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Drivers of innovation in China's AI industry: A systematic review

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Abstract: This systematic review summarizes firm-level evidence on factors influencing innovation performance in China's AI industry. A PRISMA-style search in Web of Science and Scopus identified 38 empirical studies. Innovation outcomes are mainly measured with patents (n=15) and scales or indices (n=10). Other outcomes include green innovation (n=3), product or new-product outcomes (n=2), and mixed or other outcomes (n=8). Across studies, AI adoption and related digital inputs rarely show apparent direct effects on innovation. Most evidence supports an indirect path through capability building. Key factors are organizational learning, knowledge management, human capital, and social capital. Many studies test these factors as mediators, often through an innovation-capability layer. Effects also depend on China-specific conditions, including major AI hubs and regional gaps, policy intensity and design, capital cycles and platform ecosystems, and limits in talent, compute, and data quality. Based on these findings, the review proposes a testable framework and identifies gaps in measurement, research design, and multi-level linkage.
Keywords: *Artificial intelligence industry, China, Innovation capability, Innovation performance, Knowledge management. Systematic review.*

1. Introduction

The rapid development of algorithms, computing power, and massive data has shifted artificial intelligence (AI) from a general-purpose enabling technology to a more defined, autonomous industrial sector with distinct boundaries and a layered value chain. The AI industry now operates as an ecosystem encompassing three layers: infrastructure (computers and chips), core technologies (algorithms and models), and application solutions. Firms in this ecosystem are not only technology adopters but also important producers of new technologies [1]. Value creation in this knowledge-intensive sector hinges on high R&D intensity and rapid iteration and relies on combining, integrating, and recombining heterogeneous knowledge into saleable outputs [2]. China's AI industry has ascended from the early catch-up stage to a stage of scaled, increasingly institutionalized development, giving rise to multi-layered firm populations and specialized, sophisticated SRDI enterprises [3].

China's AI industry has grown rapidly in size and policy significance [4]. Recent forecasts suggest that the global AI market could increase from around $189 billion in 2023 to $4.8 trillion by 2033. China is expected to feature prominently in both adoption and innovation [5, 6]. The Chinese AI market alone is forecast to reach about $46.53 billion in revenue by 2025 and to account for most of the global growth by 2030. Other forecasts estimate that China's core AI industry could be worth around $140 billion by 2030. The indirect economic impact could be much larger once spillovers to related sectors are included [7].

In this environment, innovation performance is vital to firm survival and growth. It comprises not only patents but also product-market outcomes and value capture. It also includes disruptive and

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ambidextrous innovation, marked by a balance between exploration and exploitation [8, 9]. These demands grow because AI technologies are uncertain and complex. They also increase because firms face stronger pressures for sustainability and long-term innovation amid rapid technological change [10, 11].

Despite rapid growth in observable innovation outputs, innovation performance in China's AI industry is uneven. Aggregate indicators show intensive innovation efforts. China's AI-related patent filings increased from 59,054 in 2019 to 188,757 in 2024, accounting for about 70% of global AI patents [12]. In 2024 alone, China filed 300,510 AI-related patents, compared with 67,773 in the United States [13]. However, high input and high output volumes do not guarantee high-quality firm-level innovation performance. This risk is higher in policy-intensive environments, where incentives may push firms toward quantity-oriented strategies [14].

China is also an analytically rich setting. Policy intensity, ecosystem formation, and spatial heterogeneity jointly shape innovation trajectories of AI firms. Policy configurations can affect both the direction and the quality orientation of innovation [14]. Targeted talent policies can reshape human-capital structures, influence intelligent transformation investments, and impact downstream innovation outcomes [15]. China-specific institutional logics may further condition innovation performance. For example, according to Yao and Xu [16], political connections can interact with corporate social responsibility in ways that differ from Western settings. Resource environments also differ across countries. Comparative evidence from Jang and Ma [17] shows that private AI investment in the United States reached $109.1 billion in 2024, nearly twelve times China's $9.3 billion. This gap implies different resource constraints and capital-market structures for Chinese AI firms [18].

Although research on AI and innovation is growing, evidence on *what determines AI firms' innovation performance* is still fragmented. Different studies emphasize different drivers, such as organizational learning and absorptive processes [19], knowledge management and sharing [20], human-capital upgrading and labor-structure channels [21], and relational or network advantages in innovation ecosystems [1]. At the same time, innovation performance is measured inconsistently. This limits comparability across studies and weakens cumulative inference.

To address these gaps, this study conducts a systematic review of empirical research on determinants of firm-level innovation performance in China's AI industry [19, 22]. The review focuses on the *industry–firm interface*. It examines AI enterprises (or AI-intensive firms in an AI-industry context) and synthesizes organizational and capability-based explanations, rather than technical model performance or purely macro indicators. The review asks: which internal capabilities and external resources shape innovation performance in Chinese AI firms, and through what mechanisms and boundary conditions?

This review makes three contributions. First, it consolidates dispersed evidence using comparable constructs and outcome families. Second, it proposes an integrative mechanism account that links organizational learning, knowledge management, human capital, and social/relational resources to innovation performance through innovation capability, while making China-specific boundary conditions explicit. Third, it translates recurring limitations into a focused research agenda that fits AI industry dynamics and the post–generative AI context.

These contributions require a systematic review because this literature uses fragmented constructs and inconsistent outcome measures. We therefore align measures, compare findings across outcome families, and synthesize mechanisms and boundary conditions on an everyday basis.

2. Methods

To reduce selection bias and improve cumulative inference in this fragmented literature, we conducted a systematic review of firm-level studies on innovation performance in China's artificial intelligence (AI) industry. We followed PRISMA 2020 reporting guidance and used a predefined screening workflow with explicit eligibility criteria to enhance transparency and replicability [23, 24].

2.1. Data Sources and Search Strategies

Two bibliographic databases were used: Web of Science Core Collection (WoS) as the primary source and Scopus as a supplementary source to mitigate database-specific indexing differences and reduce the risk of omissions. Search strings were designed to maximize recall by combining three concept blocks: (i) AI-related terms, (ii) innovation performance/outcome terms, and (iii) China context terms. Searches were restricted to English-language journal articles and the publication window 2010–2026. The overall search strategy, including search dates, fields, filters, and initial retrieval counts, is summarized in Table 1.

Table 1.
Data Sources and Search Strategies.

Item	Specification
Review type	Systematic review with PRISMA-style screening
Primary database	Web of Science Core Collection (WoS)
WoS search date	2026-01-26
WoS interface/field	Advanced Search; Topic (TS)
WoS publication window	2010–2026
WoS filters	Language: English; Document type: Article
WoS search string (final)	TS= (("artificial intelligence" OR AI OR "AI industry" OR "artificial intelligence industry") AND ("innovation performance" OR "innovative performance" OR "innovation outcome*" OR "innovation output*" OR "new product*" OR patent*) AND (China OR Chinese))
WoS records identified (N0)	115
Supplementary database	Scopus
Scopus search date	2026-02-08
Scopus field	TITLE-ABS-KEY
Scopus publication window	2010–2026 (PUBYEAR > 2009 AND PUBYEAR < 2027)
Scopus filters	Language: English; Source type: Journals; Document type: Article
Scopus search string (final)	TITLE-ABS-KEY ((“artificial intelligence” OR AI OR “AI industry” OR “artificial intelligence industry”) AND (“innovation performance” OR “innovative performance” OR “innovation outcome*” OR “innovation output*” OR “new product*” OR patent*) AND (China OR Chinese)) AND PUBYEAR > 2009 AND PUBYEAR < 2027
Scopus records identified (N0)	493
Cross-database deduplication	Scopus records were cross-checked against the WoS set using DOI/title/author/year; duplicates were removed prior to screening.
Final included studies	(WoS) + 5 (Scopus) = 38

2.1.1. Primary Database (WoS)

The WoS search was performed on 2026-01-26 using Advanced Search in the Topic (TS) field:

TS= ("artificial intelligence" OR AI OR "AI industry" OR "artificial intelligence industry") AND ("innovation performance" OR "innovative performance" OR "innovation outcome" OR "innovation output" OR "new product" OR "patent") AND (China OR Chinese)

2.1.2. Supplementary Database (Scopus)

The Scopus search was performed on 2026-02-08 in *TITLE-ABS-KEY* with an equivalent query and the publication-year constraint:

TITLE-ABS-KEY ("artificial intelligence" OR AI OR "AI industry" OR "artificial intelligence industry")

AND ("innovation performance" OR "innovative performance" OR "innovation outcome" OR "innovation output" OR "new product" OR "patent") AND ("China" OR "Chinese") AND PUBYEAR > 2009 AND PUBYEAR < 2027

2.1.3. Cross-Database Deduplication

Records retrieved from Scopus were cross-checked against the WoS set using DOI/title/author/year to remove cross-database duplicates prior to screening. Retracted records identified during the workflow were removed before screening and documented in the PRISMA counts.

