial and technical roles listed in Table 1, covering strategy, information systems, research and development, implementation, and business applications. Data were collected from July 2022 to October 2025 through 886 minutes of semi-structured interviews, four site visits, and secondary materials. Site visits to exhibition halls and production facilities provided contextual observations of AI-related applications and manufacturing processes. Supplementary materials comprised internal organizational documents, official public information, media reports, and academic materials totaling approximately 120,000 Chinese characters. The available source types were compared during interpretation to identify convergence, inconsistency, and implementation constraints.

2.2.3. Theoretical-sampling and procedural boundary

The reportable record did not show emerging categories being used to recruit later participants, add cases, or redirect

data collection; no subsequent theoretical-sampling round was documented. It also did not preserve recruitment routes, inclusion and exclusion rules, group-interview headcounts, the interview guide, recording, transcription, translation, consent, ethics review or exemption, anonymization, or field-observation protocols. Nor did it clearly distinguish whether academic materials from China National Knowledge Infrastructure (CNKI) and Web of Science were used only for context or as case evidence. These omissions prevented full procedural reconstruction and were disclosed rather than retrospectively supplied.

2.2.4. Units of inquiry, analysis, and coding

The organization was the contextual case, while accounts of particular AI initiatives were embedded empirical episodes. The unit of coding was a meaning-bearing passage, not a participant or organization-level quantitative observation. Comparisons were made at the level of concepts, categories, and process interpretations across the available materials; they were not used to estimate participant frequencies, firm-level effects, or population patterns.

2.3. Grounded-theory coding

2.3.1. Open coding procedure

The interview, observation, and documentary materials

Table 1. Overview of data collection in the five cases

Data source	Case	Role	Interview focus	Duration (min)	Transcript (characters)
In-depth interview	A	Chairperson	AI-enabled digital-transformation strategy and development priorities	28	4,573
		President	AI requirements and overall implementation progress	58	9,846
		Head of Information Department	Evolution of intelligent-technology applications, departmental roles, and implementation outcomes	68	13,482
		Information Department team members	Benefits and limitations of AI and representative innovation use cases	122	22,917
In-depth interview	B	Vice President	Current implementation status and future development plans	35	5,812
		Head of Information Department	Evolving requirements and applications of AI	48	9,103
	C	Head of Information Department	AI requirements, current applications, and implementation trajectory	38	6,587
	C	Head of R&D Department	Observed innovation outcomes and representative AI application scenarios	92	17,346
	D	Head of Information Department and R&D team member	Implementation progress, technical advantages and limitations, and innovation use cases	150	27,552
	E	General Manager and members of the business and R&D teams	Industry trends, smart-product iteration, market applications, and customer needs	247	44,328
Field observation	We conducted four on-site visits to corporate exhibition halls and production workshops, gaining firsthand insights into the practical applications of AI and its implementation in manufacturing processes.				
Secondary materials	The collection includes internal corporate documents, official public information, media reports, and academic materials from databases such as CNKI and Web of Science, totaling approximately 120,000 characters.				

Abbreviations: AI: Artificial intelligence; CNKI: China National Knowledge Infrastructure; R&D: Research and development.

were examined for meaning-bearing passages concerning task requirements, AI affordances, organizational embedding, internal and external organizational processes, or innovation outcomes. Each relevant passage was summarized as a concise initial concept that closely approximated its reported meaning. Concepts were compared within the available corpus, overlapping formulations were consolidated, and discrepant accounts such as underfit, overfit, workflow burden, and implementation constraints were retained. Codes were kept for conceptual relevance to the RQs rather than frequency. Constant comparison and consolidation generated 14

subcategories within 7 main categories. Table 2 presents illustrative source-to-concept-to-subcategory links.

