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Mapping Artificial Intelligence Research in Strategic Management: A Bibliometric Analysis and Future Research Agenda

Shanning Fu[1], Fei Kang[1]*, Dzhumabek Dzhailov[2]

[1]PhD student, Kyrgyz National University Named after Jusup Balasagyn, Bishkek, Kyrgyzstan, [2]Institute of State and Law, National Academy of Sciences of the Kyrgyz Republic, Bishkek, Kyrgyzstan. *Email: 1035893148@qq.com

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in strategic decision-making, competitive positioning, innovation management, organizational learning, and governance, yet the literature remains fragmented across management, information systems, innovation, and technology-management fields. This study provides a focused bibliometric review of AI research in strategic management. Scopus was used as the primary database, and the query "artificial intelligence" AND "strategic management" was applied to titles, abstracts, and keywords, with restrictions to Business, Management and Accounting, Article and Review document types, and English-language publications. From 126 retrieved records, relevance screening excluded 82 records, leaving 44 publications for analysis. The study examines annual trends, citation patterns, keyword co-occurrence, country distribution, science maps, TCCM synthesis, and a WoS/SSCI sensitivity analysis. Results show slow development before 2018 and marked acceleration after 2023, with 2026 treated as an incomplete year. Themes are shifting from decision support and strategic planning toward generative AI, innovation management, sustainability, organizational capabilities, and governance. By combining bibliometric mapping, TCCM, and cross-database sensitivity analysis, this study offers a knowledge-structure map and future research agenda.

Keywords: Artificial Intelligence, Strategic Management, Bibliometric Analysis, Strategic Decision-Making, Competitive Advantage, Generative AI

JEL Classifications: M10, M15, O32, O33

1. INTRODUCTION

Artificial intelligence has moved from an operational tool to a strategic organizational resource. Firms use AI to interpret competitive environments, evaluate strategic alternatives, allocate managerial attention, design products and services, coordinate supply chains, and support long-term investment decisions. Earlier studies mainly treated AI as an expert system assisting planning (Holloway, 1983; McDonald and Wilson, 1990; Keding, 2021). Current research increasingly examines how generative AI, machine learning, large language models, and human-AI collaborative decision systems participate in strategic management (Akter et al., 2023; Krakowski et al., 2023; Doshi et al., 2025).

The strategic effects of AI are not unambiguously positive. On the one hand, AI can increase information-processing capacity, detect weak market signals, improve scenario analysis, and facilitate organizational learning, thereby potentially strengthening dynamic capabilities and competitive advantage (Liu, 1998; Werle and Laumer, 2022; Mundlos, 2025; Figge et al., 2026; Cristofaro et al., 2025). On the other hand, it may reproduce bias, weaken accountability, narrow managerial attention, and increase organizational dependence on data and technological infrastructure.

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Therefore, the value of AI does not come from technology alone but depends on managerial capabilities, governance arrangements, organizational learning, and the quality of human-AI interaction (Heyder et al., 2023; Booyse and Scheepers, 2024; Štrukelj and Dankova, 2025; Botelho and Wang, 2026; Zhang et al., 2023; Day et al., 2025).

Research at the intersection of AI and strategic management has expanded rapidly but remains dispersed across strategic management, information systems, innovation, entrepreneurship, operations, marketing, and sustainability journals. Existing studies examine how AI changes the sources of competitive advantage, how generative AI affects strategic-option evaluation, the ethics of human-AI interaction, and barriers to automated organizational decision-making. The rapid growth in publications after 2023 calls for an updated and more focused mapping of this field (Keding, 2021; Alhyasat et al., 2025; Saura and Bužinskienė, 2025; Vásquez-Vásquez et al., 2026).

Based on 44 Scopus publications, this study addresses five questions: How have publication trends changed? Which publications are most influential? Which keywords and themes constitute the field? Which countries contribute most? What should future research focus on?

This focused bibliometric design is not intended to cover all AI-related management research; rather, it deliberately concentrates on publications that explicitly combine artificial intelligence and strategic management.

Relative to Keding (2021), this study is positioned in three ways. First, it extends the evidence base to 2026 and therefore captures the post-generative-AI phase after the rapid diffusion of ChatGPT, GPT-4, large language models, and AI-enabled strategic decision systems. Second, it moves beyond a conventional literature review by combining VOSviewer science mapping, Biblioshiny conceptual-structure analysis, and TCCM synthesis. Third, it uses an equivalently screened WoS/SSCI sample as a cross-database sensitivity analysis, which allows the Scopus-based findings to be evaluated against an external management and social-science database.

2. CONCEPTUAL BACKGROUND

From the resource-based view, AI itself is increasingly accessible and therefore does not necessarily possess rarity or inimitability. Sustained competitive advantage is more likely to derive from the combination of proprietary data, industry knowledge, decision rights, organizational learning, and AI capabilities. AI should therefore be viewed as part of a capability system rather than as an isolated technological resource (Helfat et al., 2023; Krakowski et al., 2023; Rosa et al., 2022; Day et al., 2025).

From a dynamic-capabilities perspective, AI can help firms sense opportunities, compare strategic alternatives, and reconfigure organizational processes. It can support environmental scanning, resource allocation, and business-model innovation (Akter et al., 2023; Zhang et al., 2023; He et al., 2026). However, these effects depend on managerial interpretation, organizational readiness, and governance mechanisms (Figge et al., 2026; Liu et al., 2026).

Strategic decisions involve high uncertainty, major consequences, and substantial irreversibility. AI can generate alternatives, identify patterns, and conduct scenario simulations, but it also raises issues of explainability, fairness, and accountability (Werle and Laumer, 2022; Doshi et al., 2025; Berensmeier et al., 2025; Mundlos, 2025; Kumar et al., 2025). The key issue is not whether humans or machines should decide alone, but how problem framing, data selection, output interpretation, review, and final responsibility should be allocated (Pandey and Ahmed, 2025; Heyder et al., 2023; Marler, 2024; Booyse and Scheepers, 2024; Štrukelj and Dankova, 2025; Botelho and Wang, 2026).

3. METHODOLOGY

This study adopts a focused bibliometric review design. Scopus was used as the primary database, and the formal query was TITLE-ABS-KEY("artificial intelligence" AND "strategic management"). The search fields were limited to titles, abstracts, and keywords; the results were further restricted to the Business, Management and Accounting subject area, the document types Article and Review, and the English language. The two original Scopus export files contained 111 Articles and 15 Reviews, for a total of 126 English-language publications. The search data were exported on 5 July 2026, and subsequent data verification was completed on 8 July 2026. The review process was reported according to transparency expectations for management evidence reviews and PRISMA 2020 (Tranfield et al., 2003; Page et al., 2021; Donthu et al., 2021; Zupic and Čater, 2015).

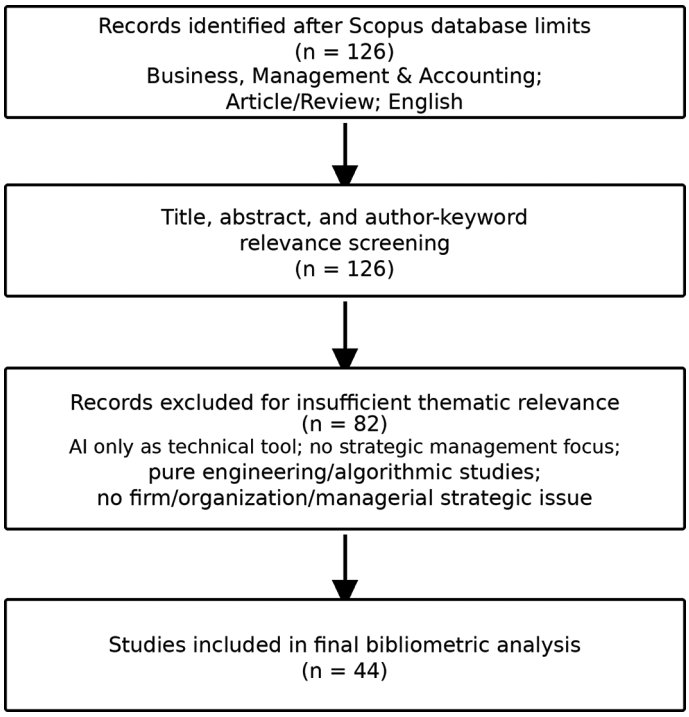
At the time the sample was frozen, 126 records remained after Scopus database limits were applied. Screening and verification were conducted by the author team. Shanning Fu first screened the titles, abstracts, and author keywords of the 126 Scopus records according to predefined inclusion and exclusion criteria. Co-first author Fei Kang then independently verified the screening results using the same criteria. A publication was retained only when AI was a core research object and the publication explicitly addressed enterprise strategy, strategic decision-making, competitive advantage, strategic capabilities, innovation strategy, organizational transformation, or long-term firm performance. In total, 82 publications were excluded for insufficient thematic relevance. Excluded records mainly treated AI merely as a technical or analytical tool, lacked a strategic-management focus, examined purely engineering, algorithmic, or computer-technical issues, or did not involve firm-, organization-, or manager-level strategic problems. For records involving disagreement or boundary ambiguity, the two co-first authors discussed the case first; when consensus could not be reached, the supervisor author Dzhumabek Dzhailov conducted a methodological review and made the final judgment. An inclusion and exclusion log was retained to record the decision and main exclusion reason for each publication. The final Scopus bibliometric sample comprised 44 publications (Figure 1).