2.2. Eligibility Criteria

Eligibility criteria were defined a priori (Table 2). Studies were included in the core evidence set if they: (i) were peer-reviewed journal articles written in English; (ii) were explicitly situated in the Chinese context; (iii) addressed AI enterprises or the AI industry context; (iv) adopted a firm-/organizational-level perspective; and (v) examined innovation performance or closely related innovation outcomes as the focal outcome variable.

To improve interpretability without diluting the core firm-level synthesis, macro- or regional-level studies relevant to China's AI innovation environment were retained as a context set to support background interpretation and the discussion of boundary conditions. However, they were excluded from the firm-level evidence synthesis. This separation was applied consistently during screening and coding.

Table 2.
Inclusion and Exclusion Criteria for Core and Context Evidence Sets.

Criterion	**Core set (included for complete synthesis)**	**Context set (included for background/context only)**	**Exclusion**
Publication type	Peer-reviewed journal articles	Peer-reviewed journal articles	Conference papers, book chapters, dissertations, reports, editorials
Language	English	English	Non-English publications
Geographic scope	China / Chinese context (sample, data, or setting explicitly China-based)	China / Chinese context (explicit)	Non-China context or unclear geographic scope
Industry relevance	AI industry / AI enterprises / AI-intensive firms (AI-related products, services, platforms, or core AI capability development)	AI industry development in China (industry/region/ecosystem context relevant to the AI sector)	Unrelated industries or generic digital transformation without AI industry relevance
Level of analysis	Firm-/organizational-level evidence (AI enterprise as the unit or primary analytical focus)	Macro/meso-level only (industry, region, city, national) *may be retained as context.*	Macro/meso-level that is not clearly connected to the AI industry innovation context, or lacks relevance to innovation outcomes
Outcome focus	Innovation performance/innovation outcomes (e.g., product/process innovation, patents, new product success, commercialization outcomes, validated innovation scales)	Innovation outcomes at industry/region level (e.g., regional innovation output in AI sector, AI ecosystem innovation indicators)	No innovation outcome variable; focuses only on adoption/attitudes, technical performance, or general firm performance without an innovation component

Criterion	Core set (included for complete synthesis)	Context set (included for background/context only)	Exclusion
Explanatory focus	Examines determinants/mechanisms (organizational, human, relational, capability-related) linked to innovation outcomes	Provides contextual drivers or constraints (policy intensity, investment environment, ecosystem maturity) relevant to interpreting firm-level innovation	Purely descriptive without drivers/mechanisms; purely technical/algorithmic studies with no organizational/managerial analysis
Methodological scope	Empirical (quant/qual/mixed) or well-grounded conceptual papers that inform determinants of firm-level innovation performance	Empirical or conceptual work informing the macro/meso AI innovation context in China	Insufficient methodological detail or not addressing determinants/context

2.3. Screening and Selection Process

The screening followed a PRISMA 2020-style workflow (Figure 1) [23] with complete stage-by-stage counts reported in Table 3. For the WoS search, 115 records were identified. After removing one retracted record, 114 records were screened by title and abstract; 34 records were excluded at this stage, leaving 80 reports sought for retrieval. Full texts were successfully obtained for 76 articles (four reports were not retrievable) and assessed for eligibility. At the full-text stage, 43 articles were excluded for documented reasons (EX-F1–EX-F5), yielding 33 included studies from WoS.

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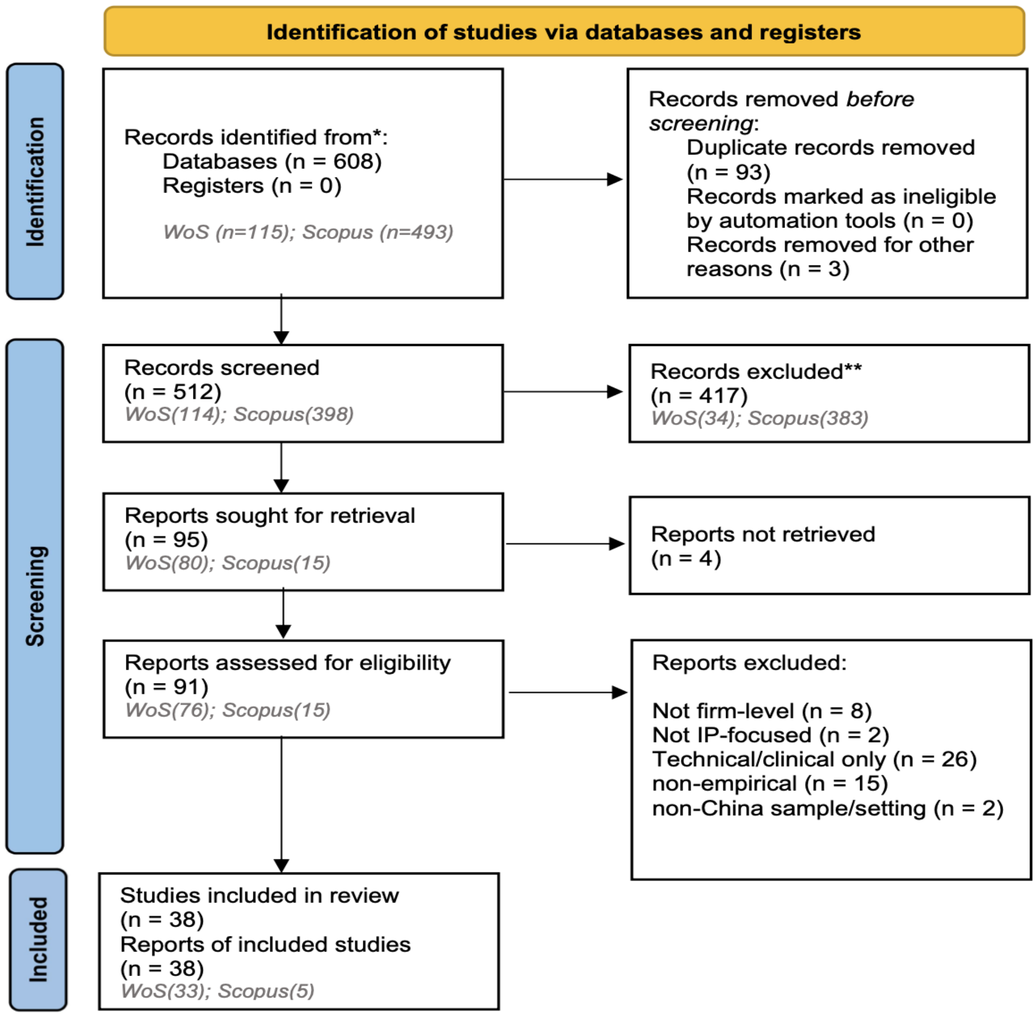

Figure 1.
PRISMA Flow Diagram for Study Selection.

For the supplementary Scopus search, 493 records were identified. After removing two retracted records and performing cross-database deduplication against the WoS set, 398 records were screened by title and abstract; 383 records were excluded at this stage, leaving 15 reports assessed at full text. Of these, 10 reports were excluded for documented reasons, yielding five additional eligible studies. Overall, the final core evidence base comprised 38 included studies (33 from WoS and five from Scopus).

2.4. Full-Text Exclusion Reasons (Auditability)

Each excluded full-text report was assigned one primary exclusion reason (EX-F1–EX-F5) to avoid double-counting. Reasons were defined as: EX-F1 (not firm-/organizational-level); EX-F2 (innovation performance not a focal outcome variable); EX-F3 (purely technical/algorithmic or clinical scope without organizational analysis); EX-F4 (review/policy/non-empirical or otherwise not eligible for determinant synthesis); and EX-F5 (non-China context). The distribution of exclusion reasons is reported in Table 3.

Table 3.
PRISMA Counts Across Databases.

Stage	WoS	Scopus
Records identified	115	493
Retracted removed	1	2
After duplicates removed	114	398
Retained after title/abstract screening (reports sought)	80	15
Full-text assessed for eligibility	76	15
Full-text excluded (EX-F1)	7	1
Full-text excluded (EX-F2)	2	0
Full-text excluded (EX-F3)	21	5
Full-text excluded (EX-F4)	13	2
Full-text excluded (EX-F5)	0	2
Studies included	33	5

2.5. Data Extraction and Synthesis

Data were extracted from each included study using a structured coding scheme (Table 4). Extracted fields included bibliographic information, study context, unit of analysis, research design, theoretical lens, key constructs, operationalization, innovation performance measures, and the main findings (including effect direction and reported mechanisms). Given heterogeneity in constructs, operationalization, and outcome measures, a qualitative thematic (narrative) synthesis was adopted rather than a statistical meta-analysis [25, 26]. Studies were grouped into thematic categories aligned with organizational and capability-related determinants of innovation performance in AI enterprises (e.g., organizational learning, knowledge management, human capital, social capital, and innovation capability). The synthesis focused on identifying recurring mechanisms, areas of convergence and divergence, and boundary conditions relevant to the Chinese AI industry context.

