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Evolution of Artificial Intelligence Adoption in Business: From Adoption Decisions to Intensity, Capabilities, and Value Creation

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ABSTRACT

Artificial intelligence (AI) adoption has moved from a binary technology-choice question toward a strategic question of how deeply AI is embedded across organizational activities and how adoption intensity translates into value. This state-of-the-art bibliometric review maps recent business and management research on AI adoption and develops an integrative interpretation of the field. The dataset comprises 475 English-language articles indexed in the Web of Science Core Collection from 2022 to September 2026, restricted to Business Economics and selected major publishers. Biblioshiny was used for performance analysis and science mapping. The corpus spans 223 sources, 1,395 authors, 28,005 references, and 1,781 author keywords; international co-authorship is 37.05%. Publication output accelerated sharply from 19 articles in 2022 to 279 records in the partial year of 2026. Technological Forecasting and Social Change is the leading source, while China is the leading corresponding-author country. Citation and keyword analyses show that the field has evolved around five interconnected domains: adoption prerequisites and readiness; organizational capabilities and complementary investments; performance and productivity; human and customer interfaces; and governance, trust, sustainability, and generative AI. The review argues that future research should distinguish adoption status from adoption level or intensity, model complementary organizational capabilities explicitly, and use longitudinal and multi-level designs to explain when deeper AI assimilation produces innovation, sustainable advantage, and performance. The study offers a focused research agenda for organizational AI adoption research and a reproducible bibliometric baseline for the 2022-2026 period.

Keywords: Artificial intelligence adoption, AI adoption intensity, Organizational readiness, Dynamic capabilities, Firm performance, Bibliometric analysis.

Introduction

Artificial intelligence has shifted rapidly from an experimental digital technology to an organizational infrastructure that can reshape decision-making, innovation, customer interfaces, operations, human resource management, and competitive positioning. The management problem is no longer limited to whether a firm adopts AI. Increasingly, the consequential question is how extensively AI is deployed, how deeply it is integrated into organizational routines, and whether complementary resources allow firms to convert adoption into measurable value. This distinction matters because organizations can be classified as adopters while differing substantially in the number of AI applications used, the breadth of functional deployment, the sophistication of use, the share of activities supported by AI, and the degree to which AI is integrated with data, cloud, knowledge, and decision systems.

Recent empirical work illustrates this transition. Kinkel *et al*. (2022) examined prerequisites for AI adoption in manufacturing, emphasizing conditions that enable the initial adoption decision. Lee *et al*. (2022), by contrast, explicitly studied AI-adoption intensity and showed that performance gains emerge only after sufficient investment and are amplified by complementary digital technologies and R&D strategy. Czarnitzki *et al*. (2023) linked AI to firm-level productivity, while Wang *et al*. (2023) examined total factor productivity in manufacturing enterprises. These

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studies suggest a conceptual progression from adoption as a yes/no event toward adoption as an organizational capability-building and value-realization process.

The literature is nevertheless fragmented. One stream focuses on technological, organizational, environmental, readiness, and trust-related antecedents of adoption. A second examines capabilities, knowledge management, leadership, and complementary investments that facilitate assimilation. A third studies performance, productivity, innovation, and business-model outcomes. Other streams address AI-enabled human resource management, customer-facing applications, ethics, governance, sustainability, and generative AI. Because these conversations span innovation, information systems, economics, marketing, operations, finance, human resource management, and sustainability journals, conventional narrative reviews can miss the field-level structure connecting them.

Bibliometric analysis is useful in this setting because it combines performance indicators with science mapping (Donthu *et al*., 2021). Publication counts reveal the speed and concentration of knowledge production; citation indicators identify influential intellectual anchors; country and affiliation indicators show the geography of the field; keyword and co-word analyses reveal the conceptual vocabulary and structural relationships among topics. A state-of-the-art review should, however, go beyond descriptive rankings. The bibliometric evidence must be interpreted analytically to answer a defined substantive question and to derive a research agenda.

Accordingly, this review asks: How has recent business and management research conceptualized and developed organizational AI adoption, and what does the structure of the literature imply for research on the level or intensity of AI adoption? Four research questions guide the analysis. RQ1 asks how rapidly the literature has grown and where it is published. RQ2 examines which authors, affiliations, countries, and documents are most influential. RQ3 identifies the dominant and emerging conceptual themes. RQ4 integrates these patterns to explain how research should move from binary adoption toward adoption level, assimilation, complementary capabilities, and value creation.

The review makes three contributions. First, it provides a current bibliometric map of 475 business-economics articles published from 2022 through September 2026. Second, it interprets the mapped field through an adoption-to-value logic rather than presenting bibliometric rankings as an end in themselves. Third, it develops a future research agenda centered on construct precision, particularly the distinction among adoption, intention, intensity, assimilation, and maturity; complementary resources and dynamic capabilities; heterogeneous performance effects; responsible AI governance; and longitudinal, multi-level, and cross-country designs.