2.3.2. Axial coding procedure

The 14 subcategories were compared by analytical role and grouped into 7 main categories: task characteristics, AI affordances, task–technology fit, organizational embedding of AI, dynamic-capability processes, innovation-network embeddedness, and innovation outcomes. Boundary checks kept perceived fit distinct from organizational embedding, focal-firm processes distinct from external relationships, and exploitative innovation distinct from

Table 2. Illustrative source-to-subcategory coding structure

Illustrative evidence excerpt	Initial concept	Subcategory
There is no standard answer to enterprise innovation challenges; it requires repeated trial and error. Innovation processes involve complex information sources and frequent iterations, making it impossible for a single individual to develop a comprehensive innovation plan.	Multi-element parallel processing with iterative workflow	Task complexity
The innovation process features tightly integrated workflows, relies on joint exploration by multiple departments and in-depth communication among employees, and requires cross-sector collaboration with supply chains, universities, and research institutions—all of which require strong coordination.	In-depth communication among employees, joint exploration by multiple departments, and cross-organizational collaboration	Task interdependence
Artificial intelligence (AI) can independently perform quality monitoring, process modeling, and resource coordination; dynamically adjust parameter settings; automatically analyze and compare external technical specifications; and achieve fully automated intelligent processing.	Autonomous sensing, decision-making, learning, and coordination	Autonomous AI affordance
The intelligent system supports natural-language interaction, allows customized information output as needed, and continuously optimizes the model based on user feedback to meet personalized work requirements.	Natural-language interaction, customized responses, and continuous optimization	Interactive AI affordance
AI can precisely address business pain points, adapt to dynamically evolving R&D and production tasks, integrate seamlessly into existing workflows, boasts strong compatibility and high employee acceptance, and incurs no additional process costs.	Static compatibility, dynamic adaptation, process alignment, and interoperability	Task–technology fit
Enterprises develop intelligent application plans aligned with their digital strategies, validate effectiveness through scenario-based pilots, progressively deepen technological integration, and extend coverage to all business operations and external collaboration scenarios.	Application planning, pilot implementation, deep integration, and extension	Organizational embedding of AI
The company continuously monitors developments across the supply chain, among industry peers, and within academia, integrates market and after-sales data, and accurately identifies industry trends as well as customers' potential innovation needs.	Tracking industry trends, identifying customer needs, comparing competitor technologies, and monitoring academic developments	Need sensing
Enterprises should swiftly map out innovation pathways; develop innovative solutions; evaluate and select them across cost, technology, and market dimensions; and continuously refine the plans to ensure successful implementation.	Rapid generation, systematic evaluation, and iterative refinement of innovation solutions	Opportunity seizing
The enterprise conducts a comprehensive review of its resource inventory; traces the entire process of resource allocation; and intelligently allocates innovative resources such as personnel, funds, and equipment in line with project timelines.	Resource-inventory identification, full-process resource traceability, and intelligent resource allocation	Resource reconfiguration
Enterprises can proactively identify technological, supply chain, and market risks, enabling them to swiftly adjust strategies, restore innovation processes, and conduct post-event reviews to optimize practices and prevent future issues.	Risk forecasting, shock response, and post-failure learning	Innovation resilience
AI supports the construction of a collaborative network map, identifies network structural characteristics, matches suitable innovation partners, and helps optimize the collaboration framework.	Network-map development, network-feature identification, and intelligent partner recommendation	Structural embeddedness
AI supports privacy-preserving integration of collaborative resources, extracts key communication information, reduces information bias, and strengthens trust and collaborative efficiency among stakeholders.	Automated integration and analysis of collaborative resources, extraction of key communication points, and data privacy protection	Relational embeddedness

(Cont'd...)

Table 2. (Continued)

Illustrative evidence excerpt	Initial concept	Subcategory
By leveraging intelligent technologies, enterprises optimize product performance, refine production processes, and develop customized upgrade solutions to reduce costs, enhance efficiency, and strengthen market competitiveness.	Product refinement, process-efficiency improvement, and customized upgrades to existing solutions	Exploitative innovation
Enterprises conduct prototype validation and trial-and-error exploration of cutting-edge technologies, promote cross-domain technological integration, and build a long-term reserve of innovative technologies.	Prototype development, frontier-technology exploration, and cross-domain innovation	Exploratory innovation

Notes. The evidence excerpts are translations or paraphrases of participant or documentary accounts. Performance claims were not independently verified, and complete passage-level case and source identifiers were not preserved in the reportable audit materials.

Abbreviation: R&D: Research and development.

exploratory innovation. Grouping was based on conceptual correspondence and the available evidence examples, not on code prevalence. Table 3 defines each subcategory and its corresponding main category.