Table 4.
Data Extraction Fields and Coding Scheme.

Field	Description/coding guidance
Bibliographic information	Authors; year; journal; DOI; WoS categories; citation count (optional)
Study context	China region (if reported); AI industry segment (e.g., computer vision, NLP, robotics, autonomous driving); firm size/age (if reported)
Unit of analysis	Firm/enterprise; business unit; project; ecosystem actor (record the primary unit)
Research design	Quantitative/qualitative / mixed-method; cross-sectional/longitudinal
Data source	Survey; archival/secondary data; interviews; multi-source (record if multi-informant)
Key constructs	Determinants (e.g., organizational learning, knowledge management, human capital, social capital, innovation capability)
Operationalization	Measurement approach for each key construct (scales, proxies, dimensions)
Innovation performance measure	Product/process innovation; patents; new product success; commercialization outcomes; composite indices
Theoretical lens	RBV/KBV; organizational learning theory; social capital theory; dynamic capabilities; TOE/other (record primary lens)
Main findings	Direction and significance of effects; mediating/moderating mechanisms; boundary conditions
Quality notes (optional)	Sample size; robustness checks; potential bias (e.g., common method bias)
Theme assignment	Assign to 1–3 themes: OL, KM, HC, SC, IC (allow multiple if justified)

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3. Results and Synthesis

To integrate heterogeneous evidence, determinants are organized into five thematic pathways that align with the final SEM construct names (OL, KM, HC, SC, IC, and IP). Figure 2 provides an overview. The subsections then synthesize study-level evidence for each pathway and highlight mechanisms and boundary conditions.

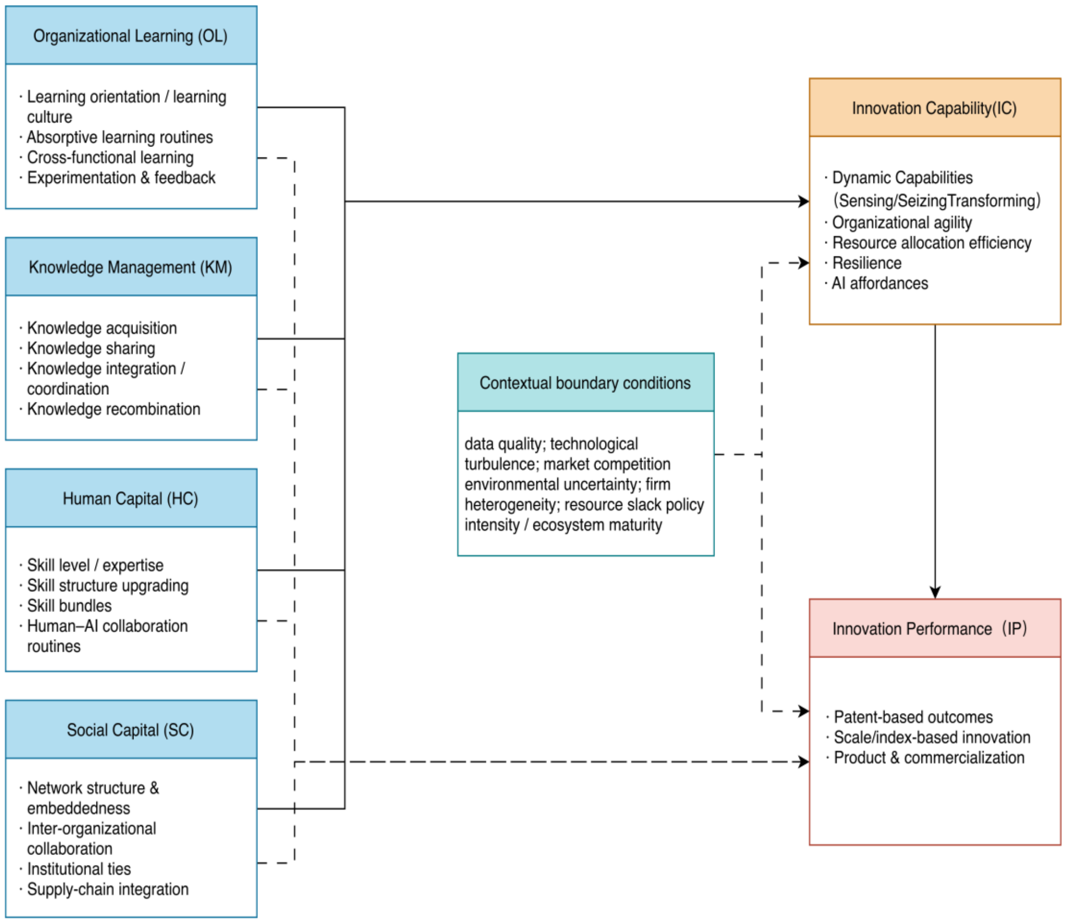

Figure 2.
Integrative Conceptual Framework Aligned to the Final SEM Construct Names (OL–KM–HC–SC–IC–IP).

3.1. Descriptive Overview of the Included Studies

This subsection profiles the final evidence base (N=38) using the structured extraction fields in the *Included_Studies_Data* dataset. Figure 3 summarizes the publication years, methods, data sources, and operationalizations of the dependent variable (DV) for innovation performance.

3.1.1. Publication Trend

The included studies span 2019–2026. Publications are concentrated in 2025 (23 studies, 60.5%), with comparatively sparse coverage in earlier years (Figure 3-Panel A). This concentration indicates that the evidence base is recent and still forming. As a result, many constructs and outcome measures have not yet stabilized across studies.

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3.1.2. Methodological Profile

Regression and econometrics dominate with 19 studies (50.0%). Network and patent-analytics approaches, DID/quasi-experimental designs, and PLS-SEM each account for 4 studies (10.5%). CB-SEM/SEM includes 3 studies (7.9%), and fsQCA appears in 1 study (2.6%). The remaining 3 studies (7.9%) cover other methods (Figure 3-Panel B). Overall, the literature relies more on archival inference and econometric identification than on survey-centric latent-variable modeling.

3.1.3. Data Sources and Units of Analysis

Most studies use archival patent or database sources (25 studies, 65.8%). Survey or questionnaire designs account for 9 studies (23.7%). A smaller set uses archival firm or region panel data without a patent focus (2 studies, 5.3%). Mixed designs (survey + archival) and other or unclear data sources each appear in 1 study (2.6%) (Figure 3-Panel C). The unit of analysis is usually the firm. A small subset uses city-, region-, or province-level panels, which are treated as contextual evidence when interpreting firm-level mechanisms.

3.1.4. Outcome Operationalization (Innovation Performance).

Patent-based innovation output/quality measures are most common, with 15 studies (39.5%), followed by general innovation performance measures at 10 studies (26.3%) (Figure 3-Panel D). Other/heterogeneous outcomes account for 4 studies (10.5%). Green innovation outcomes and non-innovation firm outcomes each account for 3 studies (7.9%). Product/new-product outcomes appear in 2 studies (5.3%), and digital innovation outcomes in 1 study (2.6%).

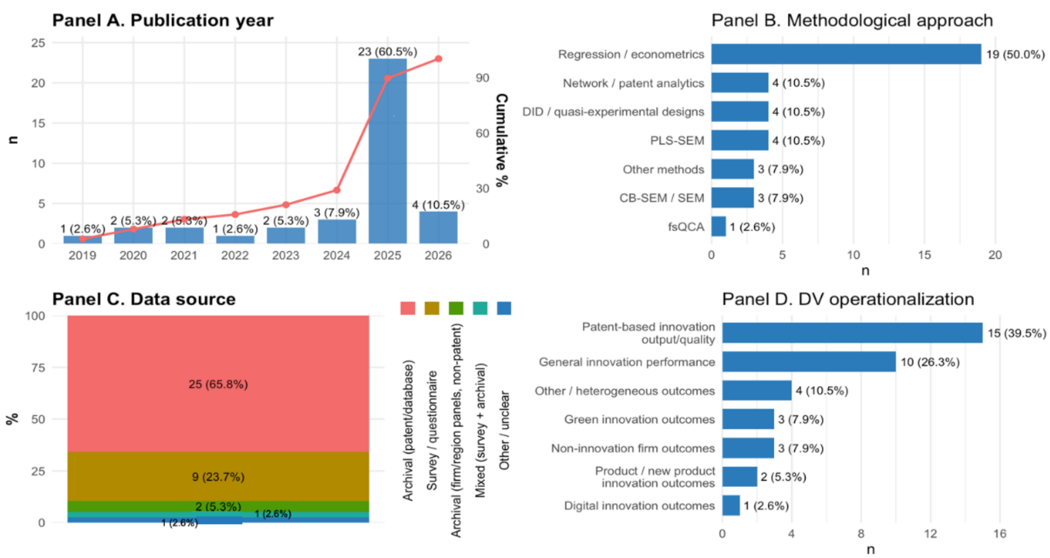

Figure 3.
Descriptive profile of the included studies (N=38): publication year, methods, data sources, and DV operationalizations.