Materials and Methods

Review design. The study adopts a bibliometric review and science-mapping design. The purpose is to characterize the recent structure of organizational AI-adoption research, identify influential contributors and documents, and synthesize the conceptual domains revealed by the bibliometric evidence. The unit of analysis is the peer-reviewed journal article. Biblioshiny, the graphical interface of the bibliometrix ecosystem, was used to generate the performance and network outputs supplied for this review (Aria & Cuccurullo, 2017).

Database and search strategy. Records were retrieved from the Web of Science Core Collection on September 3, 2026. The search interface shows the exact phrase query ("the level of AI adoption"). The search was refined to document type Article; language English; publication years 2022, 2023, 2024, 2025, and 2026; Web of Science indexes SSCI, SCI-EXPANDED, or ESCI; research area Business Economics; and publishers Elsevier, Springer Nature, Emerald Group Publishing, Taylor & Francis, Wiley, or Sage. After these refinements, 475 documents remained. The exported bibliographic file contains the same 475 records and therefore matches the Biblioshiny corpus.

The search design intentionally privileges recency and business relevance. Restricting the review to 2022-2026 is consistent with producing a state-of-the-art account of a fast-moving technology. The publisher restriction improves manageability and concentrates the sample in major international outlets, but it also reduces comprehensiveness and is therefore treated as a limitation. The 2026 search was conducted in early September, so the 2026 count represents a partial year even though it is the largest annual count.

Bibliometric indicators. Performance analysis covered the time span, number of sources and documents, annual growth rate, average document age, citations per document, references, Keywords Plus, author keywords, authors, single-authored documents, co-authors per document, international co-authorship, annual scientific production, relevant sources, authors, affiliations, corresponding-author countries, and globally cited documents. Country analysis

distinguishes single-country publications (SCP) from multiple-country publications (MCP). Fractionalized author counts were used as a complementary indicator to reduce the inflation created by large co-author teams.

Science mapping. Conceptual structure was examined using keyword frequency and co-word network outputs. The Biblioshiny co-word table reports cluster membership, betweenness, closeness, and PageRank. Betweenness indicates how strongly a term connects otherwise separated parts of the network, while PageRank provides an indicator of structural prestige. These measures are interpreted as relational prominence within the retrieved corpus rather than as evidence of causal importance or research quality.

Analytical synthesis. To transform bibliometric outputs into a review article rather than a descriptive report, the highest-impact and thematically representative papers in the Web of Science export were read at the title, abstract, keyword, and bibliographic-record level. The synthesis focuses on adoption prerequisites and readiness; complementary organizational capabilities; performance and productivity; human and customer interfaces; and governance, trust, sustainability, and generative AI. Particular attention is paid to studies that distinguish the presence of AI from adoption intensity or depth, because this distinction directly addresses the review question.

Quality and reproducibility safeguards. All numerical results in the Results section are taken directly from the supplied Biblioshiny workbook or the matching Web of Science export. The manuscript does not infer missing network outputs that were not generated. Duplicate lexical forms such as "artificial intelligence" and "artificial-intelligence" are reported as Biblioshiny produced them rather than silently merged. This transparency is important because keyword normalization can materially alter network structure.

Results and Discussion

Growth and Overall Structure of the Field

Table 1. Main characteristics of the Biblioshiny corpus.

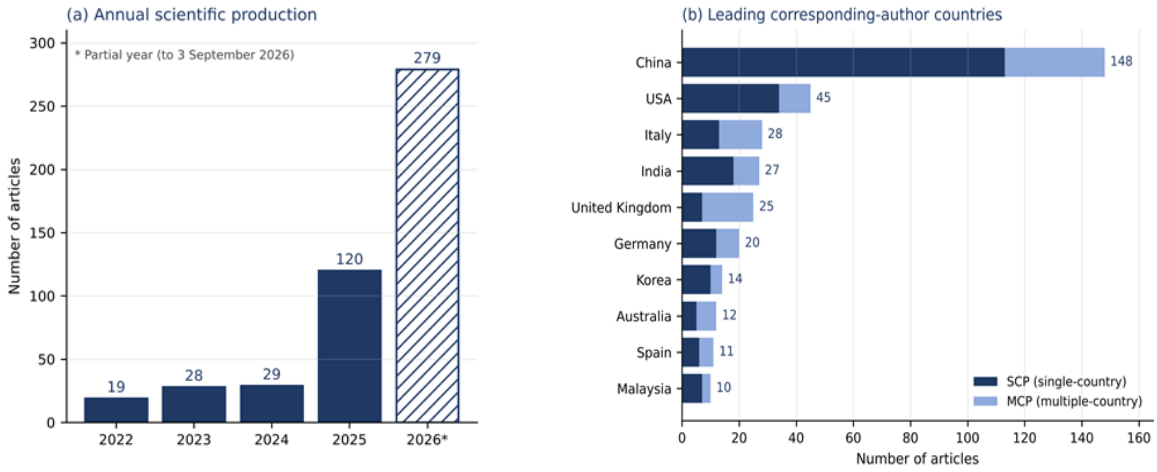
Indicator	Result
Timespan	2022:2026
Sources	223
Documents	475
Annual growth rate	95.75%
Average document age	0.712 years
Average citations/document	12.89
References	28005
Keywords Plus	806
Author keywords	1781
Authors	1395
Single-authored documents	51
Co-authors/document	3.12
International co-authorship	37.05%
Document types	336 articles; 139 articles/early access

The corpus contains 475 articles distributed across 223 sources, indicating a broad and interdisciplinary publication base rather than dependence on a small set of specialist AI-adoption journals **(Table 1)**. Biblioshiny reports 1,395 authors, 28,005 cited references, 806 Keywords Plus terms, and 1,781 author keywords. The mean number of co-authors is 3.12, while international co-authorship reaches 37.05%. Only 51 documents are single-authored. These indicators show that contemporary AI-adoption research is predominantly collaborative and increasingly international.