The analysis included annual publication counts, citation rankings, author and index keyword frequencies, country distribution,

keyword co-occurrence, keyword temporal overlay, country collaboration, and cited-reference co-citation analysis. Before keyword-frequency and co-occurrence analysis, invalid keyword entries and missing-value placeholders were removed, and a VOSviewer thesaurus was used to merge synonyms; for example, AI-related variants were merged into artificial intelligence, LLM-related variants into large language model, and the erroneous term decisions makings into decision making. VOSviewer was used to construct and visualize keyword co-occurrence, keyword temporal overlay, country collaboration, and cited-reference co-citation networks. Biblioshiny was used to generate a three-field plot linking author countries, merged keywords, and source titles, as well as a thematic map and thematic evolution map. Thematic classification was then conducted based on titles and abstracts, and the Theory–Context–Characteristics–Methodology (TCCM) framework was further used to synthesize theoretical foundations, research contexts, themes, and methodological characteristics.

VOSviewer version 1.6.21 was used for network analysis. The keyword co-occurrence map was generated from the cleaned author keywords and index keywords of the 44 Scopus publications using full counting. Missing-value placeholders and invalid keywords were removed before analysis, and a VOSviewer thesaurus file was used to merge synonymous terms. The minimum occurrence threshold for keyword co-occurrence was set at two, resulting in 37 keywords, six clusters, 180 links, and a total link strength of 300. The same cleaned keyword network was used to produce both the co-occurrence map and the average-publication-year overlay map. Country co-authorship and cited-reference co-citation maps were also generated in VOSviewer using full counting and thresholds selected to preserve network interpretability.

Figure 1: Literature identification and screening process. Scopus is the primary database; WoS/SSCI is used only for cross-database sensitivity analysis



Biblioshiny, the web interface of the bibliometrix R package, was used for supplementary conceptual-structure analysis. The three-field plot used author countries, merged keywords, and source titles, retaining the most interpretable nodes in each field. The thematic map was generated from the cleaned keyword field and interpreted according to Callon centrality and Callon density: centrality indicates the degree to which a theme is connected to the overall field, whereas density indicates the internal maturity of the theme. The thematic evolution analysis divided the sample into two periods, 1983–2022 and 2023–2026, to compare thematic changes before and after the recent acceleration. Because the sample is small and 2026 data are incomplete, the thematic-evolution results are interpreted as exploratory and directional rather than definitive evidence of a complete research life cycle.

To examine whether the findings were affected by database selection, this study further conducted a cross-database sensitivity analysis using the Web of Science Core Collection (Table 1). The formal WoS topic query was TS=("artificial intelligence" AND "strategic management"), restricted to the Social Sciences Citation Index (SSCI). As of 8 July 2026, the latest export contained 73 publications. To ensure comparability with the Scopus main sample, the same screening and verification procedures and the same inclusion and exclusion criteria were applied to the 73 WoS/SSCI records. Shanning Fu first screened the WoS/SSCI records, Fei Kang then independently verified the screening, and Dzhumabek Dzhailov methodologically reviewed boundary records and the overall screening process. AI had to be a core research object, and the publication had to directly address strategic management, strategic decision-making, competitive advantage, strategic capabilities, innovation strategy, organizational transformation, or long-term firm performance. After equivalent screening, 36 WoS/SSCI publications were retained and 37 were excluded. Matching was first conducted using standardized DOIs and then checked by normalized titles for records lacking DOIs. This process identified 17 overlapping publications between the two databases, 27 Scopus-

Table 1: Overview of literature search, screening, and analysis

Item	Specification
Database	Scopus (primary database); WoS Core Collection-SSCI (cross-database sensitivity analysis)
Search field	TITLE-ABS-KEY ("artificial intelligence" AND "strategic management")
Core search terms	"artificial intelligence" AND "strategic management"
Document types	Article (111) and Review (15)
Language	English
Initial records	126 publications (111 Articles and 15 Reviews)
Final sample	44 publications (82 thematically irrelevant records excluded)
Analytical content	Annual trends, citations, keywords, countries, co-occurrence networks, and thematic classification

WoS/SSCI data are used only for cross-database sensitivity analysis and are not merged into the 44-publication Scopus main sample

specific publications, and 19 WoS-specific publications. Because Scopus was designated as the primary database, WoS publications were not merged into the 44-publication main sample. Instead, the equivalent WoS relevant sample was compared in terms of author-keyword frequency, country full counting, source-title frequency, and thematic categories based on titles, abstracts, and author keywords.

4. RESULTS

The 44 included publications cover the period 1983–2026. Before 2018, the field produced few publications; thereafter, output gradually increased and accelerated clearly after 2023. The sample includes six publications in 2023, five in 2024, ten in 2025, and thirteen in 2026. However, the 2026 data are incomplete-year records as of 8 July 2026. The 2026 value should not be interpreted as a full-year count or used for linear trend extrapolation; it is reported only to indicate the volume of publications already indexed by the data-freezing date.

The citation analysis identifies the most cited publications within the Scopus sample retrieved for this study as of 8 July 2026. Krakowski et al. received the highest Scopus citation count in the sample, with 438 citations for their study on AI and the changing sources of competitive advantage. Akter et al.'s study on AI-powered service innovation capability received 242 citations, and Keding's review of four decades of AI and strategic management research received 180 citations. Studies on barriers to automated organizational decision-making, the ethics of human-AI interaction, and generative-AI evaluation of strategic decisions also form an important knowledge base. Because Scopus citation counts change as databases update, they are treated here as relative indicators of citation influence within the sample rather than fixed absolute measures (Figures 2-7).

The cleaned keyword results show that the field is organized around the direct intersection of AI and strategic management. High-frequency terms include artificial intelligence (35 occurrences) and strategic management (25), followed by decision making, strategic planning, and sustainability (six each), innovation management and competition (five each), decision support systems (four), and information management, competitive advantage, large language model, and adoption (three each). The appearance of generative AI and large language models indicates that research is moving from predictive systems toward interactive systems involved in creativity, scenario evaluation, and managerial communication.

In terms of country distribution, Germany, the United States, India, the United Kingdom, and China contribute relatively more publications, whereas research from Africa, Central Asia, Latin America, and low-income economies remains limited.

Thematic classification produced five directions. First, foundations of AI and strategic management include early expert systems, strategic planning, and conceptual discussions of AI's role in strategic management. Representative studies include Holloway (1983), McDonald and Wilson (1990), Martinsons and Schindler (1995), Liu (1998), Ferràs-Hernández (2018), and Keding (2021).

