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Artificial Intelligence in Economic Business: A Systematic Review and Future Research Agenda

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ABSTRACT

Purpose—This study systematically reviews the development, intellectual structure, theoretical foundations, and future research directions of artificial intelligence (AI) in economic business research.

Design/methodology/approach—The study employs a hybrid systematic literature review design that combines bibliometric and content analyses. Bibliometric analysis was conducted on 1,970 articles indexed in the Web of Science Core Collection from 1990 to June 2024. In-depth content analysis was then performed on 110 empirical articles published in Q1/Q2 journals. The analysis covers AI application categories, research topics, guiding theories, methodologies, and research contexts.

Findings—The findings identify four dominant AI application domains: market prediction and risk management, marketing and customer analytics, process automation and supply chain optimization, and strategic decision-making and HR analytics. The literature is highly concentrated in data-rich sectors such as banking, fintech, e-commerce, and retail. Most studies emphasize system design, algorithmic performance, and predictive accuracy, while theory-driven, longitudinal, governance-oriented, and context-sensitive research remains limited. Only a minority of empirical studies explicitly apply established theories, indicating a need for stronger integration between computational performance and business, organizational, and socio-technical mechanisms.

Originality/value—This study contributes by integrating large-scale bibliometric mapping with manual content analysis to provide a comprehensive synthesis of AI-economic business research. It proposes a future research agenda focused on generative AI, explainable AI, human-AI collaboration, theory-driven inquiry, and long-term societal impacts.

1. Introduction

Artificial intelligence (AI) is one of the most significant general-purpose technologies in today's global economy. As with electricity, computing, and the internet, AI has the potential to transform business processes on a fundamental level. It can reshape production systems, alter firms' capabilities, and change the competitive strategies by which companies generate and capture value. From a Schumpeterian standpoint, AI can be considered a form of creative destruction, with the potential to disrupt traditional business models while facilitating the development of digital products, platform ecosystems, algorithmic services, and data-driven market coordination (Schumpeter, 1942). The present literature review investigates the influence of AI on economic and business research across applications, theories, methods, and potential future directions.

Previous automation methods primarily relied on predefined rules, deterministic workflows, and structured processes. In the contemporary business landscape, AI systems are becoming increasingly dependent on adaptive, data-driven inference techniques that leverage machine learning, deep learning, natural language processing, computer vision, and generative models. This transition enables companies to shift from a retrospective reporting model to a predictive and prescriptive approach, thereby transforming how managers understand markets, customers, operations, risk, and organizational performance. Hanandeh et al. (2024) highlight that the importance of AI lies not only in automation but also in enhancing human decision-making, creating new organizational capabilities, and reshaping work and competition. The economic consequences of this transition are substantial. Generative AI has been estimated to generate between US$2.6 trillion and US$4.4 trillion in additional annual value across business areas, particularly in customer service, marketing, sales, software engineering, and research and development, while empirical evidence also shows that generative AI can improve knowledge-work productivity (Chui et al., 2023; Noy and Zhang, 2023). AI is therefore not only a technology but also an economic infrastructure for value generation.

The impact of AI is now evident across a wide range of business functions, including finance, marketing, operations, supply chain, strategy, and human resources. In finance, AI is widely used for algorithmic trading, credit scoring, fraud detection, portfolio optimization, sentiment analysis, and volatility prediction. These uses relate to the Efficient

Market Hypothesis, which posits that security prices reflect all available information, making it difficult to consistently generate abnormal returns (Fama, 1970). In marketing, AI plays a pivotal role in personalization, recommendation engines, chatbots, churn prediction, dynamic pricing, and sentiment evaluation. These applications align with the Technology Acceptance Model, which posits that technology adoption is driven by perceived usefulness and ease of use (Davis, 1989), and the Theory of Planned Behavior, which links actions to attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). In operations and supply chains, AI supports demand forecasting, inventory management, logistics routing, robotic process automation, supplier risk analysis, and predictive maintenance. According to Transaction Cost Economics, AI has the potential to reduce costs associated with search, monitoring, coordination, and adjustment in organizational and market relationships (Williamson, 1975). In strategy and HR, AI tools play a pivotal role in decision dashboards, scenario modeling, automated hiring, performance prediction, workforce planning, and network analysis. These applications are linked to the Resource-Based View, which highlights the importance of valuable, inimitable resources (Barney, 1991), and to Dynamic Capabilities theory, which focuses on a firm's ability to sense, seize, and reconfigure resources in dynamic environments (Teece et al., 1997).

Previous reviews have offered valuable insights but remain scattered across different business fields. In finance, Sezer et al. (2020) explored deep learning for financial time-series forecasting, Ozbayoglu et al. (2020) examined deep learning applications in finance, and Lin and Lobo Marques (2024) compiled reviews on AI-driven stock market prediction. These works highlight the significance of LSTM, neural networks, support vector machines, and ensemble models, yet they mainly focus on prediction and are only partially linked to the efficient market hypothesis and information asymmetry theory (Akerlof, 1970; Fama, 1970). In marketing, Davenport et al. (2020), Mariani et al. (2022), and Verma et al. (2021) emphasize AI-powered personalization, recommendations, customer analytics, and engagement. These studies relate to technology acceptance, UTAUT, and trust theories explaining AI-mediated interactions (Davis, 1989; Mayer et al., 1995; Venkatesh et al., 2003). In operations and supply chain management, Modgil et al. (2022), Pournader et al. (2021), and Toorajipour et al. (2021) demonstrate how AI enhances logistics, forecasting, resilience, and decision-making, aligning with Transaction Cost Economics, Dynamic Capabilities theory, and Socio-Technical Systems Theory (Teece et al., 1997; Trist and Bamforth, 1951; Williamson, 1975). In HRM, strategy, and digital transformation, Borges et al. (2021), Kraus et al. (2021), and Vrontis et al. (2022) reveal AI's influence on recruitment, workforce transformation, decision support, and organizational change, which can be explained through human capital theory, agency theory, RBV, dynamic capabilities theory, and Institutional Theory (Barney, 1991; Becker, 1964; DiMaggio and Powell, 1983; Jensen and Meckling, 1976; Teece et al., 1997).

This review highlights four main limitations. First, most prior reviews focus narrowly on individual business functions rather than on AI within the broader field of economic business. Second, many categorize AI techniques and uses but lack strong theoretical synthesis. Third, many studies are outdated, predating the widespread adoption of generative AI, large language models, multimodal AI, and AI-supported knowledge work. Fourth, few combine bibliometric mapping with manual content analysis, thereby missing either the macro-level intellectual landscape or the micro-level theoretical and methodological details. To address these issues, this study follows the approach of rigorous hybrid systematic reviews, such as Wang et al. (2024), by integrating bibliometric analysis of 1,970 articles with content analysis of 110 empirical Q1/Q2 journal papers. It conceptualizes AI not only as a computational tool but also as an economic capability, an organizational resource, an institutional pressure, a decision infrastructure, and a socio-technical governance object. Table 1 summarizes prior review studies and clarifies how the present review extends existing domain-specific syntheses.

This systematic literature review addresses three key research questions to fill the identified gaps. RQ1 explores the main categories of AI applications in the economic and business literature, including financial prediction, risk management, marketing analytics, supply chain optimization, and HR analytics. RQ2 investigates the primary research topics, significant findings, and guiding theoretical frameworks, with a focus on system development, adoption, impacts, and ethics. RQ3 assesses the current state of research design, including methodologies, contexts, and sectors, and identifies future research opportunities.

The paper is organized as follows. Section 2 reviews the existing literature and positions this study within prior domain-specific reviews. Section 3 details the research methodology, including search strategies, inclusion and exclusion criteria, bibliometric analysis, content analysis sample, and coding scheme. Section 4 presents bibliometric results, including publication trends, journal distribution, keyword co-occurrence, and co-citation networks. Section 5 discusses the content analysis findings. Section 6 synthesizes the results and proposes a future research agenda. Section 7 concludes with contributions, limitations, and implications.