Section 3.2 further refines this DV grouping into outcome families to support mechanism synthesis and avoid pooling non-commensurate measures.

3.2. Innovation Performance Measure

Innovation performance is operationalized in various ways across 38 studies. Outcomes include patent-based indicators, survey-based scales or indices, and several related proxies such as innovation inputs, firm value, and risk or resilience outcomes. To enhance comparability in the thematic synthesis, this subsection defines outcome families and reports their distribution (Table 5).

3.2.1. Patent-Based Innovation Outcomes (Quantity vs. Quality/Impact)

Patent-based outcomes are the most common family (14 studies, 36.8%). Studies distinguish patent quantity (applications, grants, joint patents) from quality or impact (citations, novelty–impact composites, invention-patent ratios, disruptive innovation indices, and generality/impact metrics). This distinction matters because "more patents" does not imply "better innovation" [3, 10, 19]. Some studies embed patent indicators within broader digital-innovation constructs; they are treated here as patent-based because the DV ultimately relies on patent evidence [27].

3.2.2. Technology-Space / Recombination Potential Indicators

Zhou et al. [2] measured outcomes as technological recombination potential derived from technology-space information. This indicator captures the structure and potential of recombination rather than realized output or impact. It is therefore reported separately to avoid conflating knowledge-position measures with outcome measures.

3.2.3. Scale- and Index-Based Innovation Performance Measures

Nine studies (23.7%) used perceptual scales or composite indices, often in survey/SEM settings [9, 11, 28]. These measures can capture commercialization- and process-oriented innovation that may not appear in patent data. However, they are more sensitive to reporting bias and construct non-equivalence across contexts. In this review, these findings are interpreted alongside the research design and data source.

3.2.4. Product/New Product Outcomes

Two studies (5.3%) used market-facing outcomes, such as new product success and related product innovation effectiveness measures [8, 16]. These measures are closer to value realization than patents. Their low frequency indicates that product-market outcomes remain underrepresented in the current evidence base.

3.2.5. Digital and Green Innovation Outcomes Beyond Patents

Cao et al. [29] (2.6%) measured digital innovation without an explicit patent component [29], while Wang and Wu [30] (2.6%) measured green innovation outcomes without patent indicators [30]. These outcomes extend the scope of innovation (digitalization and sustainability), but they are insufficient for a fine-grained synthesis.

3.2.6. Adjacent Outcomes: Innovation Inputs and Downstream Firm Outcomes

Three studies (7.9%) used innovation inputs or effort as the DV (e.g., R&D expenditure/intensity, intelligent investment level, or green R&D efficiency) [15, 31, 32]. These measures inform mechanism tracing but do not capture realized innovation outcomes; they are treated as adjacent evidence. Six studies (15.8%) use downstream firm outcomes (e.g., firm value, idiosyncratic risk, resilience/performance) [33, 34]. These outcomes may reflect consequences of innovation, but they are not direct innovation-performance measures; they are also treated as adjacent outcomes.

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3.2.7. *Macro/meso innovation outcomes (contextual evidence)*

Wang et al. [35] used a city-level innovation outcome. This evidence informs boundary conditions, but it is analytically distinct from firm-level innovation performance and is treated as contextual.

3.2.8. *Implications for synthesis*

Given this outcome diversity, synthesis is qualitative and stratified by outcome family when needed (Table 5). This avoids pooling non-commensurate DVs and supports a more straightforward interpretation of outcome-contingent mechanisms.

Table 5.
Taxonomy of Innovation Performance Measures in the Included Studies (n=38).

Outcome family	Typical operationalizations observed in the evidence base	n	%
Patent-based innovation outcomes	Patent applications/grants; joint patents; citations; novelty–impact composites; invention-patent ratios; disruptive innovation indices; generality/impact metrics (including green patent variants).	14	36.8%
Patent-derived technology-space / recombination indicators	Technological recombination potential and related technology-space measures computed from classification/recombination information	1	2.6%
Scale/index-based innovation performance	Multi-item innovation performance scales (latent constructs); exploratory/exploitative innovation performance; AI-driven innovation performance; composite innovation indices not explicitly patent-based	9	23.7%
Product/new product outcomes	New product success; product innovation effectiveness/performance measures	2	5.3%
Digital innovation outcomes (non-patent)	Digital innovation constructs or indices without explicit patent components	1	2.6%
Green innovation outcomes (non-patent)	Green innovation outcome constructs measured without patent indicators	1	2.6%
Innovation inputs (R&D / investment)	R&D expenditure/intensity; intelligent investment level; green R&D efficiency or related effort-based indicators	3	7.9%
Firm performance/risk outcomes (adjacent)	Firm value (e.g., Tobin's Q), resilience, performance, or idiosyncratic risk (downstream/adjacent rather than innovation outcomes per se)	6	15.8%
Macro/meso innovation outcomes (contextual)	City-level innovation performance indicators are used as contextual or boundary evidence	1	2.6%

3.3. *Thematic Synthesis of Determinants*

This section synthesizes determinants of firm-level innovation capability and/or innovation performance in the Chinese AI industry. Table 6 summarizes study-level evidence for each theme. Figure 4 maps the 38 studies to the synthesis structure (study, thematic block, mechanism, role, outcome family) and shows where evidence is concentrated or sparse. Because constructs and measures vary widely, the synthesis is qualitative and mechanism-oriented. It highlights recurring pathways (IV, mediator/moderator, outcome) and salient boundary conditions.

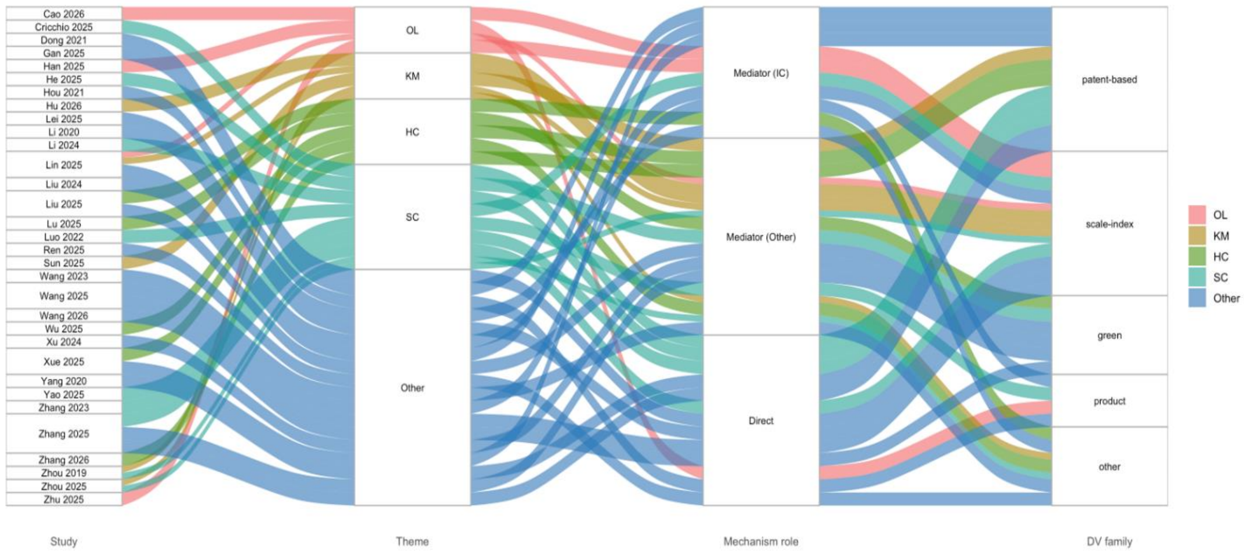

Figure 4.
Sankey Overview of the Included Evidence (N=38): Study → Thematic Block (OL/KM/HC/SC/Other) Mechanism Role → Outcome Family.

