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# MACHINE LEARNING FOR STRATEGIC AND OPERATIONAL DECISION-MAKING: A BIBLIOMETRIC PERSPECTIVE

## ABSTRACT

Besides being a buzzword, machine learning finds new areas of application in organizational decision-making processes by the day. We map the field's intellectual structure, thematic evolution, and application domains through a bibliometric analysis of 1,803 Web of Science and Scopus articles (1990-2024) to elucidate its strategic and operational roles. Six clusters, spanning risk modeling, predictive analytics, strategic intelligence, and human-centered AI, are revealed by co-authorship, keyword co-occurrence, and bibliographic coupling. The findings reveal a fragmented but methodologically diverse landscape, with algorithm adoption differing by decision type and industry. By connecting machine learning methods (like deep learning, natural language processing, and explainable AI) with decision functions (like forecasting, optimization, and classification), we can identify the situations in which machine learning has the biggest influence. We go beyond descriptive enumeration with our integration of conceptual and practical insights.

**Keywords**: *Machine learning; decision making; bibliometric analysis*.

**JEL**: B41, C55, C88.

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## 1. INTRODUCTION

Making decisions based on data rather than intuition is essential for organizational adaptability in volatile economies. Robust analytical techniques are necessary due to the overwhelming amount of available data (Kratsch et al., 2021). A subfield of artificial intelligence (AI) called machine learning (ML) offers scalable tools for pattern recognition, forecasting, classification, and optimization that improve choices in supply chains, marketing, finance, and human resources (Lee & Shin, 2020). ML-enabled decision-making is rarely treated as an integrated organizational phenomenon in current scholarship, which is still fragmented and focuses on different areas or energy (Alabi et al., 2022). There is a notable shortage of bibliometric work that differentiates between operational (day-to-day, efficiency-oriented) and strategic (long-term, resource-allocative) applications.

Two complimentary contributions arise. Firstly, the study brings together the different body of research on ML for decision-making and, by combining co-authorship, keyword co-occurrence, and bibliographic-coupling studies, reveals the field's intellectual structure and theme history. Secondly, it goes beyond descriptive counting by comparing strategic and operational ML applications across domains, thus deriving research gaps and implications for academicians and practitioners. This multi-layered contribution distinguishes our approach from previous bibliometric investigations, which seem to be predominantly enumerative.

The paper is structured in the following manner. Section 2 examines the international literature on decision-making and ML, including scholarly works that are relevant. In accordance with PRISMA guidelines, Section 3 describes the data and methodological approach. Results from bibliometric networks and the field's scientific structure are shown in Section 4. A thorough analysis and discussion of the main uses of ML in decision-making are provided in Section 5. Research limitations and future research directions are discussed in Section 6.

## 2. THEORETICAL BACKGROUND

Economic agents are increasingly using data-driven strategies in today's complex and unpredictable environments. Decision-making has moved away from depending on human knowledge and heuristic reasoning that is limited by time and cognition due to the emergence of ML (Simon, 1955; Kleinberg et al., 2018). In terms of accuracy, scalability, and pattern recognition, ML techniques frequently outperform human judgment (Jordan & Mitchell, 2015; LeCun et al., 2015). The incorporation of ML into decision support systems (DSS), which combine quantitative and qualitative reasoning to produce well-informed decisions, is a significant advancement in this change (Shim et al., 2002). Modern DSS provide intelligent, adaptive support that is enhanced by AI and expert systems. According to Merkert et al. (2015), they are increasingly depending on classification and forecasting to deal with changing circumstances.

ML's roles become clearer when strategic and operational decisions are distinguished. Operational decisions involve structured, routine tasks with immediate feedback, whereas strategic decisions are high-impact, long-term decisions that concentrate on resource allocation under uncertainty with delayed feedback (Sturm et al., 2023). Depending on complexity and data availability, ML supports both in a variety of domains, including supply chains, human resources, and finance.