2. Research Methodology

2.1 Data Collection and Bibliometric Analysis

The bibliometric dataset was collected from the Web of Science (WoS) Core Collection. WoS was selected because it provides structured bibliographic metadata, citation relationships, subject classifications, and indexed journal records suitable for multidisciplinary bibliometric mapping. Bibliometric methods are particularly useful in management, organization, and information systems research because they allow researchers to identify knowledge structures, influential sources, intellectual foundations, and thematic developments within a field (Zupic and Čater, 2015). The search window covered 1990–2024 to capture the evolution of AI in economic business from early expert systems, machine learning diffusion, big data analytics, deep learning, and the rise of generative AI and large language models. This temporal scope supports both historical mapping and contemporary thematic interpretation using science-mapping techniques (Aria and Cuccurullo, 2017).

The Boolean search string was designed to capture the intersection between AI technologies and economic business domains. The final search query was:

TS = ((“artificial intelligence” OR “AI” OR “machine learning” OR “deep learning” OR “neural network” OR “natural language processing” OR “large

Table 1. Summary of Prior Review Studies in AI-Economic Business

Author(s) & Year	Review Type	Domain Focus	Time Span	Articles Reviewed	Key Findings & Limitations
Lin and Lobo Marques (2024)	Systematic review of reviews	Stock market prediction	2014–2024	10 final review papers	Identified SVM, LSTM, and ANN as dominant AI approaches; limited attention to economic profitability and firm-level outcomes.
Sezer et al. (2020)	Systematic literature review	Financial time-series forecasting with DL	2005–2019	200+ studies	Mapped DL architectures; focused on forecasting accuracy rather than business value or governance.
Ozbayoglu et al. (2020)	Survey	Deep learning in finance	Pre-2020	150+ studies	Broad taxonomy of DL in finance; emphasized model architecture over strategic adoption.
Davenport et al. (2020)	Conceptual/narrative review	AI in marketing	N/A	N/A	Framework for AI impact on marketing strategy; limited empirical review depth.
Verma et al. (2021)	Systematic review	AI in marketing	2000–2020	100+ studies	Identified AI applications across marketing functions; limited cross-functional integration.
Mariani et al. (2022)	Systematic literature review + bibliographic coupling	AI in marketing, consumer research, psychology	Pre-2022	Not uniformly reported	Strong behavioral focus; limited firm-level and cross-functional integration.
Toorajipour et al. (2021)	Systematic literature review	AI in supply chain management	Pre-2021	Not uniformly reported	Identified AI techniques across SCM subfields; limited integration with finance, HR, governance.
Pournader et al. (2021)	Bibliometric + systematic review	AI applications in SCM	1998–2020	150	Mapped knowledge clusters; emphasized operations over strategy, marketing, or governance.
Vrontis et al. (2022)	Systematic review	AI, robotics, advanced technologies, and HRM	Pre-2021	45	Highlighted automation and human-AI collaboration; HRM-specific scope.
Borges et al. (2021)	Systematic literature review	Strategic use of AI in the digital era	Pre-2021	Not uniformly reported	Identified AI-enabled decision support and new services; strategic focus.
Kraus et al. (2021)	Systematic literature review	Digital transformation in healthcare	Pre-2021	Not uniformly reported	Mapped operational efficiency and socio-economic aspects; sector-specific, AI is one component.

Notes: AI = artificial intelligence; DL = deep learning; SCM = supply chain management; HRM = human resource management; SVM = support vector machine; LSTM = long short-term memory; ANN = artificial neural network.
Source: Authors' synthesis based on prior review studies.

language model" OR "generative AI" OR "expert system" OR "intelligent system" OR "predictive analytics" OR "algorithmic decision" OR "business analytics") AND ("business" OR "economic" OR firm* OR company* OR enterprise* OR organization* OR market* OR "business model*" OR management OR strategy OR innovation OR entrepreneurship OR marketing OR finance OR accounting OR "supply chain" OR operations OR productivity OR performance OR "competitive advantage" OR "value creation" OR "decision support" OR "e-commerce"))

The inclusion criteria were peer-reviewed journal articles and review articles, English-language publications, and studies with a substantive link between AI and business, economics, management, finance, marketing, operations, supply chain, information systems, organizational decision-making, or firm performance. The exclusion criteria were conference papers, editorials, letters, book chapters, notes, non-scholarly documents, non-English publications, purely technical AI papers without business or economic interpretation, and domain-specific AI studies unrelated to business or economics, such as purely clinical, agricultural, or education-only AI studies. Following systematic screening and eligibility procedures (Page et al., 2021; Snyder, 2019), the final bibliometric sample comprised 1,970 articles.

A bibliometric analysis was performed using the Bibliometrix R package, which enables detailed science mapping, calculation of descriptive bibliometric indicators, keyword and source analysis, co-citation examination, and thematic mapping (Aria and Cuccurullo, 2017). The study included assessments of annual scientific output, productive journals, average citations per document, keyword co-occurrence analysis, co-word networks based on author keywords, and co-citation analysis to uncover foundational intellectual structures. Visualizations of these networks were created with Bibliometrix and VOSviewer, a tool designed for bibliometric mapping and visual representation of bibliographic networks (van Eck and Waltman, 2010). The Louvain community detection algorithm was used to identify thematic clusters within the co-occurrence network, as it effectively detects communities in large weighted networks (Blondel et al., 2008). Table 2 outlines the finalized bibliometric dataset, including key metadata that evaluate the scope, quality, and analytical coverage of the review. This table offers a clear overview of the search date, screening process, final sample size, source coverage, citation patterns, keyword count, author characteristics, and indicators of international collaboration.

2.2 Content Analysis Sample and Coding Schema

From the 1,970 articles included in the bibliometric corpus, a subset of 110 empirical studies was selected for in-depth content analysis. The selection was based on three criteria. First, the article had to be published in a Q1 or Q2 journal, according to the Journal Citation Reports, to ensure scholarly quality and methodological rigor. Second, the study had to clearly describe the AI application under investigation rather than mentioning AI only tangentially. Third, the article had to include an empirical component, such as experiments, econometric analyses, surveys, case studies, machine learning model evaluations, mixed-methods designs, or secondary data analyses. Content analysis was used because it supports systematic interpretation of textual evidence and classification of concepts, themes, patterns, and meanings (Krippendorff, 2018; Neuendorf, 2017).

The coding schema was created deductively based on the three research questions and was refined inductively through pilot coding of 10 articles. It includes five main categories. First, AI Application Type covers Market Prediction & Risk Management, Marketing & Customer Analytics, Process Automation & Supply Chain Optimization, Strategic Decision-Making & HR Analytics, and Ethics & Governance. Second, Research Topic encompasses System Design & Algorithm Development, Adoption & Acceptance, Economic & Operational Impacts, and Ethics & Governance. Third, Guiding Theory is marked as Information Systems, Management, Economics/Finance, Psychology/Marketing, Ethics/Governance, or None/Not Explicit. Fourth, Research Methodology is classified as Experiment, Econometric/Secondary Data Analysis, Survey, Mixed Methods, Qualitative, or Computational/Simulation. Fifth, Research Context/Sector includes Banking & Fintech, E-commerce & Retail, General Corporate & Cross-Industry, Manufacturing &

Table 2. Summary of Bibliometric Dataset

Description	Results
Timespan	1990–2024 (June)
Database	Web of Science Core Collection
Search Date	24-Jun
Initial Search Results	4,210
Articles After Duplicate Removal	3,680
Articles After Title/Abstract Screening	2,415
Final Bibliometric Sample	1,970
Journals Included	854
Average Years from Publication	5.2
Average Citations per Document	11.8
Total Cited References	94,560
Keywords Plus (ID)	3,142
Author Keywords (DE)	8,576
Authors	5,230
Single-Authored Documents	248
International Co-authorships (%)	28.50%

Notes: The final bibliometric sample of 1,970 articles was obtained after applying inclusion and exclusion criteria to the initial Web of Science search results. Bibliometric analysis was conducted using the Bibliometrix R package (Aria and Cuccurullo, 2017).
Source: Authors' bibliometric analysis.