Publication growth is exceptionally rapid. Annual output increased from 19 articles in 2022 to 28 in 2023, 29 in 2024, 120 in 2025, and 279 in 2026 **(Figure 1a)**, producing a Biblioshiny annual growth rate of 95.75%. The sharp rise in 2025-2026 reflects the expansion of generative AI, organizational implementation, and sector-specific adoption

research. Because the search was conducted on September 3, 2026, the 279 records for 2026 are a partial-year count. The magnitude of that partial-year output nevertheless signals how quickly AI adoption has become a mainstream business and management topic.

The average document age is only 0.712 years, yet the corpus already averages 12.89 citations per document. This combination of youth and citation activity is consistent with a rapidly expanding research front. It also creates a methodological caution: raw citation rankings disproportionately favor the 2022-2024 papers that have had more time to accumulate citations, whereas many 2025-2026 papers may become influential but are too recent for citation counts to reveal their eventual impact.



a) b)

Figure 1. Annual scientific production, 2022-2026 (a), and the ten leading corresponding-author countries by single-country (SCP) and multiple-country (MCP) publications (b). Note: 2026 is a partial year.

Publication Outlets: Diffusion across Innovation, Economics, Strategy, and Management

Table 2. Fifteen most productive sources.

Source	Articles
Technological Forecasting And Social Change	22
International Review Of Economics & Finance	12
Applied Economics	8
Business Strategy And The Environment	8
Energy Economics	8
European Journal Of Innovation Management	8
Journal Of Innovation & Knowledge	8
Journal Of Business Research	7
Technology Analysis & Strategic Management	7
Technovation	7
Corporate Social Responsibility And Environmental Management	6
Engineering Construction And Architectural Management	6
Finance Research Letters	6
International Journal Of Contemporary Hospitality Management	6
Journal Of Retailing And Consumer Services	6

Technological Forecasting and Social Change is the leading outlet with 22 articles **(Table 2)**, followed by International Review of Economics & Finance with 12. Applied Economics, Business Strategy and the Environment, Energy Economics, European Journal of Innovation Management, and Journal of Innovation & Knowledge each contribute eight, while Journal of Business Research, Technology Analysis & Strategic Management, and Technovation each contribute seven. The source distribution is substantively revealing: AI adoption is being studied simultaneously as an innovation-management problem, an economic and productivity phenomenon, a sustainability issue, and a strategic organizational transformation.

No single source dominates the corpus. The leading journal accounts for only 4.6% of the 475 documents, and the top ten sources together account for 94 articles, or about one fifth of the corpus. This dispersion contrasts with mature subfields that are organized around a few specialist journals. For AI adoption, fragmentation across disciplinary outlets can stimulate theoretical variety but also create conceptual inconsistency. Terms such as adoption, use, implementation, assimilation, intensity, readiness, and transformation are sometimes used for different stages of the same process. A central task for future research is therefore construct alignment across these literatures.

The presence of Business Strategy and the Environment, Energy Economics, and sustainability-oriented work shows that the AI-adoption conversation is no longer limited to efficiency or financial outcomes. Research increasingly asks whether AI affects environmental performance, energy intensity, greenwashing, supply-chain sustainability, and ESG outcomes. At the same time, economics journals emphasize productivity and labor-market consequences, while innovation and management journals emphasize capabilities, business models, and organizational readiness.

Authors, Affiliations, and Geographic Leadership

Author productivity is dispersed. Gavurova B leads with four articles (1.08 fractionalized); Abdulmuhsin AA, Chen YT, Ding H, Gupta S, Jeong J, Jiang Y, Khan AN, Umar M, Wang L, and Zhang Y each contribute three. The low maximum author count relative to the size of the corpus suggests that the field is expanding through many research teams rather than being controlled by a small stable core. This pattern is typical of a rapidly emerging topic in which researchers from established disciplines enter AI research from different theoretical starting points.

The State University System of Florida is the leading affiliation with 12 records. The Indian Institute of Management system and the University of International Business and Economics each contribute nine, followed by Harbin Institute of Technology and Hunan University with eight. Beijing Normal University, Nanjing University, and the University System of Georgia each contribute seven. The affiliation list combines university systems and individual institutions, so the figures should be interpreted as database-generated affiliation entities rather than perfectly normalized organizational totals.