Figure 2: Annual publication trend of the 44-publication Scopus sample. 2026 is an incomplete year; records are counted as of 8 July 2026. The 2026 value should not be interpreted as a full-year count or used for trend extrapolation

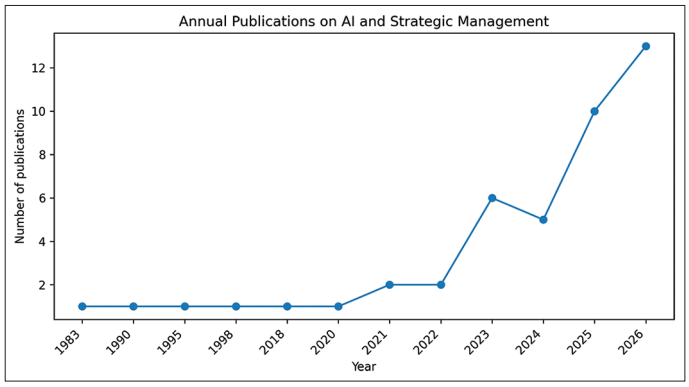


Figure 3: Top 10 most cited publications in the retrieved Scopus sample. Citation counts are Scopus records as of 8 July 2026 and may change as the database updates

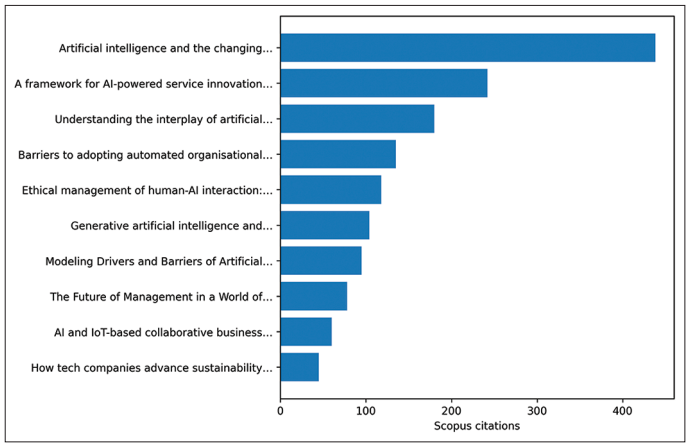
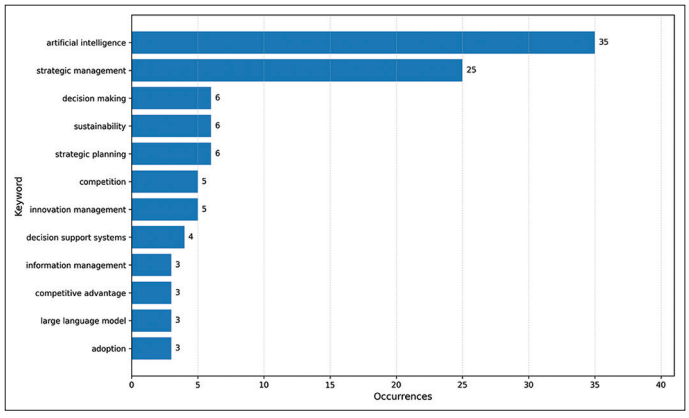


Figure 4: Most frequent keywords after keyword cleaning. Based on author keywords and index keywords from the 44-publication Scopus main sample; synonyms were merged and missing-value placeholders were removed



Second, strategic decision-making, governance, and ethics focus on how AI participates in competitor identification, scenario analysis, managerial attention allocation, strategic-option evaluation, automated organizational decision-making, and the ethics of human-AI interaction. Representative studies include

Figure 5: Keyword co-occurrence network after keyword cleaning. Generated from cleaned author and index keywords; 37 keywords, six clusters, 180 links, and total link strength of 300; full counting; minimum occurrence threshold = 2

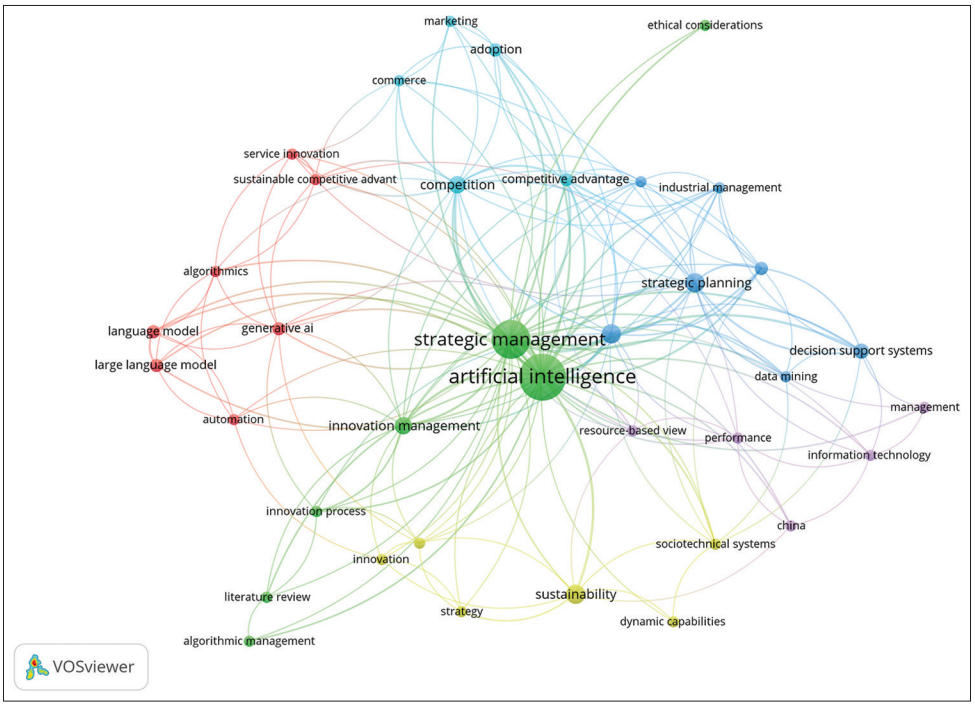


Figure 6: Leading countries by number of publications. Based on full counting of authors' institutional countries; records are counted as of 8 July 2026

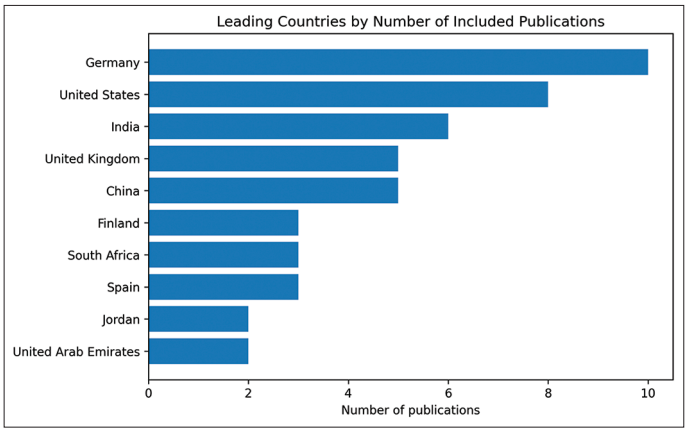
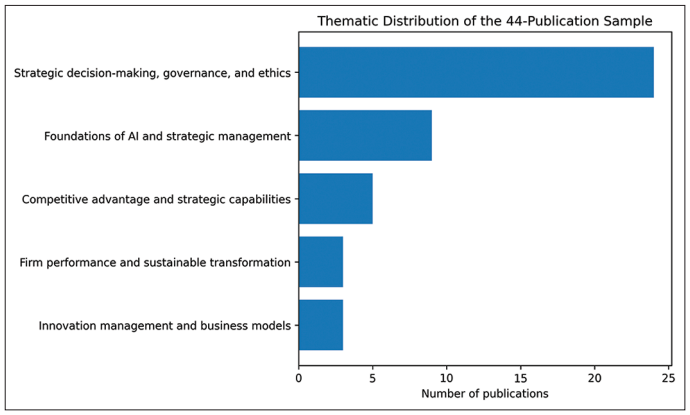


Figure 7: Distribution of five thematic categories. Thematic classification was manually coded from titles, abstracts, and author keywords; all included studies are listed in Appendix A



Werle and Laumer (2022), Heyder et al. (2023), Booyse and Scheepers (2024), Doshi et al. (2025), Berensmeier et al. (2025), Mundlos (2025), Kumar et al. (2025), Pandey and Ahmed (2025), and Vásquez-Vásquez et al. (2026).

Third, competitive advantage and strategic capabilities mainly concern AI adoption, the resource base, dynamic capabilities, organizational readiness, and AI-driven capability formation. Representative studies include Kar et al. (2021), Rosa et al. (2022), Akter et al. (2023), Krakowski et al. (2023), Zhang et al. (2023), Azzam and Beckmann (2024), Day et al. (2025), and Chang et al. (2026).

Fourth, innovation management and business models examine how AI influences product innovation, service innovation, innovation processes, business-model choices, and open-versus-closed technological paths. Representative studies include Ferràs-Hernández et al. (2023), Harmaakorpi et al. (2023), He et al. (2026), Mix et al. (2026), Palo-oja et al. (2026), Babu et al. (2026), Shonubi (2026), and Sun (2026).