Table 3. Coding Schema for Content Analysis

Coding	Sub-Categories	Description
1. AI Application Type	(a) Market Prediction & Risk Management; (b) Marketing & Customer Analytics; (c) Process Automation & Supply Chain Optimization; (d) Strategic Decision-Making & HR Analytics; (e) Ethics & Governance	Classifies the primary AI application examined in the empirical study. Studies may address multiple applications; the primary focus is coded.
2. Research Topic	(a) System Design & Algorithm Development; (b) Adoption & Acceptance; (c) Economic & Operational Impacts; (d) Ethics & Governance	Classifies the study's main research objective or focus. System design studies prioritize model building and performance evaluation; adoption studies prioritize behavioral and organizational factors.
3. Guiding Theory	(a) Information Systems Theories (TAM, UTAUT, IS Success Model, DOI, TOE); (b) Management Theories (RBV, Dynamic Capabilities, Institutional Theory, TCE, Agency Theory); (c) Economics/Finance Theories (EMH, Information Asymmetry, Game Theory, Behavioral Finance); (d) Psychology/Marketing Theories (TPB, Trust Theory, ELM, SDL); (e) Ethics/Governance Theories (Stakeholder Theory, Social Contract Theory, Socio-Technical Systems); (f) None/Not Explicit	Records the explicit theoretical framework(s) cited and used to guide the research design, hypotheses, or interpretation. "None" is assigned when the study is a-theoretical or only implicitly references theory.
4. Research Methodology	(a) Experiment; (b) Econometric/Secondary Data Analysis; (c) Survey; (d) Mixed Methods; (e) Qualitative (Case Study, Interviews); (f) Computational/Simulation	Classifies the primary research design and data source. Experiments include lab, field, and online experiments. Econometric studies use secondary datasets. Computational studies focus on model training and testing.
5. Research Context/Sector	(a) Banking & Fintech; (b) E-commerce & Retail; (c) General Corporate & Cross-Industry; (d) Manufacturing & Supply Chain; (e) Small & Medium Enterprises (SMEs); (f) Other (Healthcare Business, Energy, Telecommunications, etc.)	Classifies the industry or organizational setting in which the empirical study was conducted. Cross-industry studies are those drawing data from multiple sectors without a primary sector focus.

Notes: The coding schema was developed deductively from the three research questions and inductively refined through pilot coding of 10 articles. Two researchers independently coded the 110 empirical articles. Inter-rater reliability was assessed using Cohen's Kappa ($\kappa = 0.85$), indicating strong agreement (Landis and Koch, 1977).
Source: Authors' content analysis.

Supply Chain, SMEs, and Other. Table 3 is essential because it clarifies the coding process, enabling readers and reviewers to evaluate the transparency, reproducibility, and alignment of the qualitative synthesis with the research questions (Krippendorff, 2018; Neuendorf, 2017).

Two researchers independently coded all 110 empirical articles following the final coding schema shown in Table 3. Disagreements in coding were addressed through discussion, comparison of coding rationales, and refinement of the codebook. Inter-rater reliability was measured using Cohen's Kappa coefficient, which assesses agreement between coders on categorical data beyond chance (Cohen, 1960). The coding process resulted in a Kappa value of $\kappa = 0.85$, indicating strong agreement based on Landis and Koch (1977). This approach enhanced the transparency, consistency, and reliability of the qualitative analysis and helped minimize interpretive bias.

3. Bibliometric Analysis Results

3.1 Descriptive Statistics and Publication Trends

The bibliometric analysis of 1,970 articles shows a two-phase growth pattern in AI-related business research. From 1990 to 2016, annual publications were under 50, fluctuating between about 2 and 45, during a slow growth phase associated with expert systems, early neural networks, decision-support tools, limited computing power, and scarce data. This mirrors the early adoption stage in Rogers' Diffusion of Innovation theory, where innovators and early adopters test new technologies before widespread adoption (Rogers, 1962). Around 2017, a second phase began, with publication numbers rising rapidly from about 60 to over 550 by 2023. This rise aligns with advances in deep learning, the expansion of big data infrastructure, the rise of cloud-based machine learning platforms, and increased organizational investment in AI. From an Institutional Theory perspective, the post-2017 acceleration also reflects coercive, normative, and mimetic pressures that position AI as a strategic necessity for organizations (DiMaggio and Powell, 1983). The COVID-19 pandemic further accelerated digital transformation, automation, remote work, platform operations, and AI-enabled decision support.

Figure 1 presents the annual publication trend of AI-economic business research from 1990 to 2024. The figure combines a bar chart with a line chart. The X-axis spans from 1990 to

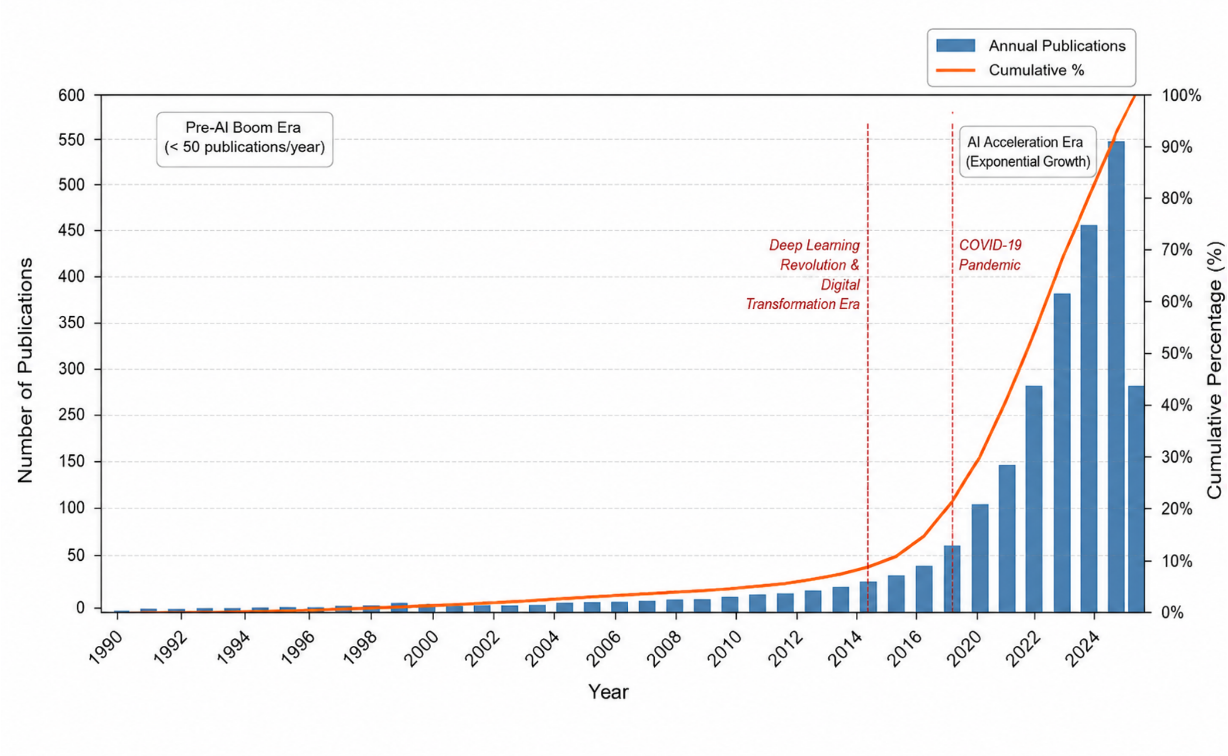

Fig. 1. Annual Publication Trends

2024, with labels every two years rotated at a 45-degree angle. The left Y-axis displays annual publication counts ranging from 0 to 600, while the right Y-axis shows the cumulative publication percentage from 0% to 100%. The bars represent yearly publication numbers, and the line illustrates cumulative percentage progress. The trend remained relatively stable from 1990 to 2016, then increased to around 60 publications in 2017, peaked at over 550 publications in 2023, and is estimated to be around 280 in 2024, based on data up to June. A vertical dashed line at 2017, labeled "Deep Learning Revolution & Digital Transformation Era," marks a shift, with another at 2020 labeled "COVID-19 Pandemic Acceleration." The figure note explains that the surge after 2017 aligns with the maturation of deep learning, the growth of big data infrastructure, and the adoption of organizational AI, while the 2020–2021 spike reflects pandemic-driven digital transformation.