3.3.1. Organizational Learning → Innovation Capability/Performance

Across the included studies, organizational learning (including learning capability and absorptive processes) mainly acts as a *conversion condition.* It determines whether AI-related inputs translate into innovation outcomes. Han et al. [19] presented evidence that showed that learning capability strengthens the link between AI technology and innovation performance, suggesting that AI technology does not raise performance on its own. Liu and Li [9] suggested that the main channels are capability-building routines. These include AI use being associated with higher R&D efficiency, labor-structure optimization, and faster experimentation–feedback cycles, which support ambidextrous innovation. At a finer level, Sun et al. [10] noted that learning also appears as knowledge recombination (creation and reuse) that connects AI applications to breakthrough-oriented outcomes. Overall, the evidence points to a conditional effect: AI is more likely to improve innovation when learning routines enable absorption, reallocation, and recombination [9, 10, 19].

In synthesis, the evidence positions organizational learning as (i) a moderator strengthening the AI–innovation relationship, and (ii) a capability-building process manifested through efficiency upgrading and knowledge recombination [9, 10, 19].

3.3.2. Knowledge Management → Innovation Capability/Performance

The included studies suggest that AI affects innovation performance mainly through knowledge management (KM), rather than through a stable direct effect. Lin and Wu [20] presented evidence showing that AI adoption increases explicit and tacit knowledge sharing, but the tacit-sharing pathway is stronger when absorptive capacity is higher. AI use also supports knowledge recombination (creation and reuse), as noted by Sun et al. [10], which links AI applications to sustained, breakthrough-oriented innovation outcomes. For ambidextrous innovation, AI improves the efficiency of knowledge integration and related organizational mechanisms, helping firms pursue both exploitation and exploration simultaneously [9]. Overall, the evidence points to a conditional mechanism: AI is more likely to improve innovation when KM routines enable sharing, recombination, and efficient integration [9, 10, 20].

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KM also has an external-facing dimension in this literature. Heterogeneous networks shape innovation by affecting access to non-redundant knowledge and the efficiency of integration [36]. AI-enabled detection of technological recombination can turn unstructured external knowledge into actionable intelligence [2]. Moreover, He et al. [37] indicated that inter-organizational integration further deepens knowledge exchange, especially tacit knowledge, with downstream implications for innovation performance. Taken together, KM functions as a conversion infrastructure that spans internal sharing and recombination, as well as cross-boundary knowledge access [2, 10, 20, 36, 37].

3.3.3. Human Capital → Innovation Capability/Performance

The included studies suggest that human capital (HC) affects innovation performance mainly through workforce structure and deployment, rather than through headcount alone. This is consistent with Wu et al. [21], who showed that AI adoption improves innovation outcomes via labor-structure upgrading and skill-biased shifts, consistent with capital–skilled complementarity and human–machine collaboration. Policy-induced changes reinforce this channel: talent introduction policies can optimize HC structures, increase investment in intelligent transformation, and improve innovation outcomes [15]. At the firm level, labor-structure optimization links AI application to ambidextrous innovation, while disruptive innovation in specialized SMEs is associated with HC upgrading (e.g., higher shares of highly educated employees) together with higher R&D investment [3, 9]. Overall, the evidence suggests a conditional mechanism: AI is more likely to yield innovation gains when firms have high-skill talent and can deploy that talent in AI-enabled routines [3, 9, 15, 21].

HC also appears as part of broader digital capacity-building and as a micro foundation of learning. Digital human capital investment is considered a foundational component of digital capability [34]. Individual learning capability can also enable collective learning routines and downstream innovation outcomes [19]. Together, these studies place HC at the base of capability formation that supports AI-enabled innovation [19, 34].

3.3.4. Social Capital → Innovation Capability/Performance

In the included studies, social capital is treated as relational resources embedded in collaboration networks, ecosystem coordination, and institutional ties in China's AI context. Network evidence researched by Zhang et al. [36] shows that innovation performance depends on network position and configuration, including centrality, structural holes, and collaboration breadth and depth, and that the optimal pattern differs between IUR and inter-firm networks. Evidence from ecosystems shows that brokerages operate as intermediaries for AI open innovation platforms because broker firms manage knowledge distribution between organizations, leading to higher innovation outcomes and improved organizational stability [1]. The main mechanisms are access and coordination. Structural holes support exploratory innovation by providing non-redundant resources, while centrality supports exploitative innovation through deeper coordination [11]. The strength of ties matters because strong ties enable resource sharing and integration, while AI reduces coordination expenses and enables organizations to work together across different fields and geographic boundaries [38, 39].

Institutional and operational ties provide additional channels. According to Yao and Xu [16], political connections can raise innovation performance through legitimacy and CSR-related mechanisms. Supply-chain integration can deepen knowledge exchange, especially tacit knowledge, with downstream implications for innovation, according to He et al. [37]. Sun et al. [40] also suggest that financing ties also shape innovation trajectories: international venture capital connections influence knowledge linkages and the persistence and direction of search. Overall, the evidence suggests three routes through which social capital affects innovation: network-based knowledge access and coordination, institution-mediated legitimacy and resource channels, and ecosystem-level brokerage [1, 11, 16, 36-40].

3.3.5. Innovation Capability as Mediator (Dynamic Capabilities / Absorptive Capacity Lens)

The studies demonstrate a consistent finding that AI-related strategies and investments lead to innovation performance through capability mediation, serving as the primary mechanism of impact rather than establishing permanent direct effects. The study shows that organizational leaders with entrepreneurial orientation and AI-driven innovation capabilities use sensing and reconfiguration routines as their primary methods to develop resilience and achieve performance success in uncertain conditions [33, 41]. From an absorptive capacity lens, learning and absorption processes determine whether AI knowledge can be identified, assimilated, and exploited to achieve innovation outcomes [19]. Several studies operationalize these mediators in more concrete process terms, including digital technology deployment, resource allocation efficiency, resilience, and AI affordances (mobility, interactivity, autonomy) [27-29]. A boundary condition also emerges: digital deployment shows an inverted-U pattern when implementation outpaces strategic and absorptive alignment, implying diminishing returns without capability fit [29].

Overall, the evidence supports a standard chain: strategic intent or AI investment, intermediate capabilities, and innovation outcomes [19, 27-29, 33, 41]. Effect sizes vary with capability fit and context-specific boundary conditions.

Table 6.
Evidence Matrix for Thematic Synthesis.

Study	Dependent Variable (DV) family	Key mechanisms – Independent Variable (IV) / mediator/moderator
Organizational learning → innovation capability/performance		
Cao et al. [29]	Patent-based outcomes	IV: AI Technology adoption; Med: Not explicitly tested; Mod: Organizational Learning Capability
Liu [42]	Patent-based outcomes	IV: Digital transformation; Med: Organizational agility; Mod: Government subsidies
Cao et al. [29]	Digital innovation (non-patent)	IV: Digital strategy, absorptive capacity; Med: Digital technology deployment; Mod: Environmental dynamism
Zhu [43]	Scale/index-based innovation	IV: AI technology; Med: Dynamic capabilities
Xue et al. [27]	Patent-based outcomes	IV: Digital transformation index; Med: Resource allocation efficiency, organizational resilience; Mod: Information transparency, market competition
Knowledge management → innovation capability/performance		
Lin and Wu [20]	Scale/index-based innovation	IV: AI technology adoption; Med: Explicit knowledge sharing, tacit knowledge sharing; Mod: Absorptive capacity
Sun et al. [10]	Patent-based outcomes	IV: AI application; Med: Knowledge recombination creation, Knowledge recombination reuse; Mod: Market competition intensity
Hu et al. [44]	Scale/index-based innovation	IV: Digital leadership, AI integration capability; Med: Knowledge management effectiveness; Mod: Technological turbulence
Human capital → innovation capability/performance		
Liu and Li [9]	Scale/index-based innovation	IV: AI application; Med: R&D efficiency, Labor structure optimization; Mod: Data resources
Wu et al. [21]	Patent-based outcomes	IV: AI adoption; Med: Labor structure upgrading; Mod: High-tech labor share
Zhang et al. [11]	Patent-based outcomes	IV: AI penetration; Med: Human capital structure, R&D investment; Mod: Region/industry heterogeneity
Wang and Wu [30]	Green innovation (non-patent)	IV: CEO AI orientation; Med: Not explicitly tested; Mod: Human resource slack