Fifth, firm performance and sustainable transformation involve green strategy, ESG, sustainable performance, supply-chain transformation, SME adaptability, and organizational governance. This theme is broader than the other categories because it contains two related sub-directions: sustainable strategy, ESG, and green performance; and supply-chain, organizational transformation, and SME adaptability. Representative studies include Yang et al. (2020), Zechiel et al. (2024), Al-Ababneh et al. (2024), Marler (2024), Saura and Bužinskienė (2025),

Figure 8: Keyword overlay map by average publication year. This figure is generated from the same cleaned VOSviewer keyword network as Figure 5; colors indicate the average publication year of publications associated with each keyword

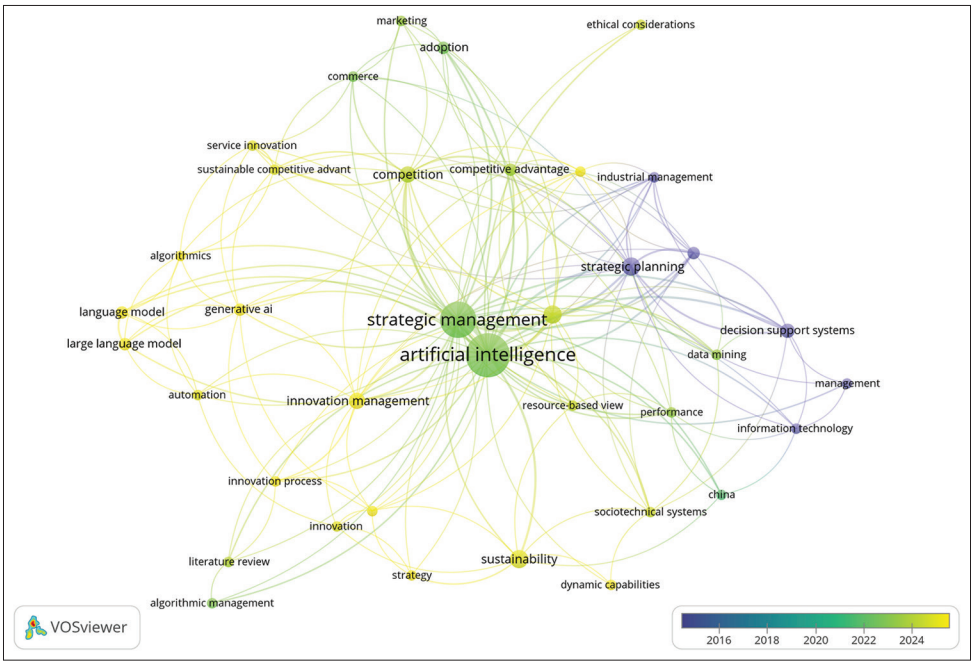


Figure 9: Country collaboration network (VOSviewer). Generated from country co-authorship relations based on authors' institutional affiliations using full counting



Singh et al. (2025), Štrukelj and Dankova (2025), Botelho and Wang (2026), Figge et al. (2026), Freedman (2026), Liu et al. (2026), and Liu et al. (2026).

To avoid citation stacking in the main text, the paragraphs above list only representative studies for each theme; all included studies are listed in Appendix A (Appendix Table 1).

4.1. VOSviewer and Biblioshiny Science-Mapping Analysis

This section mainly addresses RQ3 by clarifying the keyword, thematic, and conceptual structure of the field, while also informing RQ5 by identifying emerging future research priorities. Science-mapping analysis further reveals temporal changes in research themes, country collaboration, knowledge foundations, and conceptual-structure evolution. In VOSviewer, node size reflects the weight of a keyword or country, links represent association strength, and shorter distances generally indicate stronger co-occurrence or collaboration. In Biblioshiny thematic maps, centrality measures a theme's connection with the overall field, whereas density measures the internal maturity of the theme. Taken together, the maps show that the field is forming a conceptual core around "AI–strategic management" while rapidly expanding toward innovation, sustainability, governance ethics, and generative AI (Figure 8). The map interpretation follows VOSviewer's network-mapping and clustering principles and Biblioshiny's conceptual-structure procedures (van Eck and Waltman, 2010; Waltman et al., 2010; Aria and Cuccurullo, 2017).

The cleaned keyword overlay map shows a clear temporal trajectory. Earlier studies focused mainly on decision support systems, strategic planning, data mining, and information technology, indicating that AI was initially treated as an auxiliary tool for improving information processing and prediction efficiency. More recent studies shift toward sustainability, ethical issues, service innovation, generative AI, and large language models. This color transition from earlier to newer themes indicates that the research focus has shifted from "whether AI can support strategic decision-making" to "how firms embed AI into strategic processes through capability building, organizational learning, and governance mechanisms."

The country collaboration network is generally sparse and consists of several small collaboration chains rather than a highly interconnected global network (Figure 9). The United States plays a bridging role between India and Germany, the United Kingdom is connected mainly through India, and Germany forms a relatively independent collaboration cluster. The limited and mostly thin links suggest that international collaboration has not yet developed into a stable high-density structure. This finding implies that current theoretical and empirical conclusions may be shaped by a small number of national institutional environments. Future research requires more cross-regional teams, cross-national comparative designs, and shared data to test how regulation, infrastructure, culture, and talent supply shape the boundary conditions of AI's strategic value.

The cited-reference co-citation network reveals the main knowledge foundations of the field (Figure 10). Barney's resource-based view constitutes an important theoretical anchor by emphasizing rare resources, complementary assets, and sustained competitive advantage. Literature on organizational design, AI strategy, and strategic applications of information technology connects the two traditions of strategic management and information systems. The differently colored co-citation groups correspond to knowledge sources related to resources and capabilities, organizational design and digitalization, and strategic applications of AI. The small network size and limited intergroup connections indicate that the field has not yet formed a highly integrated theoretical core, which also explains the TCCM finding of theoretical pluralism but insufficient cross-level integration.

The three-field plot shows flows among author countries, merged keywords, and source titles; wider flows indicate more prominent connections in the sample (Figure 11). India and Germany are most strongly connected with the "artificial intelligence" core theme, whereas the United States, Jordan, Finland, and China are distributed across strategic management, competition, strategic planning, innovation management, decision-making, and sustainability themes. Strategic Management Journal is closely connected with core strategic issues, while Technological Forecasting and Social Change, Management Review Quarterly, Administrative Sciences, IEEE Transactions on Engineering Management, and Acta Innovations indicate the joint participation of technology management, information systems, and general management journals. The figure shows that the field is not concentrated within a single journal community but is driven by multiple disciplinary channels.

The thematic map distinguishes themes by centrality and density. "AI–innovation management" appears in the motor-theme quadrant, indicating that it is both highly connected to the field and internally mature, and thus acts as a major driver of current research growth (Figure 12). "Artificial intelligence–strategic management" lies near the boundary between emerging/declining themes and basic themes, with a large node size indicating high relevance in the sample. However, its lower density suggests that the core concept still consists of several dispersed subthemes and lacks stable construct relationships and a unified explanatory framework. The large-language-model theme occupies a small niche position, suggesting that specialization is beginning to form but that connections with mainstream strategic-management literature remain limited. It is therefore better understood as a rapidly emerging but not yet fully integrated research frontier rather than as a declining theme.

The thematic evolution map compares the periods 1983–2022 and 2023–2026 (Figure 13). Early research was dispersed among the abbreviation "AI," strategic management, and the full term

Figure 10: Cited-reference co-citation network (VOSviewer). Generated from cited references in the 44-publication Scopus sample to identify the field's main knowledge foundations

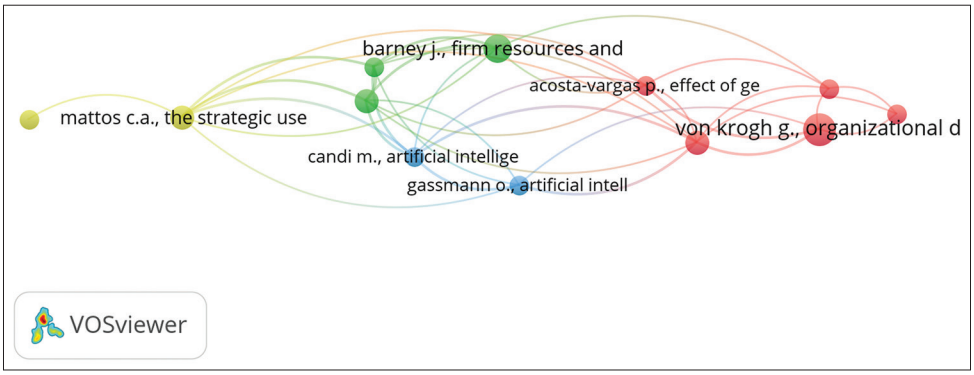
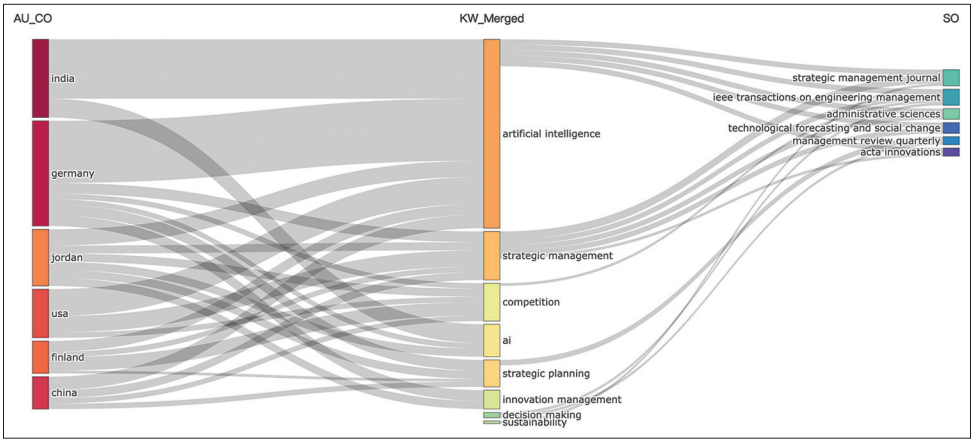