The journal distribution underscores the multidisciplinary nature of AI-economic business research. A total of 1,970 articles are distributed across 854 journals, covering subjects including computer science, information systems, management, marketing, operations, finance, decision sciences, and digital transformation. The most productive outlets are Expert Systems with Applications, with approximately 120 articles; Journal of Business Research, with approximately 85 articles; Technological Forecasting and Social Change, with approximately 75 articles; IEEE Access, with approximately 70 articles; Sustainability, with approximately 65 articles; International Journal of Information Management, with approximately 55 articles; Computers in Human Behavior, with approximately 50 articles; Information & Management, with approximately 45 articles; Decision Support Systems, with approximately 40 articles; Industrial Management & Data Systems, with approximately 38 articles; Electronic Commerce Research and Applications, with approximately 35 articles; Information Systems Frontiers, with approximately 32 articles; Business & Information Systems Engineering, with approximately 30 articles; Technovation, with approximately 28 articles; and International Journal of Production Economics, with approximately 25 articles. Trends in citations indicate an annual increase in the average number of citations per article after 2015, with a notable concentration between 2020 and 2022. From a dynamic capabilities perspective, this pattern suggests that scholars increasingly view AI as a capability for sensing disruptions, seizing digital opportunities, and reconfiguring organizational processes during periods of uncertainty (Teece et al., 1997).

3.2 *Keyword Co-occurrence and Conceptual Clusters*

Keyword co-occurrence analysis was conducted using author keywords from the 1,970 articles. The Louvain community detection algorithm identified four thematic clusters representing the conceptual structure of AI-economic business research (Blondel et al., 2008). The network map visualizes the top 50 keywords, with node size reflecting keyword frequency and edge thickness reflecting co-occurrence strength. The four clusters are Financial Market Prediction and Risk Management, Digital Transformation and Firm Performance, Intelligent Marketing and Customer Analytics, and Ethics, Governance, and the Future of Work. The centrality of ‘"artificial intelligence" and ‘"machine learning" indicates that these concepts bridge technical, organizational, customer-facing, and governance-oriented streams.

Figure 2 displays the keyword co-occurrence network and shows how AI-economic business research is organized around four major conceptual clusters. Cluster 1, shown in red, represents AI for financial market prediction and risk management. It is the largest and most technically oriented cluster, dominated by ‘ "machine learning," ‘ "deep learning," "stock prediction," ‘ "sentiment analysis," ‘ "credit scoring,"

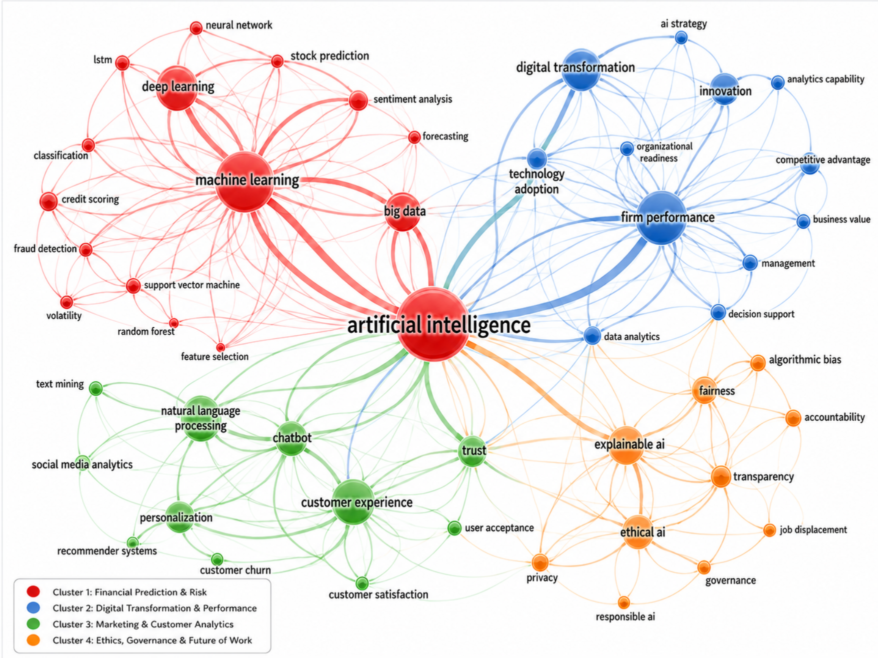

Fig. 2. Keyword Co-occurrence Network

"fraud detection," ‘ "big data," ‘ "LSTM," and ‘ "volatility." The central issue is whether AI can extract predictive signals that traditional econometric models miss. This cluster is theoretically grounded in the Efficient Market Hypothesis and information asymmetry theory because AI-based prediction challenges assumptions about market information efficiency and improves screening in credit and fraud contexts (Akerlof, 1970; Fama, 1970).

Cluster 2, displayed in blue, represents AI research on digital transformation and firm performance. The most frequent keywords include ‘"digital transformation," ‘ "innovation," ‘ "firm performance," ‘ "technology adoption," ‘ "competitive advantage," ‘ "AI strategy," ‘"analytics capability," and ‘"organizational readiness." This cluster examines how AI capabilities are translated into business value and competitive advantage. The Resource-Based View explains AI as a potentially valuable, rare, inimitable, and organizationally embedded resource (Barney, 1991). The dynamic capabilities theory explains how firms identify AI-enabled opportunities, mobilize resources to capture them, and reconfigure organizational processes accordingly (Teece et al., 1997). Institutional theory further explains AI adoption as a response to competitive and legitimacy pressures (DiMaggio and Powell, 1983).

Cluster 3, displayed in green, represents AI research on intelligent marketing and customer analytics. It includes terms such as ‘"natural language processing," ‘ " chatbot," ‘ "customer experience," ‘" personalization," ‘"recommender systems," ‘ "customer churn," ‘ "trust," and ‘"e-commerce." This cluster examines how AI-mediated interactions influence customer trust, satisfaction, engagement, loyalty, and purchase behavior. Its theoretical foundation includes TAM, UTAUT, the Theory of Planned Behavior, Trust Theory, and Service-Dominant Logic. These theories collectively explain technology acceptance, behavioral intention, trust formation, and value co-creation in AI-enabled service interactions (Ajzen, 1991; Davis, 1989; Mayer et al., 1995; Vargo and Lusch, 2004; Venkatesh et al., 2003).

Cluster 4, displayed in yellow/orange, represents AI research on ethics, governance, and the future of work. It includes terms such as ‘"algorithmic bias," ‘ "fairness," ‘ "accountability," ‘ "transparency," ‘ "explainable AI," ‘ "job displacement," ‘ "ethical AI," ‘ "privacy," ‘ "governance," and ‘"responsible AI." This cluster is smaller and less densely connected than the other clusters, indicating an emerging research frontier. Its central concern is the tension between algorithmic efficiency and societal legitimacy. Stakeholder theory emphasizes that AI affects customers, employees, regulators, and communities (Freeman, 1984), while responsible AI frameworks emphasize beneficence, non-maleficence, autonomy, justice, and explicability (Floridi et al., 2018).

3.3 Co-citation Analysis and Intellectual Foundations

The co-citation analysis identifies five intellectual foundations. The first foundation consists of AI and computational methods literature, including machine learning, deep learning, neural networks, natural language processing, ensemble methods, reinforcement learning, recommender systems, and optimization algorithms. This technical foundation provides the essential basis for prediction, classification, anomaly detection, decision automation, and real-time business intelligence. The second foundation comprises theories of information systems adoption and success. Highly co-cited works include TAM, UTAUT, the IS Success Model, Diffusion of Innovation, and the Technology-Organization-Environment framework. These theories explain why individuals and organizations accept or resist AI systems through perceived usefulness, performance expectancy, system quality, facilitating conditions, and organizational readiness (Davis, 1989; DeLone and McLean, 2003; Rogers, 1962; Tornatzky and Fleischer, 1990; Venkatesh et al., 2003).