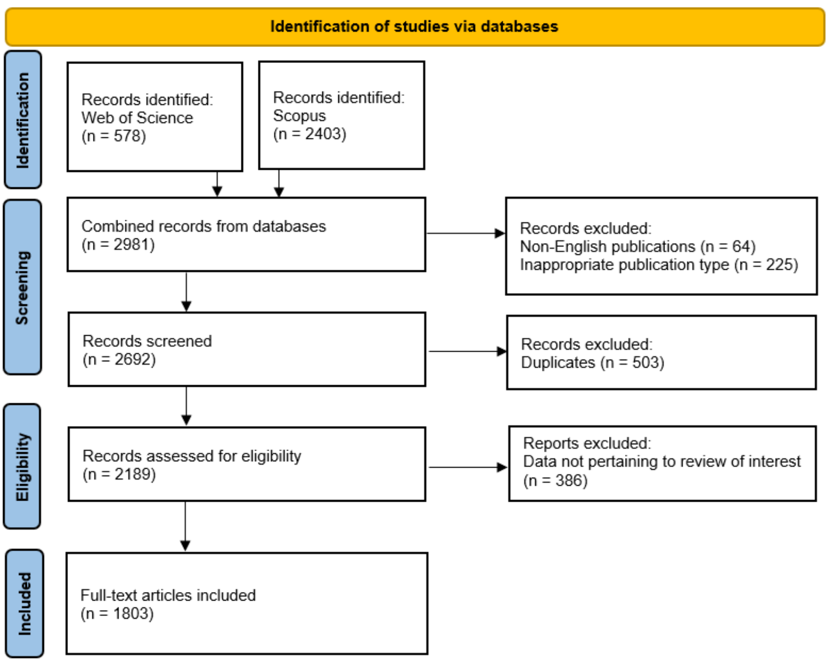
Domain-specific theoretical frameworks are crucial because ML plays different roles in different industries. Using variables like income, debt ratios, and repayment patterns, ML in banking allows for forecasting, anomaly detection, and credit risk assessment (Brygała & Karol, 2024). Early diagnosis, treatment choices, and resource allocation are all influenced by it in the healthcare industry; therefore, clinical validation and regulation are necessary (Obermeyer & Emanuel, 2016). ML improves churn prediction and segmentation in marketing (Herhausen et al., 2024), highlighting the necessity of customized models. Yet despite its increasing popularity, there is a dearth of thorough mapping and useful information about ML's practical applications in real-world decision-making in the literature. A large portion of the emphasis is still theoretical, ignoring implementation issues. By methodically examining the development, major themes, and practical contributions of ML in organizational and policy decision-making over the past few decades, this study fills that knowledge gap.

## 3. METHODOLOGY

A reliable quantitative technique for identifying trends that are frequently overlooked in narrative reviews is bibliometric analysis. It highlights important contributors, concept evolution, and thematic clusters. In accordance with best-practice guidelines (Zupic & Čater, 2015), our multi-technique approach offers a macro-level perspective of ML-driven decision-making research, which enhances conventional qualitative reviews. We use co-authorship, descriptive analysis, bibliographic coupling, and keyword co-occurrence. Our first research question is addressed by descriptive and co-authorship analyses, while the second is informed by bibliographic coupling and keyword co-occurrence, which also chart future research paths. Bibliometrics provides a transparent and reproducible method of organizing knowledge in rapidly expanding, fragmented fields (Donthu et al., 2021).

To ensure rigor, we employ the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, which is renowned for its identification, screening, eligibility, and inclusion phases (Moher et al., 2009) as well as its systematic and repeatable literature review process (Page et al., 2021). Because of their high publication standards, we concentrated on the Web of Science Core Collection and Scopus, choosing final publications from 1990 to November 24, 2024. The search was guided by fundamental ideas that connect ML and decision-making. Figure 1 shows the entire PRISMA process.

**Figure 1**. Flowchart of the applied PRISMA steps




*Used keywords in the search query: (("machine learning" OR "artificial intelligence" OR "data mining" OR "predictive analytics") AND ("decision making" OR "decision making" OR "decision support" OR "managerial decision*" OR "business decision*" OR "policy-making" OR "policy making") AND ("business*" OR "company" OR "companies" OR "firm*" OR "organization*" OR "enterprise*" OR "corporat*" OR "government" OR "policy" OR "public sector" OR "regulator*" OR "governance") AND ("application" OR "case study" OR "empirical" OR "real-world" OR "practical implementation" OR "industry application" OR "organizational decision making" OR "managerial implications")) NOT TS=("theoretical" OR "methodology" OR "algorithm development" OR "novel model" OR "mathematical model" OR "framework development" OR "conceptual model") AND WC=("Business" OR "Management" OR "Economics" OR "Public Administration" OR "Social Sciences Interdisciplinary").