Figure 11: Three-field plot of countries, merged keywords, and source titles. Generated using Biblioshiny; the three fields are AU_CO, the merged keyword field, and SO



"artificial intelligence," indicating unstable terminology and field boundaries. Recent research clearly converges around the two themes of "artificial intelligence" and "innovation management." The flow from strategic management to artificial intelligence indicates that AI has shifted from an auxiliary technological variable to the core concept organizing the field. The large flow toward innovation management shows that research attention has moved from general strategic discussion toward capability building, product and service innovation, business-model transformation, and organizational renewal. Because the sample is small, recent publications have grown rapidly, and the two time windows are unbalanced, the figure should be interpreted only as directional evidence of thematic evolution. It should not be used to compare absolute maturity across time windows or to make strict causal or life-cycle judgments.

4.2. TCCM Analysis

To complement the bibliometric maps, this study applies the Theory–Context–Characteristics–Methodology (TCCM) framework to structurally code the 44 Scopus publications.

Figure 12: Thematic map of the research field. Generated using Biblioshiny based on cleaned keywords; the horizontal axis indicates Callon centrality and the vertical axis indicates Callon density

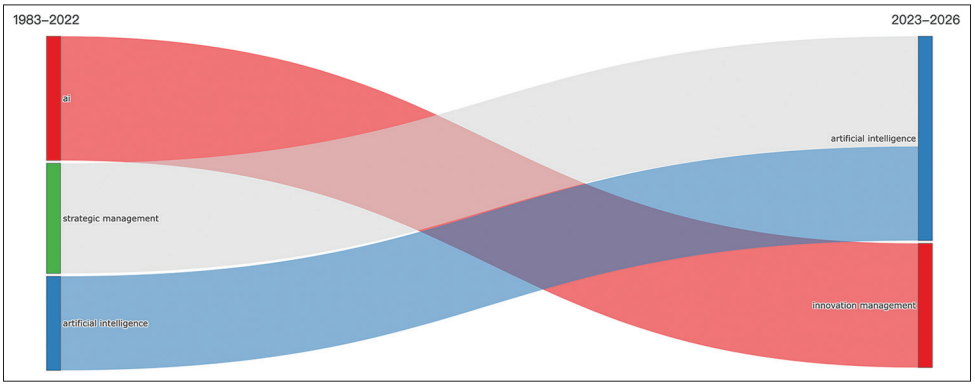


This section further addresses RQ3 by clarifying the theoretical, contextual, thematic, and methodological structure of the field, and it supports RQ5 by identifying future research priorities. The TCCM coding uses a two-level evidence structure. The first level is metadata- and abstract-level basic coding, applied to all 44 Scopus publications. Coding evidence includes titles, abstracts, author keywords, index keywords, source titles, publication years, and citation metadata. At this stage, only information explicitly reported in bibliographic records was coded, including research themes, research contexts, methods, and main findings. Theoretical foundations, sample information, research limitations, and future research directions were coded only when they appeared explicitly in titles, abstracts, or keywords; otherwise, they were marked as "not reported" and not inferred. The second level is full-text extended coding for the 19 priority publications for which full texts were obtained. Priority publications were selected based on citation influence within the sample, thematic representativeness across the five identified themes, methodological relevance, source-journal importance, and full-text availability. For these publications, full-text evidence was used to verify and revise the first-round abstract-level coding and to further identify theoretical foundations, research contexts, methodological designs, main findings, limitations, and future directions. When full-text evidence conflicted with abstract-level coding, full-text evidence was prioritized. The remaining 25 publications without full-text access or full-text review were included in the TCCM synthesis only at the metadata and abstract level unless the relevant information was explicitly reported in bibliographic information. This two-level procedure improves coding depth while avoiding overinterpretation for publications that were not available for full-text review. The TCCM structure follows framework-based review research (Paul and Rosado-Serrano, 2019), while the interpretation of resources and capabilities draws on the renewed resource-based view (Helfat et al., 2023).

4.2.1. Theory

The field has not yet developed a single dominant theory but instead displays theoretical pluralism. Within the available metadata and full-text evidence, the resource-based view and dynamic capabilities theory are the most visible perspectives, mainly explaining how AI resources combine with complementary assets and are transformed into innovation, organizational agility, and competitive advantage (Akter et al., 2023; Krakowski et al., 2023; Zhang et al., 2023; He et al., 2026) (Table 2). Sociotechnical

Figure 13: Thematic evolution from 1983–2022 to 2023–2026. Generated using Biblioshiny based on cleaned keywords and two time slices; 2026 is an incomplete year as of 8 July 2026



systems theory, sociomateriality, the attention-based view, adaptive structuration theory, dominant-design theory, capability orchestration, algorithmic cognition, and behavioral economics are used to explain human-AI interaction, managerial attention, AI adoption barriers, industry evolution, and cognitive bias (Heyder et al., 2023; Booyse and Scheepers, 2024; Mundlos, 2025; Saura and Bužinskienė, 2025; Figge et al., 2026; Liu et al., 2026). The major gap is the lack of a unified multilevel theoretical integration among technological capabilities, managerial cognition, organizational mechanisms, and institutional environments.

The comparison shows that the field does not lack theoretical sources; rather, it lacks cross-level integration. The resource-based view and dynamic capabilities theory mainly explain how AI becomes a source of capability and competitive advantage, whereas sociotechnical and governance perspectives emphasize organizational arrangements, human-AI interaction, accountability, and responsible use. The attention-based view further highlights how AI may reshape managerial cognition and strategic issue interpretation. Future research therefore needs to connect technological resources, managerial cognition, organizational learning, and institutional governance in a multilevel explanation of AI strategic value.

4.2.2. Context

Existing studies are mainly located at the organizational level and concentrate on manufacturing, high technology, hospitality, entrepreneurship, service innovation, supply chains, and sustainability contexts. China is the most common emerging-market sample, while research on South Africa, India, and Latin America remains limited. Large firms, listed companies, and technology-intensive organizations dominate the evidence base, whereas SMEs, traditional industries, public organizations, and cross-national institutional comparisons remain clearly underrepresented (Yang et al., 2020; He et al., 2026; Liu et al., 2026; Booyse and Scheepers, 2024; Chang et al., 2026; Vásquez-Vásquez et al., 2026).

4.2.3. Characteristics

The research themes can be summarized into seven categories: strategic decision-making, competitive advantage, innovation management, AI adoption, governance ethics, sustainable strategy, and supply-chain transformation. Common outcome variables include firm performance, innovation performance, decision quality, organizational agility, sustainable performance, and AI readiness. Evidence remains insufficient regarding the long-term strategic consequences of AI, the dynamic evolution of human-AI complementarity, the cumulative effects of algorithmic bias, and the performance effects of governance maturity (Akter et al., 2023; Zechiel et al., 2024; Kar et al., 2021; Figge et al., 2026; Liu et al., 2026).

4.2.4. Methodology

Systematic literature reviews, conceptual studies, and cross-sectional surveys are the most common research designs (Table 3). Existing studies use PLS-SEM, mediation and moderation models, MICMAC, TISM, LDA topic modeling, document analysis, panel data, case studies, and experiments. Overall, however, the field still relies substantially on self-reported cross-sectional data, while longitudinal studies, field experiments, multilevel models, and rigorous causal identification remain relatively scarce (Kar et al., 2021; Booyse and Scheepers, 2024; Saura and Bužinskienė, 2025; Doshi et al., 2025; Liu et al., 2026).