The third foundation consists of management and strategic management theories, including the Resource-Based View, Dynamic Capabilities theory, Institutional Theory, Transaction Cost Economics, and Agency Theory. These theories explain AI capability development, competitive advantage, institutional pressure, coordination-cost reduction, and algorithmic monitoring (Barney, 1991; DiMaggio and Powell, 1983; Jensen and Meckling, 1976; Teece et al., 1997; Williamson, 1975). The fourth foundation comprises economics, finance, and market theories, including the Efficient Market Hypothesis, information asymmetry, game theory, and behavioral finance. These theories ground AI research in financial prediction, algorithmic trading, credit scoring, pricing automation, and platform competition (Akerlof, 1970; Fama, 1970; von Neumann and Morgenstern, 1944). The fifth foundation consists of ethics, trust, and governance theories, including stakeholder theory, trust theory, socio-technical systems theory, and responsible AI frameworks (Floridi et al., 2018; Freeman, 1984; Mayer et al., 1995; Trist and Bamforth, 1951). Overall, the field is intellectually diverse but unevenly integrated: technical foundations are highly visible, whereas explanatory theories of business and governance are applied less consistently.

4. Content Analysis Results

4.1 AI Application Categories in Economic Business

The content analysis of 110 Q1/Q2 empirical journal articles supports the bibliometric mapping by examining five dimensions: AI application categories, research topics, guiding theories, research methodologies, and research contexts. The findings indicate that while AI-economic business studies are technically robust, there is room for improvement in the application of theoretical frameworks, the breadth of sector coverage, and the diversity of methodological approaches. Four major AI application categories were identified: Market Prediction and Risk Management (35%), Marketing and Customer Analytics (25%), Process Automation and Supply Chain Optimization (20%), and Strategic Decision-Making and HR Analytics (20%). This distribution aligns with the four bibliometric clusters outlined in Section 3.2, suggesting that the conceptual structure derived from keyword co-occurrence analysis is also reflected in the empirical content of the studies analyzed. Table 4 provides a comprehensive overview of representative empirical studies from each application category. The table presents the dominant AI techniques, empirical contexts, and key findings that support this classification.

Market Prediction and Risk Management is the largest category and includes stock prediction, credit scoring, fraud detection, volatility forecasting, portfolio optimization, and financial sentiment analysis. This stream typically employs machine learning algorithms such as LSTM, XGBoost, random forests, support vector machines, ensemble methods, and neural networks. The theoretical underpinnings of this approach stem from the Efficient Market Hypothesis and information asymmetry theory because AI can extract predictive signals and address screening issues in financial markets (Akerlof, 1970; Fama, 1970). Marketing and Customer Analytics is the most customer-facing category and includes chatbots, recommender systems, sentiment analysis, churn prediction, dynamic pricing, and personalization. This field is commonly explained through TAM, UTAUT, and Trust Theory, since customer engagement with AI-mediated services depends on usefulness, ease of use, performance benefits, and trustworthiness (Davis, 1989; Mayer et al., 1995; Venkatesh et al., 2003). Process Automation and Supply Chain Optimization focuses on demand forecasting, predictive maintenance, robotic process automation, logistics optimization, and digital twins. Transaction Cost Economics and Dynamic Capabilities theory explain how AI reduces coordination costs and supports operational reconfiguration (Teece et al., 1997; Williamson, 1975). Strategic Decision-Making and HR Analytics includes business intelligence dashboards, algorithmic hiring, employee sentiment analysis, workforce planning, and decision-support systems. In this context, RBV, Human Capital Theory, and Signaling Theory emphasize the role of AI analytics as a strategic asset, the significance of workforce data as a valuable resource, and the use of hiring algorithms to interpret labor-market signals (Barney, 1991; Becker, 1964; Spence, 1973).

4.2 Research Topics and Key Findings

The content analysis identifies four primary research areas: System Design and Algorithm Development (around 50%), Adoption and Acceptance (about 20%), Economic and Operational Impacts (roughly 20%), and Ethics and Governance (approximately 10%). This indicates that AI-economic business research remains largely focused on models, while studies on governance and theory are comparatively less developed. Research in System Design and Algorithm Development involves creating, testing, and comparing AI models for tasks such as prediction, classification, recommendation, optimization, and decision support, often evaluated through metrics such as accuracy, precision, recall, F1-score, AUC-ROC, prediction error, profit lift, and forecasting performance. Nonetheless, these works often view AI mainly as a technical instrument rather than an organizational, economic, or institutional phenomenon. Adoption and Acceptance research is richer in theory, examining how AI is adopted by customers, employees, managers, and organizations using frameworks such as TAM, UTAUT, and Trust Theory, focusing on perceived usefulness, ease of use, performance expectations, facilitating conditions, and trust in AI (Davis, 1989; Mayer et al., 1995; Venkatesh et al., 2003). Economic and Operational Impact studies investigate productivity, firm performance, cost reductions, customer satisfaction, innovation, and competitive advantage. Theories such as RBV and Dynamic Capabilities suggest that AI's value depends on complementary assets, routines, and reconfiguration capabilities, while the productivity paradox warns that technology investments do not always translate into clear productivity gains (Barney, 1991; Solow, 1987; Teece et al., 1997). Ethics and Governance research addresses issues such as algorithmic bias, fairness, transparency, privacy, explainability, and accountability, emphasizing that AI systems should be evaluated not only for efficiency but also for their impact on customers, employees, regulators, communities, and social legitimacy (Floridi et al., 2018; Freeman, 1984).

4.3 Guiding Theories and Theoretical Gaps

Only about 25% of the 110 empirical studies explicitly use established theories, revealing a notable gap in AI-economic business research. While some studies demonstrate an algorithm's effectiveness, they often lack explanations of why the results matter, how AI creates value, or the conditions under which the findings generalize. Table 5 shows the theories identified through content analysis, with uneven application across disciplines. Information systems theories are most common, especially in adoption studies: TAM appears in 8 articles, UTAUT in 5, Diffusion of Innovation in 3, the IS

Table 4. Representative Empirical Studies in Each AI Application Category

Category	Author(s) & Year	AI Technique	Context	Key Finding
Market Prediction & Risk Management	Fischer and Krauss (2018)	LSTM	S&P 500 stock prediction	LSTM outperformed random forest, deep neural networks, and logistic regression for directional forecasting.
Market Prediction & Risk Management	Lessmann et al. (2015)	Ensemble methods	Credit scoring	Ensemble classifiers consistently outperformed single classifiers across multiple credit datasets.
Market Prediction & Risk Management	Bollen et al. (2011)	Sentiment analysis + neural network	Twitter mood and DJIA prediction	Twitter mood indicators improved prediction of daily stock market movements.
Market Prediction & Risk Management	Bolton and Hand (2002)	Statistical learning and machine learning	Fraud detection	Supervised and unsupervised methods support detection of anomalous fraudulent behavior.
Marketing & Customer Analytics	Adam et al. (2021)	NLP chatbot	Customer service	Anthropomorphic chatbot design affected user compliance and service interaction outcomes.
Marketing & Customer Analytics	Koren et al. (2009)	Collaborative filtering	Netflix Prize recommender system	Matrix factorization improved recommendation accuracy over neighborhood-based methods.
Marketing & Customer Analytics	Verbeke et al. (2012)	Ensemble learning	Telecom churn prediction	Profit-driven churn modeling offered more managerial value than accuracy-only evaluation.
Marketing & Customer Analytics	Misra et al. (2019)	Multi-armed bandit learning	Online pricing	Adaptive pricing experiments improved learning about demand responses under uncertainty.
Process Automation & Supply Chain Optimization	Carbonneau et al. (2008)	Neural networks and SVM	Supply chain demand forecasting	Machine learning methods improved forecasting when demand patterns were nonlinear.
Process Automation & Supply Chain Optimization	Zhao et al. (2017)	Convolutional bidirectional LSTM	Machine health monitoring	Deep learning improved machine health monitoring and predictive maintenance signals.
Process Automation & Supply Chain Optimization	van der Aalst et al. (2018)	Process mining + RPA	Business process automation	RPA improved process efficiency but required process standardization and governance.
Process Automation & Supply Chain Optimization	McKinnon et al. (2015)	Logistics analytics and optimization framework	Green logistics	Sustainable logistics requires measurement, route efficiency, and operational optimization across supply chains.
Strategic Decision-Making & HR Analytics	Dastin (2018)	Supervised learning	Amazon algorithmic hiring	AI hiring tools may reproduce historical gender bias when trained on biased recruitment data.
Strategic Decision-Making & HR Analytics	Chen et al. (2012)	Business intelligence and analytics	Corporate decision support	BI and analytics improved decision support but required data quality and organizational integration.
Strategic Decision-Making & HR Analytics	Gloor et al. (2017)	Social network analysis + text analytics	Managerial turnover prediction	Communication networks and language indicators predicted managerial turnover patterns.
Strategic Decision-Making & HR Analytics	van den Heuvel and Bondarouk (2017)	HR analytics	Workforce planning	HR analytics improved workforce planning but raised concerns about privacy and organizational readiness.