2.3.3. Selective coding procedure

Selective coding organized the seven main categories into four process domains: antecedent conditions, organizational embedding of AI, internal and external organizational processes, and exploitative and exploratory innovation. This organization produced the central storyline used in the integrated qualitative framework. The proposed relationships among domains are an abductive, theory-informed synthesis of participants' accounts; they are not directly observed temporal transitions or statistically tested paths.

2.3.4. Coding protocol and end-to-end audit trail

(a) Documented analytical sequence

The reported coding chain comprised six linked moves: identifying a meaning-bearing passage; summarizing its central meaning as an initial concept; comparing and consolidating related concepts into a subcategory; relating the subcategory to a main category; locating that category within a process domain; and examining whether the resulting interpretation remained consistent with the RQs and discrepant evidence. Table 2 shows source-to-concept-to-subcategory links, Table 3 defines subcategory-to-main-category relationships, and Table 4 presents two end-to-end traces across all reported levels. The surviving materials do not permit reconstruction of a complete passage-level coding log.

(b) Illustrative audit trail

Table 4 traces two examples from evidence cue to initial concept, subcategory, main category, and process domain. The first follows accounts of innovation problems with “no standard answer” and “repeated trial and error” into Task

Complexity and the antecedent-conditions domain. The second follows prototype validation, frontier-technology experimentation, and cross-domain integration into Exploratory Innovation and the innovation-outcome domain. The examples make the reported abstraction process inspectable; they were selected to illustrate different ends of the framework, not to establish prevalence or saturation.

(c) Coder/software boundary and credibility strategy

The available record does not identify a qualitative-analysis software package, independently operating coders, independent coding rounds, a formal reconciliation procedure, or an inter-coder agreement assessment. The complete coded corpus, a versioned codebook, reflexive memos, and passage-level case identifiers were not preserved. Trustworthiness is therefore not claimed through inter-coder reliability. Instead, analytical credibility rests on explicit category definitions, visible source-to-category traces, comparison across available source types, retention of discrepant evidence, a reserved-material category-sufficiency check, external review of category clarity, and deliberately bounded interpretive claims. These safeguards improve transparency and plausibility but do not replace a fully reproducible audit archive or independent recoding.

2.4. Analytical credibility, category sufficiency, and negative evidence

2.4.1. Category-sufficiency check

The framework was developed from approximately 85% of the available material, after which the remaining 15% was examined for evidence requiring an additional main category. No additional main category was identified. Because the remaining materials came from the same case corpus and were not collected through a later theoretical-sampling round, they are reported as an internal category-sufficiency check. They do not demonstrate theoretical saturation across firms, projects, industries, or implementation contexts.

Table 3. Axial-coding structure

Main category	Subcategory	Definition
Task characteristics	Task complexity	It refers to the diversity and uncertainty exhibited by corporate innovation tasks at the levels of knowledge structure and information composition.
	Task interdependence	It refers to the degree of reliance on resource exchange, information sharing, and process integration between internal and external stakeholders in corporate innovation initiatives, encompassing both cross-departmental collaboration within the organization and cross-industry partnerships.
AI affordances	Autonomous AI affordance	The possibilities for autonomous sensing, analysis, decision support, learning, or coordination that organizational actors perceive in relation to a task.
	Interactive AI affordance	The possibilities for intent recognition, natural-language interaction, customized feedback, and iterative user-system adjustment perceived in relation to a task.
Task–technology fit	Task–technology fit	The perceived correspondence between AI functionality and the requirements, workflow, and context of a manufacturing innovation task.
Organizational embedding of AI	Organizational embedding of AI	The iterative incorporation of AI-enabled functions into R&D, production, sales, and interorganizational collaboration through planning, scenario-based pilots, workflow integration, and extension.
Dynamic-capability processes	Need sensing	The capability to monitor market trends and customer needs and to identify potential innovation opportunities.
	Opportunity seizing	The process of generating, evaluating, selecting, and refining innovation solutions.
	Resource reconfiguration	The process of identifying, integrating, and reallocating innovation resources around organizational objectives.
	Innovation resilience	The ability to adapt to and mitigate risks affecting innovation activities, restore activity, and learn from disruptions.
Innovation-network embeddedness	Structural embeddedness	The use of AI-supported information and mapping to identify partners, understand network positions, and coordinate the structure of external innovation relationships.
	Relational embeddedness	The use of AI-supported information processing and communication to support information exchange, coordination, and relationship quality with external innovation partners.
Innovation outcomes	Exploitative innovation	Incremental innovation through refinement of existing products, processes, services, and routines.
	Exploratory innovation	Innovation through experimentation, new knowledge development, emerging technologies, and movement beyond established domains.