China is the leading corresponding-author country with 148 articles **(Figure 1b)**, representing 31.16% of the corpus, followed by the United States with 45, Italy with 28, India with 27, and the United Kingdom with 25. China also produces 35 multiple-country publications, but its MCP ratio is 23.65%. The United Kingdom has a much higher MCP ratio of 72%, Italy 53.57%, Australia 58.33%, Germany 40%, and India 33.33%. Thus, publication volume and internationalization are different dimensions of geographic influence.

The geographic pattern has implications for theory. AI adoption depends on data infrastructure, labor costs, digital ecosystems, regulation, institutional support, and competitive intensity. Evidence from China, the United States, Europe, India, and other contexts should therefore not be treated as institutionally interchangeable. Diffusion research further shows that AI adoption spreads through epidemic, information-driven effects among firms, which makes local technology ecosystems consequential (Dahlke *et al*., 2024). Comparative studies can test whether the same adoption determinants predict only initial uptake in one setting but predict deeper assimilation or adoption intensity in another.

Citation Structure: Influential Foundations of the Recent Research Front

Table 3. Ten most globally cited documents.

Document	TC	TC/year	Normalized TC
CZARNITZKI D, 2023, J ECON BEHAV ORGAN	249	62.2	4.13
KINKEL S, 2022, TECHNOVATION	226	45.2	2.35

OMRANI N, 2022, TECHNOL FORECAST SOC	220	44.0	2.29
KORZYNSKI P, 2023, CENT EUR MANAG J	195	48.8	3.23
LEE JC, 2022, INT J BANK MARK	157	31.4	1.63
SONG X, 2022, INFORM MANAGE-AMSTER	151	30.2	1.57
KOPALLE PK, 2022, INT J RES MARK	141	28.2	1.46
AKBARI M, 2022, OPER MANAGE RES	136	27.2	1.41
ÅSTRÖM J, 2022, REV MANAG SCI	135	27.0	1.40
CHAKRABORTY D, 2024, J BUS RES	120	40.0	4.04

The citation ranking shows that the recent field is anchored by both organizational-adoption studies and broader analyses of AI consequences **(Table 3)**. Czarnitzki *et al*. (2023) is the most cited document in the corpus with 249 citations and examines AI and firm-level productivity. Kinkel *et al*. (2022), with 226 citations, focus directly on prerequisites for AI adoption in manufacturing. Omrani *et al*. (2022), with 220 citations, examine trust, ethics, and contextual concerns in AI-based systems. Korzynski *et al*. (2023), with 195 citations, position generative AI as a new context for management theory.

The remaining highly cited papers broaden the intellectual base. Lee and Chen (2022) analyze adoption intentions for AI mobile-banking applications; Song *et al*. (2022) examine relationships with intelligent assistants; Kopalle *et al*. (2022) map AI technologies in marketing; Akbari and Hopkins (2022) connect digital technologies with supply-chain sustainability; Åström *et al*. (2022) develop a process framework for AI business-model innovation; and Chakraborty *et al*. (2024) examine trust in generative-AI chatbots. The citation structure therefore connects organizational adoption with productivity, customer acceptance, business models, sustainability, trust, and generative AI.

For research on the level of AI adoption, two citation streams are particularly important. The first explains prerequisites and readiness: Kinkel *et al*. (2022) and later readiness research identify conditions that make adoption feasible. The second explains value realization: Czarnitzki *et al*. (2023), Åström *et al*. (2022), Wang *et al*. (2023), and related work examine productivity, innovation, and business outcomes. The unresolved theoretical bridge between these streams is how firms progress from initial adoption to extensive assimilation and how complementary investments condition the returns from that progression.

Keyword Structure: Adoption Is Embedded in a Broader Organizational Transformation Vocabulary

Artificial intelligence is the dominant term with 191 occurrences, while the hyphenated variant artificial-intelligence appears 70 times. Technology occurs 64 times, innovation 60, performance 56, impact 47, management 46, AI 45, adoption 42, information-technology 40, and model 40, followed by AI adoption (38), future (30), technology adoption (30), user acceptance (30), digital transformation (29), acceptance (28), trust (28), dynamic capabilities (27), and generative AI (26). The lexical structure demonstrates that adoption is not isolated from outcomes: innovation, performance, impact, and management are among the most frequent concepts surrounding AI.

The duplicated forms artificial intelligence and artificial-intelligence also illustrate a common bibliometric issue. Without a thesaurus or preprocessing step, semantically identical terms can be split into separate nodes, reducing the apparent centrality of the underlying concept. The present review reports the Biblioshiny output faithfully. A future robustness analysis should merge spelling variants, abbreviations, singular/plural forms, and closely related adoption labels before regenerating the conceptual network.

More substantively, the keyword profile suggests that the field is transitioning from technology acceptance toward organizational consequences. Adoption remains prominent, but performance and innovation are more frequent than many classic acceptance constructs. This supports a shift in research questions from whether decision makers intend to use AI toward how organizations deploy AI across functions, develop complementary capabilities, and obtain performance or sustainability outcomes.

Co-Word Network: Structural Centrality and Thematic Domains

Table 4. Leading co-word nodes and network centrality.