4.3. Cross-Database Sensitivity Analysis

This section provides a cross-database robustness check for the five research questions by examining whether the Scopus-based patterns remain visible under an equivalent WoS/SSCI screening logic. The revised sensitivity analysis shows that the main findings are not driven solely by the choice of Scopus. To avoid directly comparing the final Scopus sample with an unscreened WoS search sample, this study first reviewed the 73 WoS/SSCI records using the same inclusion and exclusion criteria as Scopus. After equivalent screening, 36 WoS/SSCI

Table 2: Theoretical perspectives in the TCCM theory dimension

Theoretical perspective	Core proposition	Meaning for AI in strategic management	Representative studies	Main theoretical gap
Resource-based view	Advantage derives from valuable and hard-to-imitate resource bundles.	AI creates value when combined with proprietary data, knowledge, processes, and managerial capability.	Helfat et al. (2023); Krakowski et al. (2023); Rosa et al. (2022)	How firms differentiate when general AI tools are widely available.
Dynamic capabilities	Firms adapt by sensing, seizing, and reconfiguring resources.	AI supports scanning, opportunity recognition, resource allocation, and business-model renewal.	Akter et al. (2023); Zhang et al. (2023); He et al. (2026); Liu et al. (2026)	How AI capabilities form, decay, and become institutionalized over time.
Sociotechnical systems	Performance depends on joint optimization of technology and organization.	AI value depends on alignment among data, processes, structure, skills, and governance.	Heyder et al. (2023); Booyse and Scheepers (2024); Štrukelj and Dankova (2025)	How role allocation, accountability, and learning operate in human-AI systems.
Attention-based view	Managerial attention shapes issue recognition and action.	AI can broaden information processing but may also narrow attention through overreliance.	Mundlos (2025); Doshi et al. (2025); Botelho and Wang (2026)	How AI changes top-management attention structures.
Governance and ethics	Algorithmic systems require transparency, accountability, fairness, and explainability.	Strategic AI decisions require model review, human override, and responsibility allocation.	Heyder et al. (2023); Marler (2024); Kumar et al. (2025); Pandey and Ahmed (2025)	How governance maturity affects long-term strategic performance.

publications were retained and 37 were excluded. Among the 36 retained publications, 17 overlapped with the Scopus main sample, 19 were WoS-specific, and 27 were Scopus-specific (Table 4). Both equivalently screened database samples identify artificial intelligence and strategic management as central concepts and jointly highlight innovation management, sustainability, organizational capabilities, governance, and strategic decision-making. The WoS sample is relatively more concentrated in high-impact management and organization journals, whereas Scopus maintains broader coverage of information systems, technology management, service innovation, supply chains, and emerging-market applications. These differences mainly arise from journal coverage and disciplinary scope and are complementary rather than contradictory. The overall convergence in core keywords, leading countries, source journals, and thematic structure indicates that the main conclusions remain robust across databases under an equivalent screening logic.

5. DISCUSSION, CONTRIBUTIONS, AND LIMITATIONS

5.1. Integrated Interpretation

Across the Scopus main sample and the equivalently screened WoS/SSCI sample, three converging patterns emerge. First, AI and strategic management form the conceptual core of the field, even though the surrounding applications differ across databases. Second, both databases show a migration from early decision-support and planning applications toward innovation management, sustainability, governance, organizational capabilities, and generative AI. Third, WoS provides a more selective management-oriented view, whereas Scopus captures a broader interdisciplinary and application-oriented stream. These patterns indicate that the field is conceptually converging while remaining heterogeneous in empirical contexts and disciplinary foundations (Keding, 2021; Alhyasat et al., 2025; Vásquez-Vásquez et al., 2026).

Table 3: TCCM synthesis and future research directions

Dimension	Main findings	Research gaps	Future directions
Theory	The resource-based view and dynamic capabilities theory are most common; additional theories explain cognition, governance, and human-AI interaction.	Theories remain fragmented and multilevel integration is insufficient.	Integrate resource, capability, attention-based, and sociotechnical perspectives; develop theories of generative AI and algorithmic governance.
Context	Research concentrates on large firms in manufacturing, technology, hospitality, entrepreneurship, and supply chains.	Evidence on SMEs, traditional industries, public organizations, and emerging markets is insufficient.x	Conduct cross-national, cross-industry, and SME research incorporating institutional and cultural differences.
Characteristics	Core themes include strategic decision-making, competitive advantage, innovation, adoption, ethics, sustainability, and supply-chain transformation.	Long-term consequences, human-AI complementarity, bias accumulation, and governance-performance effects remain underexamined.	Focus on AI capability formation, governance maturity, responsible AI, and long-term strategic value.
Methodology	Reviews, conceptual studies, and cross-sectional surveys account for a large share.	Longitudinal, experimental, multilevel, and multi-source designs are scarce.	Use panel data, field experiments, digital traces, multilevel models, and cross-database robustness checks.

The TCCM synthesis is based on two-level coding: metadata- and abstract-level basic coding for all 44 Scopus publications, and full-text extended coding for 19 priority publications. When theories, limitations, or future research suggestions were not explicitly reported in abstracts or bibliographic information, they were coded as "not reported" and not inferred.

Table 4: Scopus–WoS cross-database sensitivity analysis

Comparison dimension	Final Scopus sample	Equivalently screened WoS/SSCI sample	Robustness judgment
Sample size	44 publications finally included	36 publications retained after screening 73 WoS/SSCI records	Comparable comparison at the level of final relevant samples
Sample overlap	17 overlapping publications; 27 Scopus-specific publications	17 overlapping publications; 19 WoS-specific publications	Substantial overlap and complementary coverage both exist
Core keywords	Artificial intelligence, strategic management, innovation management, sustainability, decision-making, adoption	Artificial intelligence, strategic management, blockchain, innovation, AI ethics, generative AI	Core concepts of AI and strategic management generally converge
Leading countries	Germany, United States, India, China, Finland, South Africa	United States, Germany, China, Spain, United Kingdom, Saudi Arabia	Leading countries are similar, with differences in database coverage
Core journals	Administrative Sciences, Strategic Management Journal, Management Review Quarterly, TFSC, IEEE TEM	Sustainability, Technological Forecasting and Social Change, Technovation, California Management Review, IEEE TEM	WoS is more selective; Scopus has broader interdisciplinary coverage
Thematic structure	Strategic decision-making, innovation, sustainability, governance, organizational capabilities	Sustainability and strategic transformation, innovation and entrepreneurial strategy, AI governance and ethics, organizational capabilities	Main thematic structures remain consistent after equivalent screening

The WoS/SSCI sample consists of 36 relevant publications retained after applying the same screening criteria to 73 records; the Scopus sample is the 44-publication main sample

These findings can also be interpreted in relation to the five research questions. RQ1 shows a clear acceleration of publications after 2023; RQ2 identifies a small group of highly cited publications that anchor the field; RQ3 shows that the conceptual core is shifting toward innovation, governance, and generative AI; RQ4 reveals a geographically uneven and relatively sparse collaboration structure; and RQ5 points toward human-AI complementarity, governance maturity, emerging-market contexts, and longitudinal performance effects as future priorities.

Competitive advantage is one of the most prominent theoretical issues in the retrieved sample, but technological determinism is insufficient to explain firm differences. As AI tools become widely available, real advantage depends more on proprietary data, managerial knowledge, organizational learning, process reconfiguration, and governance capability (Helfat et al., 2023; Krakowski et al., 2023; Day et al., 2025).

Generative AI can formulate and evaluate strategic options, but it may also amplify framing effects and implicit bias. Firms need institutions for problem framing, model selection, cross-validation, human review, and accountability (Doshi et al., 2025; Botelho and Wang, 2026; Mundlos, 2025; Kumar et al., 2025; Štrukelj and Dankova, 2025).

Network and thematic analyses further show that the field is in transition. The keyword overlay map indicates that decision support and strategic planning are being supplemented by newer issues such as generative AI, sustainability, ethics, and dynamic capabilities. The thematic map identifies AI and innovation management as motor themes, while the broader "AI–strategic management" core still lacks internal structure. The sparse country collaboration network and co-citation structure also suggest that future research should strengthen international collaboration and deepen the integration of classic strategy theory with emerging AI-governance research.