Abbreviations: AI: Artificial intelligence; R&D: Research and development.

Table 4. Illustrative end-to-end coding audit trail

Evidence cue	Initial concept	Subcategory	Main category	Process domain
“No standard answer”; “repeated trial and error”	Multi-element parallel processing and iterative workflow	Task complexity	Task characteristics	Antecedent conditions
Prototype validation; frontier-technology experimentation; cross-domain integration	Prototype development and frontier-technology exploration	Exploratory innovation	Innovation outcomes	Innovation outcome

Notes: The examples use translated or paraphrased evidence already represented in Table 2. They illustrate the reported abstraction path but do not constitute a complete passage-level audit log.

2.4.2. Negative evidence and external conceptual review

Accounts of underfit, overfit, implementation burden, workflow incompatibility, and constraints on AI use were retained to challenge a uniformly positive interpretation. However, no formal negative-case search protocol or systematic sampling of failed, abandoned, and non-adopted projects was documented. Two management scholars and two technical directors reviewed category clarity and conceptual coherence, but they did not independently recode the corpus or establish coder reliability. These procedures support the plausibility and clarity of the category structure while leaving alternative mechanisms and boundary conditions open.

2.5. Transparency summary and inferential boundaries

Table 2 links illustrative evidence cues to initial concepts and subcategories; Table 3 links subcategories to seven main categories; Table 4 traces two examples across the complete reported chain; and selective coding integrates the categories into four process domains. Cross-source comparison, retention of discrepant evidence, the reserved-material check, and external conceptual review provide complementary credibility checks. Because the full coded corpus, versioned codebook, source identifiers, coder records, and reflexive memos are unavailable, the analysis remains only partially reproducible. Excerpt or code frequency is not treated as prevalence, effect strength, or statistical importance.

The empirical corpus is exclusively qualitative. The categories are not validated measurement scales, and the 15 participants do not constitute a statistical sample. Accordingly, terms such as “connected,” “associated,” and “proposed relationship” denote interpretive links in coded accounts rather than causal effects, coefficients, model fit, or necessary and sufficient configurations.

3. Results

3.1. Task requirements, AI affordances, and fit

Participants described manufacturing innovation work as complex and interdependent. Complexity arose from diverse information, uncertainty, repeated trial and error, and the need to evaluate multiple alternatives. Interdependence arose from coordination across departments, supply-chain partners, universities, and research organizations. These requirements made the relevance of AI contingent on the task and organizational setting.

Participants described autonomous AI affordances,

including monitoring, modeling, learning, and resource coordination, as well as interactive affordances, including natural-language interaction, customized information, and iterative feedback. Perceived task–technology fit emerged when these functions addressed identifiable business problems, adapted to changing tasks, integrated with existing workflows, and were accepted by users without disproportionate process burdens.

These accounts support a relational interpretation of task–technology fit: neither task complexity nor AI sophistication is sufficient on its own. Participants described underfit and overfit as situations in which functionality was insufficient or excessive relative to task requirements. The cases do not establish an optimal numerical relationship.

3.2. Organizational embedding of AI and innovation outcomes

Organizational embedding of AI was described as a staged process rather than a binary adoption decision. The accounts referred to aligning application plans with digital strategy, conducting scenario-based pilots, evaluating implementation, deepening workflow integration, and extending successful applications to additional activities. Participants described perceived fit as a practical basis for deciding where and how AI affordances could be incorporated into work.

Participants distinguished exploitative innovation from exploratory innovation. Exploitative innovation included product refinement, process improvement, efficiency enhancement, and customization of existing solutions. Exploratory innovation included prototype development, experimentation with emerging technologies, cross-domain integration, and the creation of longer-term technology options. The cases illustrate both types but do not show that AI uniformly improves either one.