Node	Cluster	Betweenness	PageRank
artificial intelligence	1	265.61	0.0979
technology	1	63.04	0.0507
innovation	1	52.62	0.0436
impact	1	24.99	0.0317
future	1	18.03	0.0283
generative ai	1	1.05	0.0119
automation	1	4.65	0.0213
growth	1	2.18	0.0174
productivity	1	1.37	0.0136
o33	1	1.53	0.0158
decision-making	1	0.51	0.0146
employment	1	1.09	0.0155
jobs	1	1.71	0.0164
knowledge	1	0.09	0.0095
absorptive-capacity	1	0.63	0.0107

Artificial intelligence is the dominant network node, with betweenness centrality of 265.61 and PageRank of 0.0979 **(Table 4)**. Technology follows with betweenness of 63.04, innovation 52.62, impact 24.99, and future 18.03. Generative AI, automation, growth, productivity, decision-making, employment, jobs, and knowledge also appear among the leading nodes in the same reported cluster. High betweenness indicates that AI, technology, and innovation connect multiple conceptual conversations rather than belonging to a narrow standalone topic.

The network points to an adoption-to-transformation architecture. AI and technology form the technological core; innovation and future capture strategic change; automation, productivity, employment, and jobs capture economic and work consequences; decision-making and knowledge capture organizational processes. This architecture is consistent with the proposition that AI adoption level should be conceptualized as the extent to which AI penetrates organizational tasks and decision routines, not merely as the existence of one AI application.

Generative AI is already structurally visible despite the short timespan. Korzynski *et al*. (2023) helped establish generative AI as a management-theory context, and subsequent studies examine generative AI in customer interfaces, supply chains, accounting, human resources, and organizational workflows (Chakraborty *et al*., 2024; Malhotra & Manzoor, 2026). Generative AI may therefore accelerate the transition from specialized AI applications to broader employee-level diffusion, making adoption intensity increasingly multidimensional.

Thematic Synthesis I: Prerequisites, Readiness, and the Move beyond Binary Adoption

The first thematic domain concerns prerequisites and readiness. Kinkel *et al*. (2022) provide a major empirical anchor by examining prerequisites for AI adoption across manufacturing firms. More recent work extends this logic to organizational readiness, managerial capabilities, AI literacy, and sector-specific barriers. Tehrani *et al*. (2024), for example, frame AI readiness as multidimensional, while Alghazzawi (2025) links organizational readiness with accounting efficiency. Malik *et al*. (2025) identify organizational, environmental, regulatory, economic, technological, and human barriers in AI adoption for credit-risk assessment. These studies converge on the idea that adoption is a socio-technical organizational process rather than a simple technology purchase.

This stream also reveals a measurement problem. Adoption intention, adoption status, readiness, implementation, assimilation, and adoption intensity are not interchangeable. Intention is a pre-adoption psychological state; readiness is an enabling condition; adoption status indicates whether AI has been introduced; implementation describes putting applications into use; assimilation concerns routinization and integration; and intensity captures the breadth or depth

of actual deployment. Studies that combine these stages in one construct risk obscuring mechanisms and weakening causal interpretation.

A level-of-adoption perspective addresses part of this problem by treating AI use as continuous rather than binary. Firms may have low adoption because they pilot one application, or moderate adoption. After all, some functions use AI, or have high adoption because AI is embedded across decision processes and linked with complementary data and digital infrastructures. The most theoretically useful measures should therefore specify whether level refers to breadth, depth, spending, number of applications, functional coverage, employee penetration, process criticality, or maturity. Different operationalizations may have different antecedents and outcomes.

Future adoption research should consequently model stages explicitly. Technological characteristics and perceived barriers may be strongest at the decision stage; organizational readiness and leadership may become more important during implementation; data quality, knowledge management, and complementary infrastructure may dominate assimilation; and governance, learning, and dynamic capabilities may determine whether high adoption intensity remains productive and responsible over time.

Thematic Synthesis II: Complementary Capabilities, Knowledge, and Strategic Alignment

The second domain concerns the complementary assets that convert adoption into organizational capability. Lee *et al*. (2022) provide direct evidence that AI-adoption intensity does not automatically produce revenue growth. Benefits become stronger after sufficient AI investment and when firms also invest in cloud computing, database systems, and an appropriate R&D strategy. This finding is fundamental because it challenges linear assumptions that more AI always produces more value. Adoption level can exhibit threshold effects and complementarity.

Knowledge management is another critical complement. Leoni *et al*. (2022) show that knowledge-management processes mediate the effective use of AI in manufacturing firms. The implication is that algorithms alone do not create organizational knowledge. Firms must acquire, interpret, share, and apply information; redesign routines; and enable employees to use AI outputs in decisions. This logic is consistent with dynamic-capability reasoning: sensing AI opportunities, seizing them through investment and implementation, and transforming routines are distinct organizational tasks.