It took a lot of preprocessing to standardize fields and eliminate duplicates when combining the Web of Science and Scopus datasets. To maintain consistency, we manually aligned publication details in accordance with Kumpulainen & Seppänen's (2022) method, prioritizing accuracy over automated merging techniques. There were 2,189 unique records after 503 duplicates were removed. Following the application of inclusion criteria, 1,803 publications, 407 from Web of Science and 1,396 from Scopus, were kept, accounting for 60.48% of the sample that was first identified.

## 4. RESULTS

In this section, following the framework of Donthu et al. (2021), it is necessary to focus on two main techniques – performance analysis and science mapping. Performance analysis can be understood as an evaluation of the scientific output and its academic impact, based on numerous metrics (see Table 1) such as publication metrics, citation metrics, as well as a combination of both. The field is highly collaborative, as evidenced by the fact that only 12.48% of the 1,803 papers examined are single-authored. Publications per active year, or PAY, is a measure of consistent yearly output over time. The prevalence of team-authored research is confirmed by a high collaboration index (CI), which measures the proportion of contributing authors to total publications. In a similar vein, the collaboration coefficient (CC) emphasizes the prevalence of multi-authored work and suggests a dependence on interdisciplinary knowledge in the field.

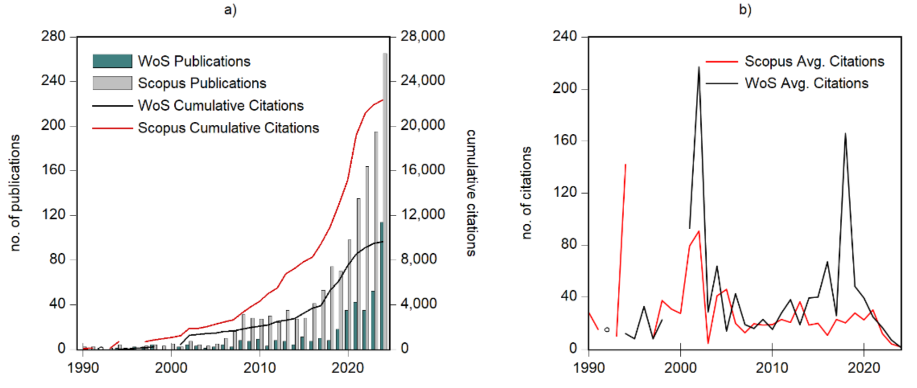
In terms of citation impact, the field exhibits a high h-index (79) and g-index (138), indicating a substantial core of highly cited papers (for instance, 138 documents have at least 19,044 citations in total). Furthermore, 578 documents in the dataset have citations, 60 have , and 17 exceed 200 citations, indicating a robust and influential body of global literature in ML-driven decision-making.

**Table 1**. Performance metrics of the identified sample of documents

| Publication-related metrics | Value | Citation and publication-related metrics | Value |
|---|---|---|---|
| Total number of publications (TP) | 1,803 | Total citations (TC) | 32,034 |
| Number of contributing authors (NCA) | 5,597 | Average citations per document (AC) | 17.7671 |
| Single-authored publications (SA) | 225 | Collaboration index (CI) | 3.1043 |
| Co-authored publications (CA) | 1,578 | Collaboration coefficient (CC) | 0.8752 |
| Number of active years (NAY) | 35 | Proportion of cited publications (PCP) | 2.6567% |
| Average productivity per active year (PAY) | 51.5143 | Citations per cited publication (CCP) | 24.4534 |

Based on Figure 2, it seems that the academic works in applications of ML for decision-making have been experiencing a notable popularity since 2017. For instance, the average number of publications between 2010 and 2019 for the Web of Science and Scopus databases are 8.5 and 40.9 documents, respectively. Since 2020 the average number of publications in the field is 55.6 and 171.4 for each database accordingly.

**Figure 2**. Publications and cumulative citations (a) and average citation (b) trends of the final sample of Web of Science and Scopus documents, 1990-2024.