The case set does not permit comparison across regions, ownership groups, or industry technology levels because the relevant firm attributes and performance measures were not systematically recorded.

3.3. Internal and external organizational processes

Four internal dynamic-capability processes were identified. Need sensing concerned monitoring customer requirements, market developments, competitors, supply chains, and academic advances. Opportunity seizing concerned generating, evaluating, selecting, and refining innovation alternatives. Resource reconfiguration concerned identifying resource inventories and reallocating personnel, finance, equipment, and information around innovation tasks. Innovation resilience concerned

anticipating risk, responding to disruption, restoring innovation activity, and learning from setbacks. Participants associated AI-supported analysis and coordination with these processes.

The data also identified structural and relational innovation-network embeddedness. Structural embeddedness included mapping collaboration networks, identifying network positions, and matching potential partners. Relational embeddedness included integrating shared resources, extracting key communication from interactions, reducing information asymmetry, protecting sensitive data, and supporting coordination. Together, these categories capture the external processes discussed in the cases.

Dynamic-capability processes and innovation-network embeddedness are interpreted as analytically distinct and potentially complementary. The cases do not rank their relative importance or establish how they interact.

3.4. Evidence synthesis across categories and sources

The coded material converged around three recurring process links. First, accounts of innovation problems with “no standard answer,” repeated trial and error, and cross-departmental and interorganizational coordination grounded in task complexity and interdependence. Perceived task–technology fit arose where autonomous or interactive AI functions addressed identifiable business problems and could be integrated into workflows. Second, organizational embedding of AI involved planning, scenario-based pilots, evaluation, deeper workflow integration, and extension beyond a single adoption event. Third, participants related embedded AI use to need sensing, opportunity seizing, resource reconfiguration, innovation resilience, network mapping, partner matching, and privacy-conscious information exchange. Outcome examples distinguished product and process refinement from prototype development, emerging-technology experimentation, and cross-domain exploration.

Interviews supplied most process descriptions. Field observations and documentary materials contextualized reported applications and enabled comparison across source types; they did not provide independent measures of capability change or innovation performance. Triangulation increased the coherence of the interpretation but did not establish temporal ordering or outcome magnitude.

The evidentiary strength differs across the proposed framework. The coding tables directly support the presence of task, affordance, organizational-embedding, capability-process, network-embeddedness, and outcome categories.

The links among them are interpretive syntheses of participants’ accounts rather than observed transitions tracked over time. Accounts of misfit, process burden, and implementation constraints qualify a one-directional success narrative, while limited coverage of failed or abandoned initiatives restricts negative-case comparison. The framework should therefore be read as a provisional organization of the available evidence.

3.5. Integrated qualitative framework

Taken together, the categories form a qualitative process framework in which task requirements and AI affordances inform perceived task–technology fit; perceived fit is related in participants’ accounts to organizational embedding of AI; and embedded AI use is associated with dynamic-capability processes and innovation-network embeddedness, which are in turn linked to exploitative and exploratory innovation.

The framework’s arrows summarize interpretive associations in the coded accounts; they do not denote estimated causal or quantitative effects. The framework does not imply that every case progressed through every stage, that stages followed a fixed order, or that internal and external processes were equally important. The materials do not support case-by-case pathway comparison or show whether a missing stage precluded an innovation outcome.

4. Discussion

4.1. Interpretation of the qualitative findings

The case material supports an interpretive framework for organizing how participants related perceived task–technology fit, organizational embedding of AI, dynamic-capability processes, innovation-network embeddedness, and differentiated innovation outcomes. The analytical ordering presents these categories without asserting a fixed sequence or outcome magnitude.

International research has examined innovators’ perceptions and implementation preferences, firm-level associations between AI and innovation, automation versus augmentation, ethical adoption, and the organizational appropriation of AI tools (Felicetti *et al.*, 2024; Füller *et al.*, 2022; Johnson *et al.*, 2022; Rammer *et al.*, 2022; Rana *et al.*, 2024). The present study contributes qualitative implementation details from available manufacturing cases rather than a competing effect estimate.

4.2. Task–technology fit and organizational embedding

Task–technology fit research establishes the importance of correspondence between task requirements and technological functionality. The case accounts add a

narrower implementation observation: participants treated fit as provisional and revisited it through pilots, workflow adjustment, and user interaction. Organizational embedding therefore serves as a conceptual bridge between perceived fit and continued organizational use.