Study	Dependent Variable (DV) family	Key mechanisms – Independent Variable (IV) / mediator/moderator
Lei et al. [33]	Other/adjacent outcomes	IV: Entrepreneurship; Med: AI-driven innovation; Mod: Environmental dynamism
Xue et al. [15]	Scale/index-based innovation	IV: Talent introduction policy; Med: Human capital structure; Mod: Ownership, firm size
Liu et al. [41]	Green innovation (non-patent)	IV: Green entrepreneurial leadership; Med: Digital innovation capability; Mod: Environmental regulation
Lu and Li [38]	Green innovation (non-patent)	IV: AI development; Med: Green innovation capability; Mod: Regional heterogeneity
Social capital → innovation capability/performance		
Zhang et al. [11]	Scale/index-based innovation	IV: Heterogeneous networks; Med: Knowledge integration; Mod: Environmental dynamism
Luo [39]	Patent-based outcomes	IV: Enterprise network structure; Med: Resource integration, Knowledge management capability; Mod: Network embeddedness
Cricchio et al. [1]	Patent-based outcomes	IV: Knowledge-brokerage roles; Med: Not explicitly tested; Mod: Technology domain maturity
Zhang et al. [11]	Scale/index-based innovation	IV: Degree centrality, Closeness centrality; Med: Not explicitly tested; Mod: Network diversity
Li et al. [45]	Scale/index-based innovation	IV: Innovation performance, public support; Mod: Social investment, institutional intermediary ties
Li et al. [45]	Scale/index-based innovation	IV: Political connections; Med: Corporate social responsibility; Mod: AI adoption
Zhou and Lan [46]	Innovation inputs (R&D/investment)	IV: Social-capital/network ties; Med: Resource acquisition; Mod: Competitive intensity
Innovation capability as mediator (dynamic capabilities / absorptive capacity lens)		
He et al. [37]	Patent-based outcomes	IV: AI adoption; Med: Internal control quality, Supply chain integration; Mod: Firm ownership, Firm size
Lin et al. [28]	Scale/index-based innovation	IV: AI-adoption intensity; Med: Mobility affordance, Interactivity affordance; Mod: Data quality
Wang et al. [34]	Other/adjacent outcomes	IV: Digitalization; Med: Business model innovation; Mod: Environmental uncertainty
Jianjun et al. [8]	Product/new product outcomes	IV: Artificial intelligence, Non-artificial intelligence; Med: Not explicitly tested; Mod: New product innovativeness.
Yang et al. [47]	Patent-based outcomes	IV: Intelligent manufacturing implementation; Med: Not explicitly tested; Mod: Industry type
Xu et al. [48]	Patent-based outcomes	IV: Intelligent manufacturing adoption; Med: Green technology innovation; Mod: Environmental regulation intensity
Gan [14]	Patent-based outcomes	IV: Patent creation policies, Patent utilization policies; Med: Ambidextrous R&D behavior; Mod: Policy synergy magnitude
Zhang et al. [49]	Scale/index-based innovation	IV: Multi-level institutional support; Med: Organizational capabilities; Mod: Regional heterogeneity
Zhang et al. [31]	Patent-based outcomes	IV: AI innovation and development; Med: AI hardware investment, Liquidity; Mod: Ownership, industry structure
Wang et al. [32]	Scale/index-based innovation	IV: AI adoption; Med: Risk-taking level, Resource allocation efficiency; Mod: Firm heterogeneity
Sun et al. [40]	Other/adjacent outcomes	IV: Frontier AI orientation; Med: Strategic choices; Mod: Institutional constraints
Ren et al. [50]	Other/adjacent outcomes	IV: Artificial intelligence; Med: Information transparency; Mod: Institutional environment

Study	Dependent Variable (DV) family	Key mechanisms – Independent Variable (IV) / mediator/moderator
Dong et al. [51]	Scale/index-based innovation	IV: R&D intensity; Med: Not explicitly tested; Mod: Patent portfolio
Wang et al. [35]	Other/adjacent outcomes	IV: AI policies; Med: Not explicitly tested; Mod: City heterogeneity
[2]	Other/adjacent outcomes	IV: Patent network topology indicators, Emerging technology criteria; Med: Sentiment analysis of technical descriptions; Mod: Expert judgment

The evidence shows four regularities. (i) AI-related inputs affect innovation performance through intermediate capabilities, which function as the primary pathway for their impact. (ii) Learning and KM routines enable absorption, sharing, and recombination, which serve as the immediate channels for knowledge transfer. (iii) HC and SC function as resource bases that enable organizations to complete their operations because HC delivers AI routine skills while SC determines network and ecosystem access and coordination. (iv) The mechanisms combine to form innovation capability, which functions as a direct mediating element of the process. As a result, heterogeneity is expected: effects should vary with capability fit and with ecosystem and institutional conditions.

3.4. Boundary conditions specific to the Chinese AI industry

The Chinese AI industry exhibits systematic boundary conditions, as the evidence supports. Different factors at various levels produce distinct effects on AI-related resources and capabilities, shaping innovation outcomes. The four fourth-order contextual drivers of this study emerge from three specific domains: industrial clusters and spatial heterogeneity; policy intensity and regulation; capital cycles and ecosystem orchestration; and talent, compute, and data quality constraints. The domains of this study should be treated as contextual drivers that moderate research results, rather than as residual controls in studies of firm-level estimates. Table 7 explains these domains using common modeling elements, including networks, platforms, capital, compute, and data quality.

3.4.1. Industrial Clusters and Spatial Heterogeneity

When industrial clustering is stronger and complementary infrastructures are denser, the path from AI-related inputs and capabilities to innovation outcomes is stronger. The mechanism involves better knowledge flow, richer partner access, and lower coordination costs within regional ecosystems, which can amplify mediation through collaboration and capability building [10, 31, 37, 38, 48]. When clustering is weaker or regional bases are thin, the same inputs may yield smaller or more heterogeneous returns because knowledge access and complementary resources are harder to mobilize [38, 48]. In models, spatial clustering can be specified as a moderator of the conversion paths of AI inputs → (KM/IC) and (KM/IC) → innovation performance.

3.4.2. Policy Intensity and Regulation

When policy support is more substantial and continuous (e.g., subsidies, procurement, and a coherent policy mix), the AI–capability–innovation chain is more likely to translate into observable outcomes because incentives and resource buffers support experimentation and scaling [5, 9, 14, 35, 47]. At the same time, when regulatory constraints tighten, especially in data governance, the path from AI adoption to innovation outcomes can weaken or change form, as model development and deployment incur higher compliance costs and narrower feasible data uses [9, 35]. In policy-intensive settings, the direction of the effect can also shift toward quantity-oriented innovation if incentives reward volume more than quality [14]. In models, policy intensity and regulation can moderate both AI inputs →

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capability formation (KM/IC) and capability → outcomes, and can also shift outcomes toward quantity versus quality depending on incentive design.

3.4.3. Capital Cycles and Ecosystem Orchestration

When venture capital is active and investment capital is abundant, Sun et al. [40] found that the path from AI strategies to innovation outcomes can be strengthened, as financing supports risky search and helps retain firms on particular trajectories. When capital is tight, feasible strategies narrow, and the same AI investments may yield weaker payoffs because exploration becomes harder to sustain [40]. When ecosystem orchestration is stronger, for example, through platform-centric coordination and brokerage, the AI–innovation link tends to be stronger because knowledge flows are organized and entry barriers fall [1, 48]. Network structure and tie strength further moderate this process: effects are more potent when networks enable access to non-redundant knowledge and efficient integration, and weaker when integration is costly, or ties are misaligned with the innovation task [36, 39]. In models, capital regimes, and ecosystem orchestration can moderate AI input capability building and the capability-performance link by changing the feasible strategy set and the efficiency of knowledge coordination.

3.4.4. Talent, Compute, and Data-Quality Constraints

When high-skill workers become more available, and organizations develop stronger employee skills, companies achieve stronger business results through AI adoption by integrating AI into their daily operations and creating synergies between their technological assets and employees' abilities [3, 21, 38]. This channel can then receive support from policy-driven talent development, as it creates a new human capital system that enables greater investment in intelligent transformation. When compute resources become limited and data quality decreases, the AI adoption path towards innovation becomes more difficult, as organizations need to handle the intricate processes of developing and testing their models and applications [28]. Consistent with this logic, higher data quality strengthens the innovation payoff of AI adoption intensity [28]. Internal control and supply-chain integration can further bound realization by shaping access to complementary resources and the exchange of tacit knowledge [10, 37]. In models, talent, compute readiness, and data quality can moderate AI adoption → capability deployment and AI adoption intensity → innovation performance, with HC structure sometimes operating as a mediator through workforce upgrading. Table 7 summarizes how these boundary conditions are operationalized across the included studies and provides a compact reference for future model specification and measurement choices.

Table 7.
Boundary Conditions and Contextual Drivers.