Business-model research reinforces this interpretation. Åström *et al*. (2022) describe AI business-model innovation as a process of value creation and value capture. AI adoption can alter value propositions, activities, customer interactions, and revenue mechanisms, but these changes require strategic alignment. High adoption intensity without business-model coherence can increase cost and complexity without generating proportional returns. Conversely, firms with strong strategic alignment may obtain substantial value from targeted rather than ubiquitous AI deployment.

Leadership and managerial cognition also matter. Recent studies of talent management and organizational readiness (Abid, 2026; Alghazzawi, 2025) suggest that differences between early and lagging adopters cannot be reduced to technology availability. Managerial dynamic capabilities shape how leaders interpret AI opportunities, allocate resources, coordinate stakeholders, and manage uncertainty. This suggests a moderated relationship: the effect of adoption level on innovation or performance should be stronger when complementary managerial and organizational capabilities are high.

Thematic Synthesis III: Performance, Productivity, and Value Realization

Performance and productivity constitute the third major domain. Czarnitzki *et al*. (2023), the most globally cited paper in the corpus, examine AI and firm-level productivity. Wang *et al*. (2023) provide evidence on AI and total factor productivity in Chinese manufacturing enterprises, while Venturini (2022) examines productivity spillovers from intelligent technologies. Chen *et al*. (2023) further identify the determinants of AI-adoption performance in the hospitality industry. Together with Lee *et al*. (2022), these studies move the literature beyond adoption determinants toward economic consequences.

The evidence also cautions against treating performance as a single immediate outcome. AI can influence process efficiency, decision quality, innovation, revenue, cost, labor productivity, total factor productivity, customer experience, resilience, and sustainable performance through different pathways and time horizons. Some benefits may

appear only after organizational learning and complementary investments. Short cross-sectional studies can therefore underestimate delayed gains or mistake implementation costs for negative long-run effects.

The relationship between adoption level and performance may also be nonlinear. At very low levels, AI may be too peripheral to affect firm outcomes. At moderate levels, firms may realize process efficiencies. At high levels, benefits can accelerate through data network effects and organizational learning, but complexity, governance costs, technical debt, and coordination burdens may also increase. Theoretical models should therefore test threshold, diminishing-return, or inverted-U patterns rather than assuming a constant marginal effect.

A further issue is endogeneity. Productive and innovative firms may be more likely to adopt AI intensively, making it difficult to infer that AI caused superior performance. Future research should exploit longitudinal panels, instrumental variables, difference-in-differences designs, matched samples, natural experiments, or detailed pre/post implementation data. Bibliometric growth has outpaced causal identification; the next stage of the field should prioritize stronger designs.

Thematic Synthesis IV: Employees, Customers, and the Human-AI Interface

The fourth domain concerns the human interface of AI adoption. AI-augmented HRM research examines antecedents, assimilation, and multilevel consequences (Prikshat *et al*., 2023), while personalized HR analytics studies consider how AI changes employee management (Huang *et al*., 2023). Customer-facing studies investigate mobile banking, hotel voice assistants, service robots, chatbots, anthropomorphism, and trust. These literatures demonstrate that organizational adoption level can be experienced differently by employees and customers even when the same firm is classified as a high adopter.

For employees, deeper AI adoption can alter task allocation, skill requirements, autonomy, monitoring, learning, and job design. The co-word network includes employment and jobs, indicating that labor consequences are part of the field's structural core. A high level of AI adoption may improve productivity while simultaneously creating adjustment costs or perceived threats. Organizational outcomes therefore depend partly on whether AI is designed as augmentation, substitution, or a hybrid arrangement.

For customers, trust, explainability, anthropomorphic design, and perceived usefulness influence acceptance of AI-enabled services. Yet customer adoption should not be conflated with organizational AI adoption. A bank can intensively deploy AI internally even if customers rarely interact with AI, while a service firm can deploy one highly visible chatbot without having broad organizational AI assimilation. Future research should distinguish the level of firm-side adoption from user-side acceptance and examine how the two interact.

This distinction is especially important for generative AI because diffusion can occur bottom-up through employee use rather than only through centrally approved enterprise systems. Measures of organizational adoption level may need to capture sanctioned and unsanctioned use, centralized and decentralized deployment, and differences between experimental and mission-critical applications.

Thematic Synthesis V: Trust, Governance, Sustainability, and Responsible Scaling

Trust and governance form a fifth domain. Omrani *et al*. (2022) show the prominence of trust, ethics, and contextual concerns, and later studies examine explainability, governance quality, regulatory conditions, and responsible deployment (Montealegre-Lopez, 2025). As adoption intensity increases, governance becomes more consequential because AI influences a larger share of organizational decisions and exposes the firm to broader privacy, fairness, security, accountability, and compliance risks.

Responsible scaling should therefore be incorporated into theories of adoption level. High adoption intensity without governance capability can create a liability rather than an advantage. Governance mechanisms include clear accountability, model validation, human oversight, data governance, documentation, monitoring, and escalation procedures. These mechanisms may moderate the relationship between AI adoption level and sustainable competitive advantage by reducing downside risk and increasing stakeholder trust.