4.3. Dynamic capabilities and ambidextrous innovation

Dynamic-capability theory identifies sensing, opportunity seizing, and resource reconfiguration, whereas ambidexterity research distinguishes exploitation from exploration. The cases do not add a new capability dimension or resolve the tension between these innovation orientations. Instead, they show how participants placed AI-supported information and coordination within established dynamic-capability processes and associated different activities with exploitative or exploratory innovation.

4.4. Interorganizational network embeddedness

Network research distinguishes structural position from the quality of particular relationships. The case accounts provide implementation examples—partner search, network mapping, information exchange, and coordination—through which participants related AI use to innovation-network embeddedness. They do not demonstrate that AI creates trust or that greater embeddedness is uniformly beneficial.

4.5. Theoretical implications and evidentiary scope

The framework distinguishes perceived task–technology fit from organizational embedding: fit concerns the relevance of AI functionality to task requirements, whereas embedding concerns its iterative incorporation into strategy, pilots, and workflows (Goodhue & Thompson, 1995; Volkoff & Strong, 2013). AI is treated as an input to focal-firm sensing, opportunity seizing, and resource reconfiguration, not as a substitute for them (Teece, 2007; Winter, 2003). AI-supported partner search and information coordination remain interorganizational processes, and exploitative and exploratory innovation remain distinct outcome types. The contribution is cross-level construct alignment within a bounded qualitative framework.

4.6. Managerial implications and implementation challenges

Managers can begin with a bounded task rather than an enterprise-wide claim about AI value. Before selecting a tool, the responsible team should document the current workflow, the information and coordination problem, decision rights, required data, recurring exceptions,

and points at which human judgment must be retained. AI affordances can then be assessed against these requirements. If the problem cannot be specified, the data are unsuitable, or accountability cannot be assigned, wider deployment should be deferred.

A pilot should have a named process owner, a technical owner, and participating frontline users. Evaluation can record performance on representative cases, error and exception patterns, human overrides, rework, workflow disruption, explanation needs, and resources required for legacy-system integration. Both favorable and unfavorable cases should be retained. Expansion should follow only when the organization can explain what the application supports, where it fails, who intervenes, and what additional burden it creates. These are practical implementation checks, not study-derived thresholds.

External collaboration requires a separate governance step. Before exchanging data or AI-supported recommendations with partners, firms should agree on access rights, data provenance, confidentiality, intellectual property, cybersecurity responsibilities, error escalation, and human review. Managers should consider exploitative improvement and exploratory experimentation separately because they may require different time horizons, risk tolerances, and resource commitments. The framework can structure these discussions but does not prescribe a funding decision or guarantee an innovation outcome.

4.7. Policy implications

The policy implications are necessarily cautious because the study does not evaluate a specific policy intervention. The framework nevertheless suggests that public support for manufacturing AI should address organizational implementation and technology acquisition. Task-oriented demonstration projects, access to implementation expertise, workforce capability development, interoperability and data-governance guidance, shared testing infrastructure, and platforms for privacy-conscious interorganizational collaboration may help firms examine task–technology fit and organizational embedding before large-scale deployment. These are framework-informed directions for policy design, not estimated policy effects.

5. Parsimonious qualitative process framework

The framework reduces the coded material to one central ordering: task–AI alignment, organizational embedding of AI, analytically distinct internal and external processes, and differentiated innovation outcomes. This ordering is a communication device for the qualitative interpretation, not a fixed temporal pathway.

5.1. Framework structure

5.1.1. Antecedent and fit layer

Task complexity and task interdependence represent task requirements, while autonomous and interactive AI affordances represent perceived possibilities for action. Their correspondence informs perceived task–technology fit. Task–technology fit is treated as a relational and provisional judgment, rather than a fixed property of either the task or the technology.

5.1.2. Organizational embedding layer

Participants described perceived fit as informing scenario selection, pilot testing, workflow incorporation, and the extension of AI applications. Deployment alone is not treated as effective organizational use.

5.1.3. Internal and external process layer

Embedded AI use is associated with dynamic-capability processes and innovation-network embeddedness in the coded accounts. The internal process comprises need sensing, opportunity seizing, resource reconfiguration, and inductively observed innovation resilience. The external process comprises structural and relational embeddedness.