Notes: Table 4 presents representative empirical studies from the 110-article content analysis sample. The studies illustrate the diversity of AI techniques, business contexts, and substantive findings across the four application categories.
Source: Authors' content analysis.

Success Model in 2, and TOE in 2. These theories cover AI adoption, analytics use, chatbot acceptance, organizational readiness, and digital transformation (Davis, 1989; DeLone and McLean, 2003; Rogers, 1962; Tornatzky and Fleischer, 1990; Venkatesh et al., 2003).

Management theories include RBV in 6 articles, Dynamic Capabilities in 5, Institutional Theory in 4, Transaction Cost Economics in 3, Agency Theory in 2, and Absorptive Capacity in 1, addressing AI capabilities, competitive advantage, adoption pressures, coordination costs, algorithmic monitoring, and organizational learning (Barney, 1991; Cohen and Levinthal, 1990; DiMaggio and Powell, 1983; Jensen and Meckling, 1976; Teece et al., 1997; Williamson, 1975). Economic and financial theories such as the EMH, information asymmetry, game theory, and behavioral finance primarily appear in studies of financial prediction, credit scoring, algorithmic pricing, platform competition, and investor sentiment (Akerlof, 1970; Fama, 1970; Kahneman and Tversky, 1979; von Neumann and Morgenstern, 1944). Psychology and marketing theories, such as Trust Theory, the Theory of Planned Behavior, the Elaboration Likelihood Model, and Service-Dominant Logic, explain chatbot trust, AI-mediated services, personalized persuasion, and value co-creation (Ajzen, 1991; Mayer et al., 1995; Petty and Cacioppo, 1986; Vargo and Lusch, 2004). Ethics and governance theories are the smallest group, with Stakeholder Theory and Socio-Technical Systems Theory supporting analysis of algorithmic fairness, AI governance, human-AI collaboration, and organizational design (Freeman, 1984; Trist and Bamforth, 1951).

The main theoretical gap lies in the dominance of a-theoretical system design studies, which hinders the accumulation of knowledge, meaningful theoretical contributions, and practical relevance beyond model performance alone. Future research should aim to link AI model performance with organizational mechanisms, market behavior, governance conditions, and socio-technical outcomes by developing clear theoretical frameworks.

4.4 Research Methodologies

Empirical studies are primarily focused on quantitative and computational methods. Experiments account for around 35% of the sample and are common in chatbot interaction, recommender systems, marketing personalization, human-AI decision support, and algorithmic fairness. Approximately 30% of analyses are econometric and use secondary data, with a notable presence in finance, firm performance, platform commerce, and productivity studies. Approximately 15% of studies are survey-based, with a particular emphasis on TAM-, UTAUT-, and trust-based adoption studies. Approximately 10% of the studies use mixed methods, while qualitative studies, including case studies, interviews, and content analyses, account for approximately 10%. The field is strong in computational modeling, experimentation, and secondary-data analysis, and somewhat weaker in longitudinal, interpretive, and process-based inquiry. Future studies should adopt longitudinal designs to monitor the evolving impact of artificial intelligence, employ mixed methods to triangulate mechanisms, and use qualitative research to examine human-AI collaboration, algorithmic governance, generative AI, organizational accountability, and implementation processes.

4.5 Research Contexts and Sectors

Research contexts are primarily concentrated in data-rich sectors. Banking and fintech account for approximately 40

Table 5. Guiding Theories in AI-Economic Business Research

Category	Theory Name (Author, Year)	Count	Primary Application Domain
IS	Technology Acceptance Model (Davis, 1989)	8	AI adoption, chatbot acceptance, analytics use
IS	UTAUT (Venkatesh et al., 2003)	5	AI adoption, digital transformation
IS	Diffusion of Innovation (Rogers, 1962)	3	AI adoption, organizational diffusion
IS	IS Success Model (DeLone and McLean, 2003)	2	AI system success, analytics platforms
IS	Technology-Organization-Environment (Tornatzky and Fleischer, 1990)	2	AI readiness, organizational adoption
Management	Resource-Based View (Barney, 1991)	6	AI capability, competitive advantage
Management	Dynamic Capabilities (Teece et al., 1997)	5	AI-enabled sensing, seizing, reconfiguration
Management	Institutional Theory (DiMaggio and Powell, 1983)	4	AI adoption pressures, isomorphism
Management	Transaction Cost Economics (Williamson, 1975)	3	AI in supply chain, coordination-cost reduction
Management	Agency Theory (Jensen and Meckling, 1976)	2	Algorithmic monitoring, principal-agent dynamics
Management	Absorptive Capacity (Cohen and Levinthal, 1990)	1	AI capability development
Economics	Efficient Market Hypothesis (Fama, 1970)	4	Stock prediction, algorithmic trading
Economics	Information Asymmetry (Akerlof, 1970)	2	Credit scoring, fraud detection
Economics	Game Theory (von Neumann and Morgenstern, 1944)	1	Algorithmic pricing, platform competition
Economics	Behavioral Finance / Prospect Theory (Kahneman and Tversky, 1979)	2	Sentiment analysis, investor behavior
Psychology	Trust Theory (Mayer et al., 1995)	4	Chatbot interaction, AI trust, customer acceptance
Psychology	Theory of Planned Behavior (Ajzen, 1991)	3	AI adoption intention, customer behavior
Psychology	Elaboration Likelihood Model (Petty and Cacioppo, 1986)	2	Personalized recommendation persuasion
Psychology	Service-Dominant Logic (Vargo and Lusch, 2004)	1	AI-enabled value co-creation
Ethics	Stakeholder Theory (Freeman, 1984)	3	Algorithmic fairness, AI governance
Ethics	Socio-Technical Systems (Trist and Bamforth, 1951)	2	Human-AI collaboration, organizational design

Notes: Table 5 shows that only approximately 25% of the 110 reviewed empirical articles explicitly employ one or more established theories. The remaining studies are largely a-theoretical system design or performance evaluation studies. Counts exceed the number of theory-driven articles because some articles use multiple theories.
Source: Authors' content analysis.

4.6 Discussion and Future Research Agenda

A total of 1,970 Web of Science articles were analyzed using bibliometric analysis, and 110 empirical Q1/Q2 journal articles were examined through content analysis. The integrated findings reveal a rapidly expanding, multidisciplinary research field organized around four thematic clusters. However, the field remains fragmented by business function, theoretically underdeveloped, and concentrated in data-rich sectors. This discussion summarizes the most important findings, presents an overall conceptual framework, and proposes a structured agenda for future research in AI-related economic business.

First, AI-economic business research is organized primarily by business function rather than by integrative enterprise-level frameworks. The bibliometric co-word analysis revealed four relatively distinct clusters: financial market prediction and risk management; digital transformation and firm performance; intelligent marketing and customer analytics; and ethics, governance, and the future of work. The subsequent content analysis revealed a consistent pattern: finance studies emphasize predictive accuracy and risk classification; marketing studies focus on customer experience, trust, and personalization; operations studies stress efficiency, resilience, and automation; and strategy/HR studies analyze managerial decision-making and workforce analytics. This fragmentation reflects the disciplinary structure of business research, but AI applications are inherently cross-functional. For instance, an AI-driven demand forecasting system simultaneously affects inventory planning, pricing strategies, revenue forecasting, and workforce allocation. Future research should therefore treat AI as an enterprise-level capability rather than a function-specific tool. The Resource-Based View posits that, when complemented by substantial data, competencies, and established processes, AI can serve as a strategic asset, while Dynamic Capabilities theory explains how organizations discern, adopt, and adapt to AI-driven opportunities across diverse functions (Barney, 1991; Teece et al., 1997).