Sustainability is also increasingly visible. Akbari and Hopkins (2022) connect digital technologies with supply-chain sustainability; Calabrese *et al*. (2023) examine the intersection of sustainability and Industry 4.0; Bai *et al*. (2025) study AI and greenwashing; Tian *et al*. (2025) link AI adoption with ESG performance; and recent work examines

energy intensity and green digital transformation. This literature expands the outcome domain from economic value to environmental and governance consequences.

A key future question is whether more AI adoption is always environmentally desirable. AI can optimize energy, logistics, maintenance, and resource allocation, yet computational infrastructure itself consumes energy and resources. Research on adoption level should therefore distinguish AI for environmental sustainability from environmentally efficient AI deployment. Such a distinction can clarify when deeper AI use improves net sustainability rather than merely shifting environmental costs.

Integrative Framework: From Adoption Decision to Adoption Intensity and Organizational Value

Table 5. Integrative adoption-to-value framework derived from the bibliometric and thematic synthesis.

Stage	Core question	Representative constructs	Priority outcomes
1. Readiness	Can the firm adopt AI?	Infrastructure, data, skills, resources, leadership, regulation, trust	Adoption decision/status
2. Implementation	Can AI be put into effective use?	Project capability, vendor integration, change management, employee acceptance	Operational use
3. Assimilation	Is AI embedded in routines?	Knowledge management, process redesign, learning, governance	Routinization and breadth
4. Adoption level/intensity	How extensively is AI deployed?	Functional coverage, depth, investment, application portfolio, process criticality	Innovation, productivity, agility
5. Value realization	When does deeper adoption pay off?	Complementary digital assets, dynamic capabilities, R&D, business-model alignment	Performance, advantage, sustainability
6. Responsible scaling	Can high adoption remain trusted and sustainable?	AI governance, oversight, ethics, cybersecurity, environmental efficiency	Resilience, legitimacy, long-term value

The bibliometric evidence supports a six-stage adoption-to-value framework **(Table 5)**. The framework is not a claim that every firm progresses linearly through identical stages. Rather, it separates constructs that are often collapsed in empirical models. Readiness precedes or enables adoption; implementation converts a decision into use; assimilation embeds use in routines; adoption level captures the extent of deployment; value realization concerns organizational outcomes; and responsible scaling concerns whether extensive use can be sustained under governance and stakeholder constraints.

This separation has direct implications for hypothesis development. Antecedents of initial adoption need not have the same effect on adoption intensity. Complexity, for example, may deter initial adoption, but once a firm has developed implementation experience, its effect on additional deployment may weaken. Top-management support may be important at all stages but operate through different mechanisms, from resource commitment during adoption to strategic alignment during scaling. Competitive and regulatory pressures may trigger adoption, while technological turbulence may strengthen the value of rapid assimilation and flexible capabilities.

The framework also suggests that adoption level is best positioned as an intermediate strategic construct rather than an outcome. Its importance lies in linking organizational conditions to downstream innovation, competitive advantage, sustainability, and performance. Researchers should therefore avoid treating a high adoption score as inherently successful. High adoption can be inefficient if applications are fragmented, poorly governed, weakly integrated with data, or misaligned with strategy.

Research Agenda for the Next Stage of AI-Adoption Scholarship

Table 6. Research agenda for organizational AI-adoption research.

Priority	Current weakness	Recommended research direction
Construct precision	Adoption, intention, use, assimilation, intensity, and maturity are often blurred.	Define the stage and unit of analysis; validate multidimensional adoption-level measures.
Causal inference	Cross-sectional associations dominate many streams	Use longitudinal panels, quasi-experiments, matched designs, and implementation event studies.
Complementarity	AI is sometimes modeled as an isolated resource.	Test interactions with data, cloud, R&D, knowledge management, leadership, and dynamic capabilities.
Nonlinearity	Linear more-AI-is-better assumptions	Test thresholds, diminishing returns, and configuration effects.
Multi-level effects	Firm adoption and employee/customer acceptance are mixed	Separate firm, team, employee, and customer levels and model cross-level mechanisms.
Responsible AI	Governance is often treated as a barrier only.	Model governance capability as an enabler of trusted high-intensity adoption.
Sustainability	Economic outcomes dominate	Measure both AI-enabled environmental benefits and AI computational/resource costs.
International generalizability	Country concentration and institutional heterogeneity	Conduct harmonized cross-country studies and institutional moderation tests.
Generative AI	Rapid diffusion outpaces validated measurement.	Capture decentralized use, shadow AI, human-AI collaboration, and workflow integration.
Bibliometric robustness	Keyword variants and restricted database/publisher choices	Use thesaurus cleaning, multiple databases, sensitivity analyses, and transparent search protocols.



Table 6 summarizes the resulting research agenda. The first priority is measurement. A defensible adoption-level construct should use behavioral indicators of actual organizational deployment rather than intention items. Researchers should specify the organizational referent, such as firm, business unit, or function, and decide whether the construct is reflective, formative, or higher-order. Breadth and depth may be complementary dimensions: breadth captures how many functions or processes use AI, while depth captures how extensively AI is embedded within those processes.