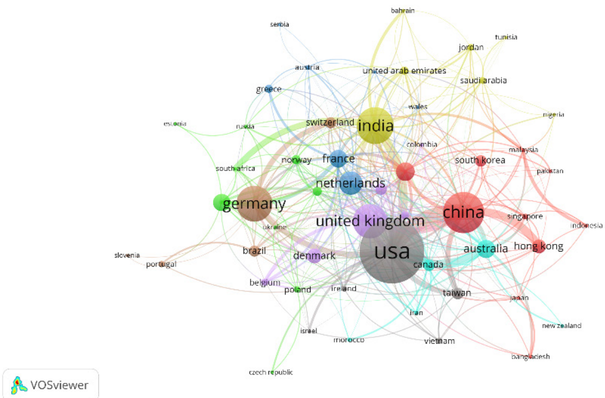

Only between 2014 and 2020 is there a notable difference in the average number of citations per document published in each database. For the entire analyzed period, the average number of citations is 39.75 per document published in sources indexed in the Web of Science, while for those indexed in Scopus the average seems to be a bit lower, i.e. 28.84 citations.

### 4.1. Co-authorship analysis

In mapping international collaborations, we analyzed 54 highly prolific nations ( articles,  citations) using fractional counting. Eight partnership clusters emerge, topped by the United States (286 publications; average 34.6 citations), China, and India. Although production is increasing globally, cross-cluster linkages remain limited thus underscoring the need for more extensive international knowledge sharing and cooperative works. As Perianes-Rodriguez et al. (2016) argue, when conducting a co-authorship analysis "the most reasonable approach is to consider each publication to be equally important", advocating in favor of fractional over full counting.

Eight separate country clusters are shown in Figure 3, with at least five countries in each cluster to guarantee significant patterns of collaboration. With 286 publications, 114 collaboration links, and 9,899 citations, an average of 34.61 citations per paper, the USA leads the field. Asia's increasing involvement in ML-driven decision-making research is further supported by the quick expansion of China and India. These nations, along with Germany, the UK, and the Netherlands, are at the center of international research cooperation, which is heavily impacted by financial resources and technological prowess.

**Figure 3**. Co-authorships between countries.




A shifting global nexus can be seen in the temporal overlay data (Figure 4). Recent increases in the scholarly presence of nations like South Africa, Nigeria, Jordan, and Saudi Arabia suggest a more varied level of research activity. With a large portion of its output occurring after 2021 and only marginally trailing China's earlier growth, India's surge is especially remarkable. Citation overlays (Figure 5), however, show that many smaller countries, such as Denmark, Finland, Wales, and the Netherlands, have a disproportionately high citation effect relative to the number of publications. These trends point to expanding centers of excellence, which may offer bright opportunities for international cooperation and knowledge sharing in the years to come.

**Figure 4**. Overlay network of co-authorship of countries, by average publication year.

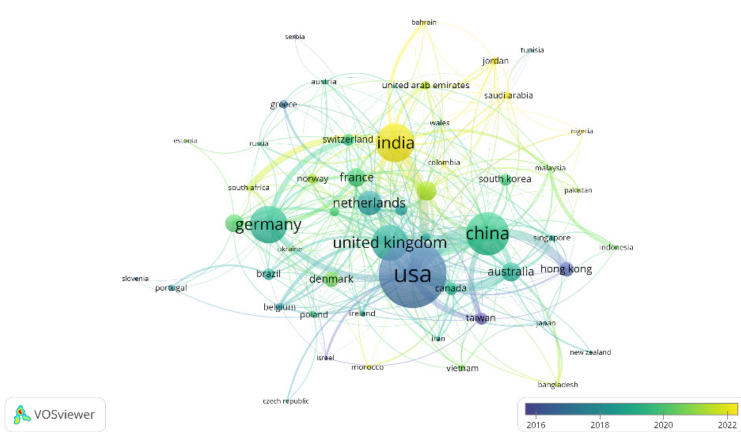
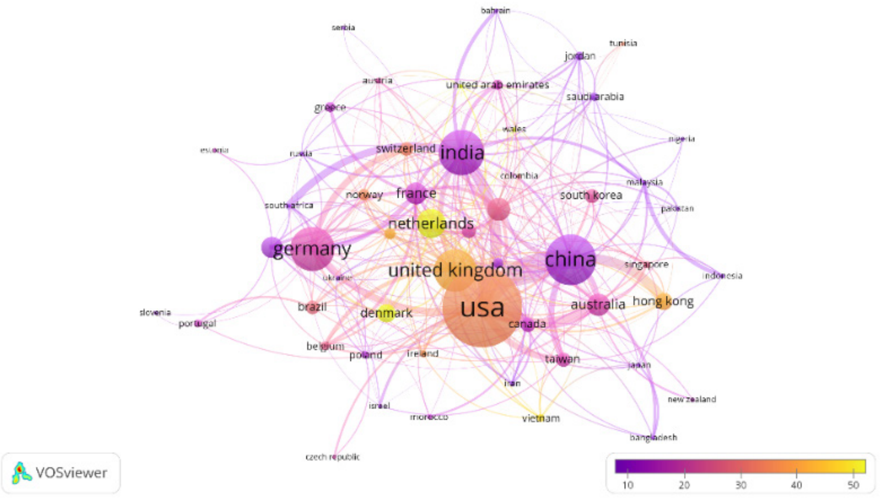