Second, the field is technically sophisticated but theoretically thin. Only approximately 25% of empirical studies explicitly draw on established theories, while the remaining studies are largely a-theoretical, focusing on system design or performance evaluation. This creates a major limitation: studies may demonstrate that an algorithm achieves high accuracy but fail to explain why AI creates value, for whom, through what mechanisms, and under what conditions it generalizes. This pattern mirrors the findings of Wang et al. (2024) in AI-in-education research, where system design dominates while theoretical contributions remain limited. Existing theory use is concentrated around technology acceptance, RBV, Dynamic Capabilities, and market-efficiency perspectives, but broader explanatory lenses remain underused. Organizational Learning Theory can explain how firms absorb and institutionalize AI insights; Institutional Theory can explain legitimacy pressures; Stakeholder Theory can explain distributive consequences; and Socio-Technical Systems Theory can explain human-AI work design (Argyris and Schön, 1978; DiMaggio and Powell, 1983; Freeman, 1984; Trist and Bamforth, 1951).

Third, AI does not automatically generate business value. The review demonstrates that the impact of AI is contingent on complementary organizational resources, capabilities, and governance arrangements. Research consistently shows that data quality, IT infrastructure, top management support, organizational readiness, governance maturity, and human capability are essential conditions for successful AI adoption. This finding aligns with the Resource-Based View, which holds that technology confers competitive advantage only when integrated with complementary organizational resources (Barney, 1991). It also aligns with Dynamic Capabilities theory, which emphasizes identifying opportunities, strategically allocating resources to capitalize on them, and adapting processes to generate value (Teece et al., 1997). The productivity paradox further cautions that advanced technologies may not immediately produce measurable productivity gains without organizational change, complementary investments, and learning (Solow, 1987). Managers should therefore avoid

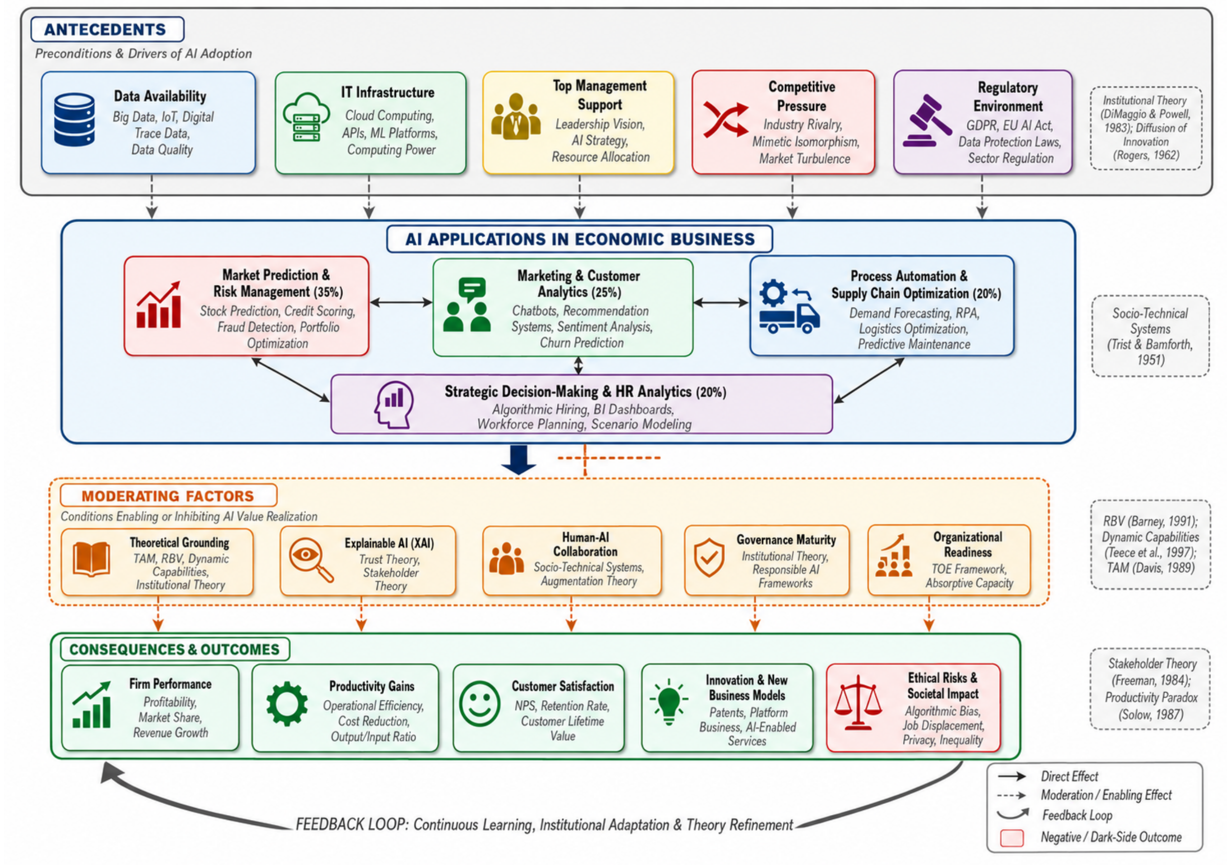

Fig. 3. AI Business Value Framework

treating AI as a ready-made solution. AI value creation depends on systematic investment in data governance, human capital, process redesign, explainability, and organizational learning.

Figure 3 synthesizes the integrated findings into an AI business value framework. The framework links antecedents, AI applications, moderating factors, consequences, and feedback mechanisms to show that AI value realization depends not only on technological deployment but also on organizational readiness, governance maturity, human-AI collaboration, and continuous institutional adaptation.

Based on the integrated findings and identified gaps, this review proposes a structured future research agenda with five interconnected pillars: Generative AI, XAI and trust, theory-driven research, human-AI collaboration, and longitudinal societal impact. Table 6 summarizes these pillars, the key research questions, relevant theories, and expected contributions. The table is intended to guide scholars toward research that is technically rigorous, theoretically grounded, managerially useful, and socially responsible.

The first pillar concerns the shift from predictive AI to generative AI. Generative AI systems such as ChatGPT, GPT-4, and Gemini represent a paradigm shift from prediction and classification toward content generation, knowledge synthesis, software production, and creative augmentation. Existing empirical AI-business research largely predates the widespread diffusion of generative AI. Schumpeter's creative destruction lens suggests that generative AI may disrupt consulting, software development, marketing content, and professional services while enabling new business models (Schumpeter, 1942). Task-Technology Fit theory can explain when generative AI improves or degrades knowledge-worker performance (Goodhue and Thompson, 1995), while Dynamic Capabilities theory can explain how firms reconfigure capabilities around generative AI (Teece et al., 1997).

The second pillar concerns explainable AI for trust and regulatory compliance. As AI enters high-stakes decisions such as credit, hiring, investment, and insurance, explainability becomes essential for trust, accountability, and legitimacy. The review shows that XAI remains peripheral in the keyword network and that ethics/governance studies represent only a small share of empirical work. Trust Theory suggests that users accept AI when they perceive ability, benevolence, and integrity (Mayer et al., 1995). Stakeholder Theory emphasizes that explanations must serve customers, employees, managers, regulators, and communities (Freeman, 1984). Institutional Theory further suggests that regulatory pressure will increasingly shape explainability requirements (DiMaggio and Powell, 1983).

The third pillar calls for robust, theory-driven AI research. The field must move beyond a-theoretical system design toward research that explains mechanisms, boundary conditions, and causal pathways. RBV can test how AI capabilities become competitive advantage through data, infrastructure, human capital, and routines (Barney, 1991). Dynamic Capabilities theory can examine the processes of sensing, seizing, and reconfiguring (Teece et al., 1997). Institutional Theory can explain cross-industry pressures for adoption (DiMaggio and Powell, 1983). Transaction Cost Economics can measure whether AI reduces coordination, search, and monitoring costs (Williamson, 1975). Agency Theory can be applied to algorithmic monitoring and incentive alignment (Jensen and Meckling, 1976).