Context layer	**How it is operationalized/discussed**	**Typical role in models**	**Representative studies**
Industrial clusters & spatial heterogeneity	Regional comparisons; cluster-based heterogeneity; differences in network density, infrastructure, and local innovation environments	Moderator (AI→KM/IC; KM/IC→IP)	Zhang, et al. [11]; Zhang, et al. [31] and Lu and Li [38]
Policy & regulation	Policy intensity/mix and continuity; subsidies/procurement as resources and signals; data governance and compliance constraints	Moderator (AI→KM/IC; KM/IC→IP); incentive-shift driver	Liu and Li [9], Gan [14], Wang, et al. [35] and Xu, et al. [48]
Capital cycles & investment regimes	Venture-capital selection/retention; funding constraints and follow-on financing; investment-driven search trajectories	Moderator/selection environment	Sun, et al. [40]
Platform ecosystem orchestration & brokerage	Open-innovation platforms; orchestrator/broker roles; ecosystem-level coordination of knowledge flows and complementors	Moderator/coordination mechanism	Cricchio, et al. [1] and Zhang, et al. [11]
Network embeddedness & value-network structure	IUR vs. inter-firm networks; centrality/structural holes; tie strength; resource integration capacity	Moderator (knowledge access/coordination)	Zhang, et al. [36] and Luo [39]
Talent constraints & human-capital structure	Skill share and labor upgrading/polarization; talent-introduction policies shaping HC structure and intelligent transformation investment	Mediator (HC upgrading) and moderator (skill share)	Xue, et al. [15] and Wu, et al. [21]
Compute readiness & digital infrastructure (discussed)	Compute and infrastructure readiness as an enabling condition for AI use, scaling, and experimentation; often discussed as a background constraint	Contextual enabler (often implicit moderator)	Liu and Li [9] and Sun, et al. [40]
Data quality and data-related constraints	Data quality as a moderator of AI-adoption intensity → innovation performance; data access/quality frictions shaping AI affordances and deployment	Moderator (AI intensity→IP)	Lin, et al. [28] and He, et al. [37]

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3.5. Research Gaps and Agenda

Despite a growing body of firm-level evidence on AI-related determinants of innovation outcomes in China, the included studies expose several *systematic* limitations that constrain cumulativeness, comparability, and mechanism-based theory development. Across the evidence base, five recurring gaps are especially salient: (i) non-unified innovation-performance measurement and insufficient modeling of "quality" dimensions; (ii) a design bias toward cross-sectional and single-source data, limiting causal inference and dynamic capability tracing; (iii) concentration at the firm level with limited multi-level linkage to ecosystems/platforms; (iv) under-specified mechanisms and insufficient granularity of "innovation capability"; and (v) a post–Generative AI shift that introduces new strategic variables and constraints (compute, data governance/provenance, model capability, compliance), which existing "AI adoption" measures may not capture [9, 28].

Building on these gaps, the research agenda emphasizes moving from *heterogeneous indicators* to harmonized measurement families (quantity vs. quality), from static associations to longitudinal and quasi-experimental identification strategies, from single-level firm models to ecosystem-linked multi-level mechanisms, and from unitary mediators to decomposed innovation-capability chains aligned with dynamic capabilities and absorptive capacity lenses. Table 8 consolidates these gaps and translates them into prioritized research questions and testable propositions tailored to the Chinese AI industry and the post–GenAI regime.

Table 8.
Research gaps and agenda.

Gap (systematic)	What is missing / why it matters	Future research questions/propositions (examples)
Outcome measurement inconsistency	Innovation performance is measured with non-comparable families; quality dimensions (novelty/impact/commercial success) are under-modeled; and cumulative synthesis is limited.	**RQ1.** How do AI-related capabilities affect *innovation quantity* vs. *innovation quality* differently? **P1.** The effect of AI adoption on innovation performance is stronger for quantity metrics (counts/volume) than for quality-weighted metrics unless mediated by governance and evaluation capability.
Cross-sectional and single-source design bias	Limited causal inference; endogeneity and common-method bias; capability evolution is dynamic but rarely observed	**RQ2.** How do AI-enabled capabilities evolve, and what is the lag structure from capability building to innovation outcomes? **P2.** The AI adoption → innovation performance relationship exhibits delayed effects, mediated by learning and recombination routines, and is observable only in longitudinal designs.
Limited multi-level linkage (firm ↔ ecosystem/platform)	Ecosystem effects (platform rules, cluster conditions, policy mix) are not integrated with firm mechanisms; cross-level interactions are missed	**RQ3.** When do platform/ecosystem conditions amplify or dampen firm-level OL/KM/HC/SC effects? **P3.** Platform dependence positively moderates the effect of social capital on innovation quality but weakens the direct effect of internal resources unless governance capability is high.
Mechanisms under-specified; "innovation capability" not decomposed	Innovation capability is often treated as a single mediator; difficult to interpret what capabilities drive which innovation outcomes	**RQ4.** Do product-, process-, and business-model innovation capabilities constitute distinct mediation pathways in AI-intensive firms? **P4.** AI adoption primarily affects product innovation through model iteration routines, process innovation through integration/control mechanisms, and business-model innovation through data governance and complementarities.
Post–GenAI variables not modeled	Traditional AI adoption measures are too coarse for GenAI; new constraints and governance risks	**RQ5.** How do we compute readiness, data provenance, model capability, and compliance capability jointly condition GenAI-driven innovation performance?

Gap (systematic)	What is missing / why it matters	Future research questions/propositions (examples)
(compute, data, model capability, compliance)	reshape innovation processes.	**P5.** GenAI increases the marginal returns to compliance capability and evaluation/monitoring routines, shifting the dominant mechanism from "adoption" to "governed deployment."
Comparability and construct alignment across studies	Different operationalizations of key mediators/moderators reduce comparability and replication, impeding synthesis and SEM integration.	**RQ6.** Can a standardized construct set and measurement protocol improve cross-study comparability in China's AI context? **P6.** Using a harmonized measurement battery for OL/KM/HC/SC and decomposed innovation capability increases the stability and portability of effect estimates across clusters and industries.

4. Discussion

4.1. Synthesis of the Integrative Framework

Figure 2 synthesizes the included evidence base (N=38) into a capability-centered, testable narrative of innovation performance in China's AI industry. Across studies, AI-related inputs and digital-resource endowments rarely operate as a uniform productivity shock; instead, their innovation payoff is realized primarily through the formation and orchestration of innovation capability (IC) via organizational learning (OL), knowledge management (KM), human capital (HC), and social capital (SC), with effectiveness conditioned by China-specific boundary layers. This transmission logic is consistent with evidence that learning capability strengthens the AI–innovation link [19], and that AI adoption affects innovation outcomes through differentiated knowledge-sharing channels under absorptive-capacity constraints [20]. AI application also enables breakthrough-oriented innovation via knowledge recombination, creation, and reuse [10].

It also aligns with findings that AI-driven capability shifts shape ambidextrous innovation performance through mechanisms of efficiency and resource reallocation Liu and Li [9]. Lin et al. [28] also revealed that AI-related affordances mediate adoption-intensity effects under data-quality constraints. That ecosystem embeddedness governs access to non-redundant complements and innovation returns [1, 11, 36]. Under this view, Chinese policy intensity and design reshape incentives and innovation orientation [14, 35] while spatial clustering, platform orchestration, and supply-chain integration condition the strength of mechanisms and the realization of outcomes [37-40]. Accordingly, Figure 2 encodes falsifiable expectations: AI-related determinants should exhibit heterogeneous effects on innovation performance (IP) to the extent that firms differ in capability formation (IC) and in exposure to contextual constraints such as data quality, governance, and ecosystem dependence [1, 9, 28].

4.2. Theoretical Contributions

Based on the synthesized evidence, the following theoretical propositions summarize the capability-based logic of AI-firm innovation performance. Section 3.5 then translates this logic into agenda propositions (P1–P6) under measurement and design constraints.

TP1 (Capability mediation). AI-related resources and investments improve innovation performance mainly through intermediate capabilities, rather than through stable direct effects [27-29, 33, 41, 50].

TP2 (Organizational learning as a feedback loop). The AI–innovation link is stronger when firms run an AI-specific learning loop that connects data, models, productization, and market feedback [19, 42].

TP3 (KM beyond interpersonal sharing). AI yields higher innovation returns when knowledge management includes data governance and model-asset stewardship, rather than just interpersonal sharing [1, 10, 20].

TP4 (KM and novelty through recombination). AI supports sustained and breakthrough-oriented innovation by increasing knowledge recombination (creation and reuse), enabling the firm to integrate that recombined knowledge into products and processes [10, 20].

TP5 (HC as skill bundles and routines). AI improves innovation outcomes when firms have high-skill talent and collaboration routines that support human–machine complementarity, rather than merely a larger labor force [9, 21, 34].

TP6 (Policy-induced HC shocks). According to Zhang et al. [3], talent policies strengthen AI-related innovation gains by shifting the human capital structure and increasing investment in intelligent transformation.