**Figure 5**. Overlay network of co-authorship of countries, by average citations.




Although intra-cluster collaborations are becoming more common, they frequently reflect established research networks or geographic proximity, such as China's cluster with South Korea and Singapore or the UK's with Belgium and Denmark. Nonetheless, cross-cluster collaborations have grown in recent years, particularly between China and the United States. Underrepresented areas like Latin America, Sub-Saharan Africa, the Arab world, and the Balkans are also highlighted by co-authorship analysis. These fields present exciting opportunities for further study and could be the focal points of cutting-edge ML applications suited to new markets and situations that aren't as well-studied in traditional research environments.

### 4.2. Keyword co-occurrence analysis

After removing general, uninformative terms, we performed a keyword co-occurrence analysis ( occurrences) to find the primary research themes. As a result, 189 pertinent keywords were generated, creating the conceptual framework for ML-driven decision-making. Based on the strength of co-occurrence, six clusters were identified using LinLog/modularity optimization (Figure 6). AI, ML, and decision support systems are central nodes that represent their fundamental roles in the field.

*Cluster 1 (red) - ML-driven predictive analytics*. Built around 43 high-frequency terms, Cluster 1 focuses on predictive modeling for risk assessment and classification, including sentiment analysis of social media and credit-risk prediction. It demonstrates how ML increases the precision of decisions made in banking, marketing, and policy. Nonetheless, this study has an operational focus, prioritizing automation and accuracy over interpretability or strategic alignment.

*Cluster 2 (grey) - AI-enabled decision support in operations and supply chains*. This cluster documents the integration of AI with optimization methods (e.g. genetic algorithms, fuzzy logic, MCDM) to improve enterprise planning, manufacturing scheduling, and logistics efficiency.

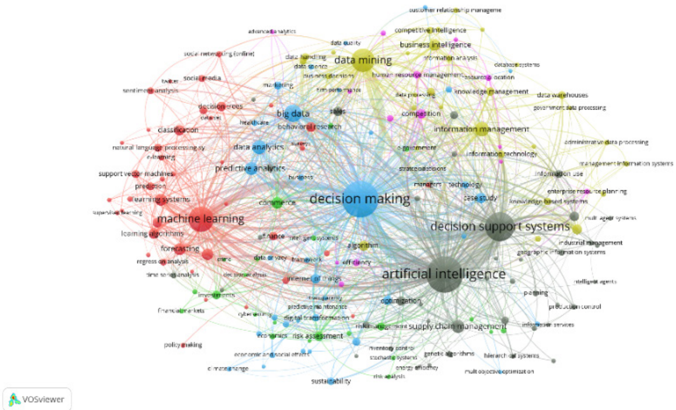
*Cluster 3 (blue) - Big-data analytics for strategic intelligence*. Out of the 36 keywords examined, this cluster's research emphasizes how vast data infrastructures and analytics platforms influence competitive intelligence, market positioning, and strategic decision-making. Cluster 3 places more emphasis on data as a strategic asset than Cluster 1, which is more focused on algorithmic modeling. Its weak ties to clusters centered on human decision-making, however, point to a lack of attention to the social aspects of analytics adoption and use.