Table 6. Future Research Agenda—Research Questions by Theme

Research Pillar	Key Research Questions	Relevant Theories	Expected Contributions
Generative AI & New Business Models	How does GenAI alter knowledge-worker productivity? What new business models emerge? How does GenAI affect Dynamic Capabilities?	Creative Destruction (Schumpeter, 1942); Task-Technology Fit (Goodhue and Thompson, 1995); Dynamic Capabilities (Teece et al., 1997)	Empirical evidence on GenAI's business impact; new business model typologies; productivity frameworks
Explainable AI & Trust	How does XAI affect stakeholder trust? What are accuracy-interpretability trade-offs? How does regulation shape XAI?	Trust Theory (Mayer et al., 1995); Stakeholder Theory (Freeman, 1984); Institutional Theory (DiMaggio and Powell, 1983)	XAI design principles; trust calibration frameworks; regulatory compliance models
Theory-Driven AI Research	Through what mechanisms does AI create competitive advantage? How do institutional pressures shape adoption?	RBV (Barney, 1991); Dynamic Capabilities (Teece et al., 1997); Institutional Theory (DiMaggio and Powell, 1983); TCE (Williamson, 1975); Agency Theory (Jensen and Meckling, 1976)	Mediation/moderation models; theory-driven adoption frameworks; cross-industry evidence
Human-AI Collaboration	What are optimal human-AI team configurations? How do trust calibration and aversion affect performance?	Socio-Technical Systems (Trist and Bamforth, 1951); Augmentation Theory (Engelbart, 1962); Algorithmic Aversion (Dietvorst et al., 2015)	Human-AI team design principles; trust calibration interventions; augmentation assessments
Longitudinal & Societal Impact	What is AI's long-term effect on productivity and inequality? How does bias perpetuate systemic inequality?	Productivity Paradox (Solow, 1987); Stakeholder Theory (Freeman, 1984); Responsible AI (Floridi et al., 2018)	Longitudinal evidence on AI's economic impact; bias mitigation methods; governance frameworks

Notes: Table 6 presents a structured agenda for future research based on the bibliometric and content-analysis findings. The five pillars address theoretical, methodological, managerial, and societal gaps in AI-economic business research.
Source: Authors' synthesis based on bibliometric and content analysis.

The fourth pillar concerns human-AI collaboration. Future research should shift from AI as replacement to AI as augmentation. Most studies evaluate AI systems in isolation, while fewer examine human-AI team configurations, trust calibration, decision rights, and joint performance. Socio-Technical Systems Theory emphasizes that technical and social systems must be jointly optimized (Trist and Bamforth, 1951). Engelbart's augmentation perspective argues that computing should extend human intellect rather than merely automate work (Engelbart, 1962). Algorithmic aversion research shows that people may reject algorithmic advice even when algorithms outperform humans (Dietvorst et al., 2015).

The fifth pillar concerns longitudinal, societal, and ethical impact studies. Most empirical studies use cross-sectional data, historical datasets, or short-term experiments, leaving limited knowledge about AI's long-term impact on firms, workers, markets, and society. The productivity paradox suggests that AI's productivity effects may be delayed, uneven, or dependent on complementary investments (Solow, 1987). Stakeholder Theory requires evaluation of AI's effects on multiple affected groups (Freeman, 1984), while responsible AI frameworks emphasize fairness, accountability, transparency, justice, and explicability (Floridi et al., 2018). Future research should examine productivity, employment, wage inequality, systemic bias, and governance over time.

5. Conclusion

This review examined the rapid yet fragmented development of artificial intelligence (AI) in economic and business research. Using a hybrid systematic review design, the study combined bibliometric analysis of 1,970 Web of Science articles with content analysis of 110 empirical Q1/Q2 journal articles. The findings address the three research questions. First, AI applications in economic business are concentrated in four major categories: market prediction and risk management, marketing and customer analytics, process automation and supply chain optimization, and strategic decision-making and HR analytics. Second, the field is dominated by studies of system design and algorithm development, while only approximately 25% of empirical studies explicitly use established theoretical frameworks. Third, the methodological and contextual landscape remains uneven, with experiments and econometric studies dominating the field, while banking, fintech, e-commerce, and retail receive disproportionate attention relative to SMEs, traditional industries, and emerging-market contexts.

Theoretical Implications

This review contributes by mapping AI in economic business research into four thematic clusters and showing that the field remains theoretically underdeveloped. Consistent with Wang et al. (2024), many studies still emphasize model performance rather than explaining how AI creates value, through which mechanisms, and under what conditions. Future research should integrate the Resource-Based View, Dynamic Capabilities theory, Institutional Theory, Trust Theory, Stakeholder Theory, and Socio-Technical Systems Theory to connect technical AI performance with organizational, market, ethical, and governance outcomes.

Methodological Contributions

Methodologically, this review demonstrates the value of combining bibliometric analysis with manual content analysis. Bibliometric analysis identifies macro-level structures, including publication trends, journal distribution, keyword networks, and co-citation foundations. Content analysis adds interpretive depth by examining AI applications, topics, theories, methods, and contexts. This hybrid approach provides a more complete synthesis than bibliometric mapping or narrative review alone and offers a replicable framework for reviewing fragmented, multidisciplinary, and fast-moving research fields.

Practical Implications

The findings provide implications for managers, organizations, and policymakers. Managers should not treat AI as a ready-made technological solution. AI value depends on complementary investments in data infrastructure, human capital, organizational readiness, governance maturity, explainability, and human-AI collaboration. Firms should align AI systems with business processes, decision rights, workforce capabilities, and governance structures. For policymakers, the findings support risk-based and adaptive AI governance that promotes transparency, accountability, fairness, privacy, and explainability while still enabling responsible innovation.

Research Limitations

This review has several limitations. First, the bibliometric dataset relies only on Web of Science, excluding studies indexed elsewhere. Second, only English-language publications were included, creating potential language bias. Third, the content analysis covers 110 empirical Q1/Q2 articles, which may underrepresent niche or early-stage studies. Fourth, citation indicators are affected by publication time lag. Fifth, many reviewed studies predate the rapid diffusion of generative AI, large language models, multimodal AI, and AI-supported knowledge work. Therefore, the framework should be updated as the field develops.

Future Research Directions

Future research should examine generative AI and its implications for productivity, creativity, knowledge work, business models, and professional services. Greater attention is also needed on explainable AI, trust, and regulatory compliance in high-stakes decisions such as credit scoring, recruitment, investment, insurance, and pricing. Researchers should develop theory-driven models explaining how AI affects firm performance, innovation, customer outcomes, and governance. Longitudinal, mixed-methods, and broader contextual studies are needed to examine AI's effects across SMEs, emerging markets, traditional industries, logistics, healthcare, and agriculture.

Concluding Remarks

The future of AI in business is socio-technical rather than purely technological. Without theory, AI research risks becoming a collection of model comparisons with limited cumulative knowledge. Without ethics, AI adoption may weaken trust, fairness, accountability, and legitimacy. Without human-centered design, AI may automate tasks while reducing organizational learning, autonomy, and responsibility. Future AI-economic business research must integrate technical excellence with theoretical rigor, ethical responsibility, managerial relevance, and societal awareness.

Author Contributions

Andri Octaviani is the sole author of this manuscript and contributed to conceptualization, methodology, data collection, bibliometric analysis, content analysis, formal analysis, writing the original draft, writing review and editing, visualization, and final manuscript preparation. The author has read and approved the final version of the manuscript.

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Conflict of Interest

The author declares no conflict of interest related to this manuscript.

Data Availability Statement

The bibliometric data used in this study were obtained from the Web of Science Core Collection. The content-analysis dataset and coding results are available from the author upon reasonable request.

Ethical Statement

This study is based exclusively on bibliographic metadata and previously published scholarly articles. It does not involve human participants, personal data, experiments with individuals, surveys, interviews, or primary data collection. Therefore, informed consent and institutional ethics approval were not required.

Declaration of Originality

The author confirms that this manuscript is original, has not been published previously, and is not under consideration for publication elsewhere.

Declaration on the Use of Artificial Intelligence

The author declares that artificial intelligence tools may have been used only for language refinement, grammar checking, formatting assistance, and improving the clarity of academic expression. AI tools were not used to fabricate data, generate false references, manipulate findings, replace the author's scholarly judgment, or make substantive scientific decisions. All content, citations, interpretations, and conclusions were reviewed and verified by the author, who remains fully responsible for the accuracy, originality, integrity, and scholarly content of the manuscript.

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