5.1.4. Innovation outcome layer

The framework distinguishes exploitative innovation within established domains from exploratory innovation beyond them.

5.1.5. Interpretive status

The framework is a provisional qualitative interpretation; its arrows indicate interpretive associations, not causal or quantitative effects (Figure 2).

5.1.6. Boundary conditions and future validation

Environmental dynamism, digital culture, region, ownership, industry technology intensity, and project maturity are potential conditions for future comparative or quantitative research.

5.2. Transferability, scope conditions, and non-applicability

The framework supports analytical rather than statistical transferability. Transferability is most plausible in manufacturing-related settings where AI is applied to innovation tasks involving uncertainty, information processing, workflow integration, or coordination across organizational boundaries. It depends on the similarity between a new setting and the processes represented in these cases; it should not be inferred from the number of organizations or participants. The framework does not

establish that the same sequence or relative emphasis will occur across countries, firm sizes, ownership structures, industries, or levels of AI maturity.

The framework is not intended for individual use of general-purpose AI, technical-accuracy benchmarking, legal-compliance assessment, direct return-on-investment estimation, or population-level performance prediction. Its explanatory value may be limited where AI is not embedded in organizational workflows, innovation is not an intended outcome, external collaboration is immaterial, or routine tasks can be adequately supported without AI. These are conceptual scope limits rather than empirically established failure conditions, because the study did not systematically sample counterexamples, failed initiatives, or non-adopters.

5.3. Interpretive boundaries

In summary, the framework distinguishes perceived task–technology fit from organizational embedding, dynamic-capability processes from innovation-network embeddedness, and exploitative from exploratory innovation. It should be interpreted as a context-bound analytical guide, not as an implementation algorithm or a forecast of outcome magnitude.

6. Conclusion

This qualitative multiple-case study organizes interviews, observations, and documentary material into a provisional analytical framework. The cases contain recurring accounts of task–technology fit, organizational embedding of AI, dynamic-capability processes, innovation-network embeddedness, and exploitative or exploratory innovation. The contribution lies in keeping these theoretical elements and levels of analysis distinct while showing how participants related them in the available settings. The framework is a basis for comparison and future research, not a population-level explanation.

6.1. Limitations

This study has several limitations. First, the 5 organizations and 15 participants form a small, analytically selected sample and cannot represent Chinese manufacturing firms. Firm size, ownership, region, technology intensity, and AI maturity were not systematically reported, limiting structured cross-case or subgroup comparison. Second, the evidence relies substantially on retrospective accounts from managers and technical personnel and may be affected by respondent, social-desirability, favorable-case, and survivorship biases. Third, project-level accounts and organization-level interpretations are not always clearly separated, and the data do not support aggregation into

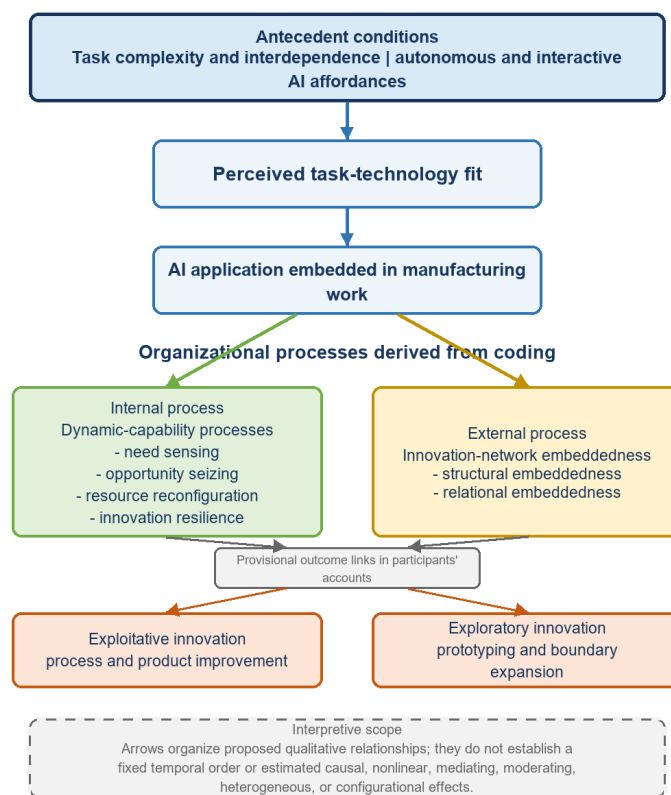


Figure 2. Parsimonious qualitative process framework of artificial intelligence (AI) application and innovation outcomes. Boxes represent categories derived from the coding analysis; arrows depict interpretive associations rather than estimated causal or quantitative effects.