Existing research comes largely from developed economies, and emerging-market studies often focus on adoption barriers or single industries. Institutional environment, digital infrastructure, managerial skills, ownership, and access to capital should become important explanatory variables in future research (Yang et al., 2020; Booyse and Scheepers, 2024; Vásquez-Vásquez et al., 2026; Liu et al., 2026).

5.2. Methodological Contributions

This study makes two methodological contributions. First, it combines descriptive bibliometrics, VOSviewer science mapping, Biblioshiny conceptual-structure analysis, and TCCM content coding, thereby identifying not only what has been studied but also how theory is used, in which contexts, and with which methods. Second, it uses an equivalently screened WoS/SSCI sample as a cross-database sensitivity analysis rather than simply comparing Scopus with an unscreened external database. This design improves the transparency and robustness of the review and reduces the risk that the findings are driven only by database coverage.

5.3. Theoretical Contributions

This study also makes two theoretical contributions. First, the findings show that AI should not be treated as an isolated general-purpose technological resource but should be located within a capability system composed of proprietary data, managerial cognition, organizational learning, process reconfiguration, and governance mechanisms. This extends the resource-based view and dynamic capabilities perspective into human-AI collaboration contexts. Second, the study reveals a conceptual migration from decision-support tools toward strategic cognition, innovation capabilities, and governance systems. It also shows that although "AI–strategic management" is a highly relevant core theme, internal theoretical integration remains insufficient, thereby clarifying directions for future multilevel theory building (Helfat et al., 2023; Akter et al., 2023; Krakowski et al., 2023; Heyder et al., 2023; Mundlos, 2025; Figge et al., 2026).

5.4. Limitations

This study has several limitations. First, the main sample uses a focused search string and is restricted to Scopus Business, Management and Accounting, which may omit studies using adjacent terms without explicitly mentioning "strategic management." Second, the 44-publication sample is appropriate for focused mapping, but its small size makes network structures, thematic quadrants, and evolution paths sensitive to thresholds and keyword normalization. Third, although the two-level TCCM coding procedure reduces the risk of overinterpretation, the coding depth is not identical for all 44 publications. Nineteen priority publications were coded from full texts, while the remaining publications were coded mainly from metadata and abstracts. Therefore, for publications without full texts, fields such as limitations and future research suggestions may be underestimated or insufficiently identified. Fourth, full counting of countries and institutions should not be interpreted as proportional author contribution. Fifth, bibliometric associations reflect co-occurrence or co-citation and do not demonstrate causality. Although the equivalently screened WoS/SSCI sensitivity analysis supports the core conclusions, future research can improve robustness through broader search strings, forward and backward citation tracking, double independent coding, and larger-scale full-text analysis.

6. CONCLUSION

This study conducted a focused bibliometric analysis of AI research in strategic management. The 44-publication sample shows that the field has accelerated markedly after 2023, although the 2026 data are incomplete-year records as of 8 July 2026. VOSviewer results show that research attention is shifting from decision support and strategic planning toward generative AI, sustainability, ethics, and dynamic capabilities, while country collaboration and cited-reference co-citation networks remain sparse. Biblioshiny results identify AI and innovation management as motor themes and indicate that the "AI–strategic management" core has high relevance but insufficient internal development; recent themes converge clearly around artificial intelligence and innovation management. The TCCM synthesis further shows theoretical pluralism, the dominance of organizational and technology-intensive contexts, the continued expansion of governance and sustainability issues, and the prevalence of reviews and cross-sectional research designs. Future research should reduce broad claims about technological value and focus on human-AI system design, long-term capability

evolution, governance mechanisms, causal performance effects, and institutional differences. This study uses Scopus as the primary database and an equivalently screened WoS/SSCI sample as an external sensitivity sample. The cross-database comparison shows that the core patterns are not unique to Scopus. The study is still limited by a focused search string, a relatively small sample, and the partial reliance of TCCM coding on abstract-level information. Future studies can use broader search-string combinations, forward and backward citation tracking, double independent coding, and larger-scale full-text analysis. Compared with earlier reviews such as Keding (2021), this study adds post-generative-AI coverage, a combined bibliometric–TCCM synthesis, and an equivalently screened WoS/SSCI sensitivity analysis, thereby clarifying how the field has changed after the recent acceleration of AI-related strategic-management research.

6.1. Future Research Agenda

First, research should examine human-AI complementarity. Strategic scanning, option generation, option evaluation, negotiation, and resource commitment may require different human-AI configurations (Table 5). Existing evidence suggests that aggregated AI evaluations may approach expert judgment, while human-AI combinations may form capabilities different from those of either humans or AI alone (Krakowski et al., 2023; Doshi et al., 2025).

Second, AI governance research should be strengthened, including data sources, model ownership, intellectual property, cybersecurity, accountability, and the right to challenge algorithmic recommendations. Existing research has emphasized ethics, trust, transparency, and leadership responsibility (Heyder et al., 2023; Booyse and Scheepers, 2024; Marler, 2024; Štrukelj and Dankova, 2025).

Third, longitudinal research is needed. Cross-sectional studies cannot explain how firm-level AI capabilities accumulate, decline, or become institutionalized. Panel data and long-term case studies should therefore be used. Existing cross-sectional studies have linked AI capabilities to innovation, operations, and sustainable performance, but they still cannot explain how capabilities accumulate, decay, or become routinized (Zhang et al., 2023; He et al., 2026; Liu et al., 2026).

Fourth, emerging-market research should be expanded to compare how infrastructure, institutional quality, ownership, and skill supply affect the value of strategic AI. Future cross-national comparisons can build on research on collaborative ecosystems, automated decision-making, and business decision-making in Latin America (Yang et al., 2020; Booyse and Scheepers, 2024; Vásquez-Vásquez et al., 2026).

Fifth, objective performance indicators should be used to assess the long-term effects of AI on innovation, organizational resilience, sustainable performance, and profitability.

In addition to these directions, three illustrative research propositions can guide future empirical work. RP1: In strategic scanning tasks, moderate human-AI complementarity is more likely to enhance scanning breadth and decision quality than either minimal AI involvement or excessive AI reliance. RP2: AI-governance maturity positively moderates the relationship between AI capability and long-term strategic performance by reducing bias, accountability gaps, and model-risk exposure. RP3: The strategic value of AI capabilities is contingent on emerging-market institutional conditions, including digital infrastructure, regulatory quality, managerial skill supply, and access to complementary resources.

6.2. Managerial Implications

For C-suite executives and board members, AI should be treated as a capability system rather than as a stand-alone information-technology project. Strategic value requires clear decision problems, reliable data, accountable actors, industry knowledge, and process reconfiguration. Leadership commitment, talent development, infrastructure investment, and organizational learning mechanisms are therefore prerequisites for value creation (Kar et al., 2021; Akter et al., 2023; Chang et al., 2026).

For CIOs, CDOs, and digital transformation leaders, the findings highlight the need for human-AI decision protocols. Firms should specify who is responsible for problem framing, data validation, model comparison, output interpretation, human override, and final accountability. These protocols directly address trust, transparency, ethics, and bias in strategic evaluation (Heyder et al., 2023; Booyse and Scheepers, 2024; Botelho and Wang, 2026).

Table 5: Future research agenda

Future research direction	Core question	Suggested methods
Human-AI complementarity	How should strategic tasks be allocated between humans and AI?	Experiments, field studies, process tracing
Managerial attention	Does AI expand or narrow managerial attention?	Longitudinal studies, digital behavioral data
Explainable strategic systems	What explanations increase trust without creating overreliance?	Behavioral experiments, system-design comparisons
Generative-AI governance	How should data, prompts, outputs, intellectual property, and responsibility be governed?	Case studies, policy comparison
Dynamic capability evolution	How do firms develop and institutionalize AI capabilities over time?	Panel data, longitudinal multiple cases
Bias and strategic evaluation	When does AI reproduce or reduce bias?	Algorithm audits, controlled experiments
Emerging-market contexts	How do infrastructure, institutions, and ownership affect AI's strategic value?	Cross-national comparison
Long-term performance	How does AI affect innovation, resilience, sustainability, and profitability?	Objective firm-level panel data

Future research directions are synthesized from the bibliometric results, science maps, and TCCM analysis

For middle managers, AI adoption requires change-management capabilities rather than simple system deployment. Managers need to translate AI outputs into operational routines, coordinate cross-functional learning, and prevent excessive reliance on automated recommendations. Training should therefore focus not only on technical literacy but also on judgment, explanation, and critical review of AI-generated strategic options.

For innovation and marketing managers, AI can support product development, service innovation, market sensing, and customer-segment analysis. However, its value depends on the integration of AI insights with domain knowledge and market experience. Managers should use AI to expand the range of strategic alternatives while preserving human responsibility for final strategic choices.