The second priority is temporal design. AI adoption is a process, and the costs and benefits unfold at different speeds. Longitudinal data can identify whether readiness predicts later adoption, whether adoption intensity grows through learning, and whether performance improvements lag implementation. Such designs can also reveal abandonment, retrenchment, or replacement, which binary cross-sectional measures cannot capture.

Third, configurational and contingency approaches deserve greater attention. The value of high AI adoption may depend on combinations of leadership, data capability, absorptive capacity, R&D strategy, governance, and environmental turbulence. PLS-SEM can estimate net effects and mediation or moderation, while fsQCA can identify multiple sufficient configurations. Used together and theoretically justified, these methods can address equifinality without treating every determinant as universally necessary.

Fourth, generative AI requires new measurement logic. Unlike traditional enterprise systems, generative AI can diffuse rapidly through individual employees using general-purpose tools. Organizational adoption may therefore precede formal governance. Future scales should distinguish formal enterprise deployment, employee-initiated use, integration with proprietary data, workflow automation, and decision authority. This will make the construct more sensitive to the actual organizational reality of AI use (Korzynski *et al*., 2023; Malhotra & Manzoor, 2026).

Finally, responsible and sustainable adoption should be integrated with performance research. Governance and environmental efficiency should not be added only as limitations after positive performance effects are estimated. They are part of the mechanism through which high adoption intensity becomes durable organizational value (Omrani *et al*., 2022; Montealegre-Lopez, 2025; Tian *et al*., 2025).

Managerial Implications

For managers, the bibliometric evidence suggests that adoption should be managed as a portfolio and capability-development process. The strategic objective is not to maximize the number of AI tools but to deploy AI where data quality, process fit, employee capability, governance, and complementary infrastructure allow value to be captured. Pilot projects can establish feasibility, but scaling decisions should be tied to explicit performance or sustainability objectives.

Managers should also distinguish readiness metrics from adoption metrics and adoption metrics from outcome metrics. Readiness dashboards can track data availability, skills, infrastructure, leadership commitment, and governance. Adoption dashboards can track functional coverage, active users, process penetration, investment, and integration. Outcome dashboards can track productivity, innovation, customer experience, risk, employee effects, and environmental performance. Keeping these categories separate improves accountability and reduces the temptation to treat technology deployment itself as proof of success.

The rapid rise of generative AI makes governance particularly urgent. Firms need policies for approved use, data handling, human verification, model selection, monitoring, and accountability, while still allowing experimentation. Overly restrictive governance can suppress learning, but absent governance can increase operational and reputational risk. The managerial challenge is therefore governed experimentation followed by evidence-based scaling.

Limitations

This review has several limitations. First, it uses the Web of Science Core Collection rather than combining Web of Science and Scopus. The resulting corpus should therefore be described as a Web of Science bibliometric sample, not as the complete universe of AI-adoption research. Second, the search uses the exact phrase "the level of AI adoption" and Web of Science's query processing, which retrieved a broader set of AI-adoption and AI-related business articles than a literal title search would imply. This improves thematic breadth but reduces precision around the specific construct of adoption level.

Third, the review restricts the research area to Business Economics, English-language articles, the years 2022-2026, and six publisher groups. These decisions align the corpus with a recent business-focused review but exclude relevant work in information systems, computer science, public administration, health, engineering, and journals from other publishers. Fourth, 2026 is incomplete, so annual production should not be used for a full-year trend comparison without qualification.

Fifth, the supplied Biblioshiny workbook contains keyword frequency and co-word network outputs but not all possible science-mapping modules such as thematic evolution, historiography, or co-citation networks. The manuscript reports only generated evidence. Sixth, keyword variants were not fully normalized. Finally, bibliometric centrality and citation counts measure visibility and structural influence, not methodological quality or causal validity.

Conclusion

Research on AI adoption in business has expanded at extraordinary speed. The 475-document corpus published from 2022 through September 2026 spans 223 sources and 1,395 authors, with publication activity accelerating sharply in 2025-2026. The field is geographically led by China and the United States but displays substantial international collaboration. Innovation, economics, strategy, sustainability, marketing, operations, and human resource journals all contribute to the knowledge base, confirming that organizational AI adoption is inherently interdisciplinary.

The substantive evolution of the field is equally important. Early and continuing research asks what enables or constrains adoption; a growing body of work asks how organizational readiness, knowledge management, leadership, complementary digital investment, and dynamic capabilities shape implementation and assimilation; and an increasingly influential stream evaluates productivity, innovation, business models, sustainability, and performance. Trust, governance, employee consequences, customer acceptance, and generative AI now form essential parts of the research frontier.

The central conclusion is that future scholarship should move beyond binary adoption. The level or intensity of AI adoption is a theoretically meaningful construct when it captures actual breadth and depth of organizational deployment and is clearly distinguished from intention, readiness, implementation, and maturity. Its effects are

unlikely to be universally linear or automatic. Complementary capabilities, strategic alignment, governance, institutional conditions, and time determine whether deeper AI adoption produces sustainable organizational value. A rigorous next generation of studies should therefore combine precise measurement with longitudinal, multi-level, cross-country, and causal designs.

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