firm-level performance measures. Fourth, the record does not establish independent coding, coding rounds, formal reconciliation, software use, inter-coder agreement, a complete versioned codebook, or passage-level source identifiers. The transparent coding chain, illustrative audit trail, cross-source comparison, negative evidence, reserved-material check, and external conceptual review are partial credibility safeguards, not substitutes for independent recoding or a complete audit archive. Finally, the qualitative design cannot resolve measurement validity for quantitative constructs, endogeneity, reverse causality, or causal identification.

In addition, the case material provides limited coverage of failed, abandoned, or non-adopted AI initiatives and does not systematically include frontline employees, customers, or other external stakeholders. The technical quality, representativeness, and explainability of the AI systems themselves were not independently evaluated. These omissions constrain negative-case comparison and may favor accounts from visible or continuing implementation efforts.

The study therefore claims only internal category

sufficiency within the available corpus. It does not claim iterative theoretical sampling, theoretical saturation, or exhaustion of alternative mechanisms across firms, projects, industries, or implementation outcomes.

6.2. Future research

Future qualitative research should expand the sample to include failed, discontinued, and non-adopted AI initiatives as well as firms that differ in size, ownership, region, industry, and AI maturity. Longitudinal observation could distinguish initial adoption expectations from later workflow integration, dynamic-capability processes, innovation-network embeddedness, and innovation outcomes. Future studies should prospectively document case and participant selection, any theoretical-sampling decisions, changes prompted by emerging categories, and the basis for stopping or saturation claims. They should preserve case and source identifiers, the unit of coding, a versioned codebook, decision and reflexive memos, coder roles, software where used, independent coding or calibration procedures where appropriate, disagreement resolution, negative-case searches, and an end-to-end audit trail. These records would permit readers to distinguish

conceptual credibility from inter-coder reliability and to evaluate both on their own terms.

Future multi-source research should measure technical conditions rather than infer them from adoption. Operational AI may be constrained by sensors, computational resources, cost, and deployment context (Mittal *et al.*, 2023), while unrepresentative training data may undermine validity and subgroup transferability (Ruga *et al.*, 2025). Manufacturing studies should therefore document data provenance and representativeness, technical-performance variation across use settings, explanation and human-oversight requirements, legacy-system integration, and the consequences of error. These technical measures should be connected to, but kept conceptually distinct from, task–technology fit and organizational process constructs.

Any future quantitative evaluation of the framework would require a new sampling design, numerical indicators, an appropriate unit of analysis, and independently developed and validated measures. It would be a separate study, not a quantitative model retrofitted to the present interviews and inductive categories.

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Conflict of interest

Li Fu is an employee of Jiangxi Qiangyu New Energy Co., Ltd., and Xinguo Jiang is an employee of Beijing Taisheng Tongying Technology Co., Ltd.; however, they were not involved in any activities that could constitute a conflict of interest in relation to this study. The authors declare that they have no competing interests.

Author contributions

Conceptualization: Zhiping Jiang

Investigation: Li Fu

Methodology: Xinguo Jiang

Validation: Xinguo Jiang

Writing–original draft: Li Fu

Writing–review & editing: Zhiping Jiang

Ethics approval and consent to participate

Ethics approval was not applicable to this study. All 15 interviewees provided written informed consent to participate before the interviews.

Consent for publication

No identifiable personal information or participant images are included in the manuscript. All participants authorized publication of the anonymized interview material included in the manuscript.

Availability of data

The interview, observation, and organizational materials are not publicly available because they may contain confidential organizational or participant information. Appropriately de-identified supporting materials are available from the corresponding author upon reasonable request, subject to ethical and confidentiality restrictions.

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