For policymakers and regulators, the findings suggest that AI governance should balance innovation support with accountability, fairness, privacy, and explainability. Regulatory frameworks should encourage experimentation while clarifying responsibility for data quality, algorithmic bias, intellectual property, and the right to challenge automated recommendations.

When evaluating the strategic value of AI, firms should look beyond short-term cost savings. Useful indicators include decision-cycle time, quality of strategic alternatives, forecasting accuracy, learning speed, innovation outputs, governance maturity, organizational resilience, sustainable performance, and profitability.

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APPENDIX

Appendix A: List of Included Publications (44-Publication Scopus Main Sample)

The following table lists all 44 Scopus publications included in the bibliometric analysis, science mapping, and TCCM coding. Each included study has been cited in the thematic synthesis or subsequent interpretation to ensure consistency among the review sample, in-text citations, and the reference list.

Appendix Table 1: List of Included Publications (44-Publication Scopus Main Sample)

No.	Authors and Year	Title	Source journal
1	Werle and Laumer (2022)	Competitor identification: A review of use cases, data sources, and algorithms	International Journal of Information Management, 65, 102507
2	Vásquez-Vásquez et al. (2026)	Artificial intelligence for business decision-making in Latin America: A systematic review of evidence, contributing countries, and key insights	Administrative Sciences, 16 (3), 121
3	Heyder, T., Passlack, N., and Posegga, O. (2023)	Ethical management of human-AI interaction: Theory development review	Journal of Strategic Information Systems, 32 (3), 101772
4	Alhyasat et al. (2025)	Technology trends in strategic management in the AI era: Systematic literature review	Human Systems Management, 44 (5), 764–781
5	Palo-oja et al. (2026)	AI in innovation: Impacts on management functions	Organization Management Journal, 23 (1), 132–147
6	Al-Ababneh et al. (2024)	Optimization of strategic management of marketing and logistics of companies as part of the implementation of artificial intelligence	Acta Logistica, 11 (4), 665–676
7	Doshi et al. (2025)	Generative artificial intelligence and evaluating strategic decisions	Strategic Management Journal, 46 (3), 583–610
8	Freedman (2026)	Strategic edge architecture: AI-augmented cognitive infrastructure for SME adaptability and sustainable growth	Administrative Sciences, 16 (6), 291
9	Saura and Bužinskienė (2025)	Behavioral economics, artificial intelligence and entrepreneurship: An updated framework for management	International Entrepreneurship and Management Journal, 21 (1), 67
10	Holloway (1983)	Strategic management and artificial intelligence	Long Range Planning, 16 (5), 89–93
11	Babu et al. (2026)	Artificial intelligence-enabled digital twin architecture for strategic innovation management and real-time decision optimization in entrepreneurial ecosystems	Acta Innovations, 59, 260–268
12	Yang et al. (2020)	AI and IoT-based collaborative business ecosystem: A case in Chinese fish farming industry	International Journal of Technology Management, 82 (2), 151–171
13	Krakowski et al. (2023)	Artificial intelligence and the changing sources of competitive advantage	Strategic Management Journal, 44 (6), 1425–1452
14	Ferràs-Hernández et al. (2023)	The emergence of dominant designs in artificial intelligence	California Management Review, 65 (3), 73–91
15	He et al. (2026)	The impact of digital intelligence on product innovation: Investigating the interactive effect of dynamic capability and heterogeneous top management teams	Journal of Research in Interactive Marketing, 20 (2), 286–303
16	Keding (2021)	Understanding the interplay of artificial intelligence and strategic management: Four decades of research in review	Management Review Quarterly, 71 (1), 91–134
17	Zechiel et al. (2024)	How tech companies advance sustainability through artificial intelligence: Developing and evaluating an AI x Sustainability strategy framework	Industrial Marketing Management, 119, 75–89
18	Ferràs-Hernández (2018)	The future of management in a world of electronic brains	Journal of Management Inquiry, 27 (2), 260–263
19	Liu et al. (2026)	Driving sustainable performance through green business strategy, artificial intelligence capability, and green supply chain management: The mediating roles of knowledge integration and green innovation	Corporate Social Responsibility and Environmental Management, 33 (3), 4531–4546
20	Mundlos, P. (2025)	The impact of artificial intelligence on managerial attention allocation for discontinuous change: A conceptual framework	Management Review Quarterly, 75 (2), 1–45
21	Rosa et al. (2022)	Gaining competitive advantage through artificial intelligence adoption	International Journal of Electronic Business, 17 (4), 386–406
22	Sun (2026)	DeepSeek's innovative breakthroughs and choice between open versus closed-source	CASE Journal, 22 (3), 515–529
23	Mix et al. (2026)	Genius innovation management – a typology of GenAI use in innovation management	European Journal of Innovation Management. Advance online publication
24	Chang et al. (2026)	Artificial intelligence (AI) preparedness in hospitality: A framework and research agenda for building organizational capacities	International Journal of Contemporary Hospitality Management, 38 (4), 1237–1256
25	Berensmeier et al. (2025)	How discriminative artificial intelligence drives scenario planning: A systematic literature review and research agenda	Futures and Foresight Science, 7 (3), e70021

(Contd...)

Appendix Table 1: ***(Continued)***

No.	Authors and Year	Title	Source journal
26	McDonald and Wilson (1990)	State of the art developments in expert systems and strategic marketing planning	British Journal of Management, 1 (3), 159–170
27	Harmaakorpi et al. (2023)	Will machines innovate for and with us - what kind of strategic themes could belong to innovation automation?	Journal of Innovation Management, 11 (4), 143–169
28	Marler (2024)	Artificial intelligence, algorithms, and compensation strategy: Challenges and opportunities	Organizational Dynamics, 53 (1), 101039
29	Zhang et al. (2023)	Does AI-infused operations capability enhance or impede the relationship between information technology capability and firm performance?	Technological Forecasting and Social Change, 191, 122517
30	Azzam and Beckmann (2024)	How AI helps to increase organizations' capacity to manage complexity - a research perspective and solution approach bridging different disciplines	IEEE Transactions on Engineering Management, 71, 2324–2337
31	Kumar et al. (2025)	Strategic decision-making in the era of artificial intelligence: A multi-dimensional evaluation of opportunities, challenges and ethical concerns	International Journal of Accounting and Economics Studies, 12 (5), 950–955
32	Kar et al. (2021)	Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective	Intelligent Systems in Accounting, Finance and Management, 28 (4), 217–238
33	Martinsons and Schindler (1995)	Organizational visions for technology assimilation: The strategic roads to knowledge-based systems success	IEEE Transactions on Engineering Management, 42 (1), 9–18
34	Pandey and Ahmed (2025)	Strategic management practices for AI-enabled financial planning in technology-intensive manufacturing firms	Archives for Technical Sciences, 34 (3), 316–323
35	Akter et al. (2023)	A framework for AI-powered service innovation capability: Review and agenda for future research	Technovation, 125, 102768
36	Liu (1998)	Strategic scanning and interpretation revisiting: Foundations for a software agent support system - part 2: Scanning the business environment with software agents	Industrial Management and Data Systems, 98 (8), 362–372
37	Figge et al. (2026)	AI-human learning systems: Investigating the strategic role of AI for organizational learning	Strategic Organization, 24 (2), 307–342
38	Booyse and Scheepers (2024)	Barriers to adopting automated organisational decision-making through the use of artificial intelligence	Management Research Review, 47 (1), 64–85
39	Botelho and Wang (2026)	Bias in, symbolic compliance out? GPT's reliance on gender and race in strategic evaluations	Strategic Management Journal. Advance online publication
40	Štrukelj and Dankova (2025)	Ethical leadership and management of small- and medium-sized enterprises: The role of AI in decision making	Administrative Sciences, 15 (7), 274
41	Day et al. (2025)	Extending the resource-based view of social entrepreneurship: The role of artificial intelligence in scaling impact	Journal of Risk and Financial Management, 18 (7), 341
42	Singh et al. (2025)	AI and ESG performance: An empirical study of the high-tech sector	Prabandhan: Indian Journal of Management, 18 (6), 8–25
43	Shonubi (2026)	Unwrapping generative AI paradigms for product and service innovation differentiation	Journal of Strategy and Innovation, 37 (1), 200562
44	Liu et al. (2026)	Intelligence by design: Large language model work integration as strategic enablers for supply chain regeneration through digital and cognitive capabilities	Technological Forecasting and Social Change, 224, 124497