*Cluster 4 (yellow) - Data mining and business intelligence frameworks*. This cluster combines knowledge-management techniques with decision-theoretic principles to facilitate evidence-based strategic planning. While the research located in this cluster has the ability to integrate data-driven and knowledge-based methods, it prioritizes technical system design above interpretative models of decision justification.

*Cluster 5 (green) - ML under uncertainty*. The application of ML algorithms for uncertainty modeling in financial and commercial risk management is highlighted by this 22-keyword cluster. Its weak ties to ideas like accountability and transparency, however, suggest that ethical risk modeling is an unexplored field. It is still imperative that socio-ethical factors be incorporated into ML frameworks, particularly in unstable economic environments.

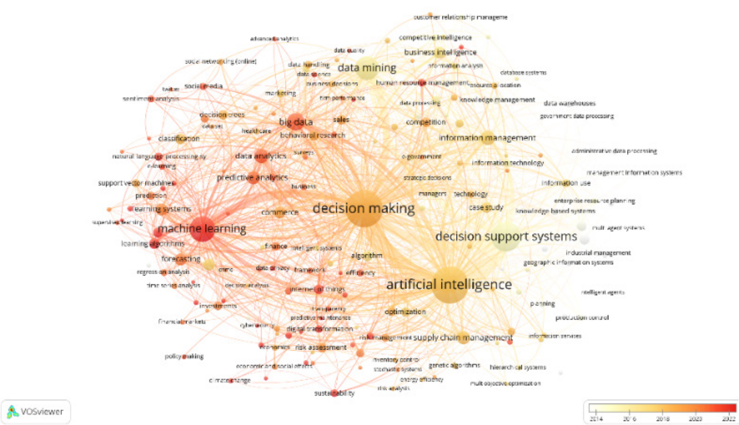
*Cluster 6 (pink) - AI-enhanced competitive strategy and HRM*. Despite being the smallest cluster with only 14 keywords, it effectively conveys the expanding significance of predictive analytics in strategic workforce planning, ERP integration, and people management. It shows how internal governance is moving toward AI-driven strategic foresight. However, its tenuous connections to algorithmic explainability and transparency raise questions about black-box implementations in labor management, where XAI and ethical oversight are crucial.

**Figure 6**. Network of all keywords (min. 10 occurrences), LinLog/ modularity normalization




When overlayed by publication year (Figure 7), a temporal gradient emerges, illustrating how concepts like "machine learning," "deep learning," and "data analytics" have gained prominence in more recent years, while more traditional terms like "decision support systems" and "information management" which originated earlier but continue to remain integral. While post-2010s terms like "learning algorithms," "NLP," "social media," "e-government," and "climate change" indicate a shift toward modern priorities, keywords like "database systems," "ERP," and "intelligent agents" in this context reflect legacy information management. These consist of data-driven financial risk assessment, algorithmic management, cybersecurity, sustainability, ESG compliance, and behavioral analysis.

**Figure 7**. Overlay network of keywords as chronological development of topics



With "decision-making" at the center and ethical or behavioral terms on the periphery, the map shows a conceptually disjointed but methodologically robust field. Advanced algorithms are the focus of Clusters 1 and 2, whereas less technically complex strategic and human-centered issues are the focus of Clusters 3 and 6. We compare clusters based on keyword co-occurrence to determine which ML techniques are appropriate for a given decision domain. These results lend credence to an integrative framework (Table 2) that associates ML techniques with their key characteristics, decision-making scenarios, and regions of greatest influence.