TP7 (SC as coordination and brokerage capital). Social capital strengthens AI-related innovation by improving network positions and brokerage roles, thereby enhancing access to non-redundant knowledge and reducing coordination costs across ecosystems and platforms [1, 11, 36, 39].

TP8 (Institutional channels in China). In China, institutional ties, according to Yao and Xu [16], such as political connections, can alter the AI–innovation relationship by altering legitimacy and access to CSR-related resources beyond purely market-based network mechanisms.

TP9 (Innovation capability as a portfolio). Innovation capability is best modeled as a portfolio of routines (dynamic capabilities and affordance-enabled deployment) that govern how AI is deployed; without such governance, marginal returns can diminish when deployment outpaces strategic and absorptive alignment [9, 27-29, 33, 50].

Section 3.5 translates these propositions into prioritized research questions and testable agenda propositions, subject to measurement and design constraints.

4.3. Methodological Implications: Operational Guidelines for Future Studies

Future work should treat measurement, identification, and multi-level linkage as primary design choices. This is necessary to improve cumulativeness and causal credibility in a literature with heterogeneous constructs and outcomes.

(1) Measure innovation performance in outcome families. Innovation performance should be reported in harmonized families that separate quantity from quality and commercialization-sensitive outcomes. This separation is important in policy-intensive settings, where incentives can shift firms toward quantity-oriented strategies [1, 8, 10, 14, 38, 47].

(2) Upgrade identification beyond cross-sectional, single-source designs. The dominance of cross-sectional and single-source studies motivates a shift toward panel and quasi-experimental designs. China offers usable instruments for identification, such as policy mix and timing variation, patent-incentive configurations, subsidies and procurement, and targeted talent programs [14, 15, 35, 48].

(3) Model dynamics, lags, and nonlinearity. Capability formation is dynamic and may show diminishing returns. Studies should therefore explicitly model lag structures and dynamic mediation. This is consistent with evidence that deployment intensity can follow an inverted-U pattern when strategic and absorptive alignment are weak [29].

(4) Use multi-source data to reduce common-method bias and improve construct validity. Data strategies should combine archival records with patents, citation networks, hiring and skill traces, supply-chain ties, and collaboration graphs. Such pipelines can reduce common-method bias and enable triangulation for OL, KM, IC, and network-based SC [1, 9, 11, 39].

(5) Build multi-level links from firm mechanisms to ecosystems and platforms. Multi-level models are necessary to connect firm-level capability mechanisms to platform and ecosystem exposures. Brokerage, orchestration, and cluster environments can influence the returns to firm capabilities [1, 36, 38, 40]. Post–GenAI work should also measure compute readiness, data quality, and provenance, model

capability, and compliance, rather than treating them as background conditions, because data quality can govern whether AI functions as an innovation agent [9, 28].

4.4. Practical & Policy Implications

For firm leaders, the evidence implies a simple point: innovation returns come from governed deployment, not from adoption volume. Priority actions include improving data quality and lineage controls, institutionalizing a model-iteration cadence to shorten feedback latency, and building cross-domain transfer routines so that knowledge and models can be reused across scenarios [9, 10, 19, 28]. These actions harden the data–model–product–market learning loop that converts AI inputs into innovation outcomes [10, 19].

For platform and ecosystem orchestrators, open innovation platforms and brokerage roles can lower SMEs' entry barriers by reorganizing knowledge flows and access to complements [1, 11, 36, 39, 40]. Governance matters because coordination can also create lock-in and trajectory dependence. Practical levers include clear interface standards, evaluation protocols, and value/IP allocation rules so that complementors can innovate without dependence on a single focal actor [1, 36, 39, 40].

Policymakers achieve effective results through policy implementation that creates incentives matching their desired outcomes. The patent system should provide financial incentives that reward exceptional work rather than support businesses producing high volumes of low-quality work as measured by patent-related tools Gan [14]. Xu et al. [48] observed that subsidies and procurement processes must be designed to provide resource support while delivering trustworthy market signals. However, they should not create advantages that yield immediate results. Data governance functions as an essential framework that enables organizations to access data while minimizing legal compliance challenges, thus supporting their innovation efforts, according to Liu and Li [9]. The investment in computing and digital infrastructure should be considered a quasi-public good that enables organizations to develop capabilities beyond major industrial centers, given existing regional disparities and clustering patterns [10, 38, 39].

4.5. Limitations

This review presents three specific limitations.

First, research studies use different methods to measure both innovation performance and their related intervention capabilities. The synthesis process is affected by this pattern because it favors constructs that researchers commonly observe, while it leads to an inaccurate assessment of study similarities due to different quality weight allocations. Future work can mitigate this risk by adopting harmonized outcome families and by decomposing measures of quantity, quality, and commercialization [8, 14].

Second, many existing studies rely on cross-sectional or single-source research designs. As a result, they have limited ability to infer causality in the presence of endogeneity and are likely to overestimate the mediation effect due to common-method bias. Future research is encouraged to adopt panel data, leverage quasi-experimental policy shocks, measure constructs using multiple informants, and integrate data from multiple sources [15, 35, 48].

Third, part of the evidence base predates widespread GenAI deployment. The framework may therefore underweight emerging constraints and governance variables, including compute scarcity, data provenance, model capability, and compliance. Future studies should model these constructs explicitly and test whether they shift the relative importance of OL/KM/HC/SC mechanisms and the mediated innovation-capability pathway in the post-GenAI regime [9, 28, 50].

5. Conclusions

This systematic review combines evidence from multiple studies to determine which factors affect innovation performance in research on China's artificial intelligence sector. The researchers selected 38 studies using a PRISMA workflow, with WoS as the primary source and Scopus as an additional resource. The review organizes evidence around (i) how innovation performance is measured, (ii) mechanisms that link AI-related resources and organizational antecedents to innovation outcomes, and (iii) boundary conditions specific to the Chinese AI context. Figure 2 summarizes the integrated mechanism logic, and the review also derives implications for firms, ecosystem orchestrators, and policymakers.

Three conclusions follow from the evidence. First, AI adoption or adoption intensity functions as an enabling input, not a guaranteed driver of innovation outcomes. Innovation gains depend on capability building and complementary assets. Organizational learning, knowledge management, and human capital upgrading shape whether AI inputs translate into innovation, and effect sizes often vary with data quality, institutional conditions, and firm heterogeneity [9, 28, 52]. Put simply, adoption is not the outcome. Conversion capability is.

Second, different methods assess innovation performance because different outcome measures lead to different assessment results. Gan [14] stated that patents remain the dominant proxy, but patent *quantity* alone is risky in policy-intensive settings, where incentives can shift effort toward filing volume rather than substantive advancement. The process of cumulative inference needs outcome portfolios that differentiate between quantity and the measurement of actual quality and value attainment. A practical structure is to distinguish (i) patent quantity versus quality, (ii) commercialization and new-product performance, (iii) process innovation and operational KPIs, and (iv) business-model and ecosystem-value outcomes.

Third, key mechanisms are better described as loop-based rather than one-pass mediation. Several studies model learning, KM, or innovation capability as a single mediator [20, 52]. The synthesis instead points to a reinforced feedback system in AI firms: data quality and governance shape model development; model iteration converts organizational knowledge into product features; and market signals feed back into data collection, labeling, and capability upgrading. This data–model–product–market loop helps explain why learning and KM matter in AI settings, and why governance and operational routines become central under post–generative-AI constraints.

The review contributes in three ways. Conceptually, it consolidates fragmented determinants into an integrative capability framework. Organizational learning, knowledge management, human capital, and social capital act as capability-producing antecedents. Innovation capability is a multi-dimensional mediator that channels AI inputs into innovation outcomes (Figure 2). Methodologically, it links recurrent limitations to a focused agenda on construct alignment, stronger identification, and multi-level designs. Practically, it points to governed deployment as the primary lever: firms need routines that stabilize the learning loop, ecosystems need coordination without lock-in, and policy mixes need incentive compatibility under resource and compliance constraints.

China-specific boundary conditions are not peripheral. Cluster geography, policy intensity and policy mix, capital and platform ecosystems, and constraints in talent, compute, and data governance shape which mechanisms dominate and how significant effects are [1, 14, 28]. Results from one region or policy regime should therefore not be assumed to generalize without explicit modeling of institutional and resource conditions. Table 7 summarizes how these contextual drivers are operationalized in the included studies.

Future research should shift from "AI adoption and innovation performance" associations to mechanism-based tests suitable for the generative-AI era. Data quality, compute constraints, model capability, and compliance should be treated as first-class moderators. Designs should utilize longitudinal data or quasi-experiments around policy shocks and pilots. Multi-level models should

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connect platform and ecosystem conditions to the formation of firm-level capabilities. These steps can transition the literature from merely documenting correlations to explaining when, how, and for whom AI becomes a durable engine of innovation in China's AI industry.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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