**Table 2**. Cluster summary and domain contextualization

| | Label | Top keywords | Decision focus | Domain | Main Gap |
|---|---|---|---|---|---|
| C.1 | ML-driven predictive analytics | Machine learning Forecasting Neural networks | Predictive classification Risk assessment | Finance Marketing Public policy | Interpretability Organizational integration |
| C.2 | AI decision support in operations/ supply chain | Artificial intelligence Decision support systems Supply chain management | Optimization Real-time planning | Manufacturing Logistics Industry 4.0 | Balancing automated efficiency vs. managerial control |
| C.3 | Big data strategic intelligence | Decision making Big data Data analytics | Strategic intelligence Market positioning | Corporate strategy Smart cities Healthcare | Human factors and adoption behavior |
| C.4 | Data mining and BI | Data mining Information management Decision theory | Evidence-based planning Decision support | E-commerce Knowledge management | Interpretative justification of ML |
| C.5 | ML for risk and uncertainty | Commerce Risk assessment Investments | Risk modelling | Finance Commerce Cybersecurity | Ethical transparency in uncertain context |
| C.6 | AI-enhanced competitive strategy and HRM | Competition Human resource management Efficiency | Workforce analytics Competitive strategy | HRM ERP Competitive strategy | XAI for labor decisions |

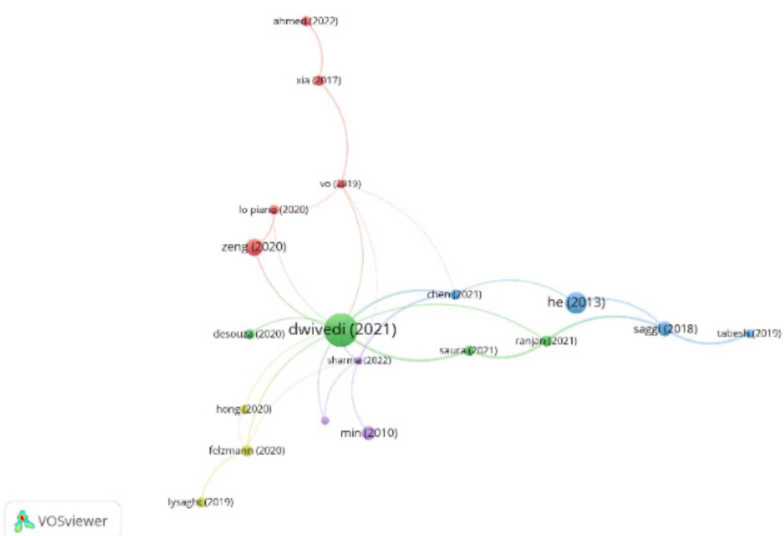
### 4.3. Bibliographic coupling

Bibliographic coupling, which finds similarities between articles based on shared references, is the last bibliometric technique used. The number of shared references between articles that cite similar sources determines how closely they are related

(Zupic & Čater, 2015). Even though the publications were written in different eras and did not directly cite one another, this method allowed us to find thematic connections between them. We used fractional counting on papers with at least 50 citations to get a more comprehensive picture of the research environment. Out of these, 145 satisfied the criterion, creating the largest connected collection of 40 documents arranged into five different clusters, each of which had at least five papers and was weighted according to the number of citations.

60 well-known works are grouped into five theme groups with a minimum cluster size of three using fractional counting and a 100-citation threshold (see Figure 8). Coupling strength highlights common points of reference and shows how the main discourses in the field align. We selected citations as weights because our goal with the bibliographic coupling was to examine the most influential work in the field, not the output of the dominant scientific voices.

**Figure 8**. Bibliographic coupling of documents with at least 100 citations.




*Cluster 1 (red) - Machine learning in finance and ethical complexity*. The first cluster investigates ML applications in finance and service-based industries, such as fraud detection (Ahmed et al., 2022), ethical investing (Vo et al., 2019), and loan evaluations (Xia et al., 2017). Additionally, it discusses robotics-based crisis innovation in tourism (Zeng et al., 2020). Lo Piano (2020) draws attention to ethical blind spots in domains such as autonomous systems, where accountability issues are brought up by ML's opacity.

*Cluster 2 (green) - Cross-sector ML adoption and innovation challenges*. This cluster looks at institutional limitations and cross-sector applications of ML in both the public and private spheres. Interdisciplinary integration, data ethics, and innovation opportunities in management, technology, and government are highlighted by Dwivedi et al. (2021). Desouza et al. (2020) discuss the adoption of AI in government settings with limited resources, while Saura et al. (2021) and Ranjan and Foropon (2021) concentrate on ML-driven improvements in B2B marketing and CRM. When taken as a whole, these pieces present ML as a disruptive tool as well as a coordination challenge that calls for cross-sectoral alignment.

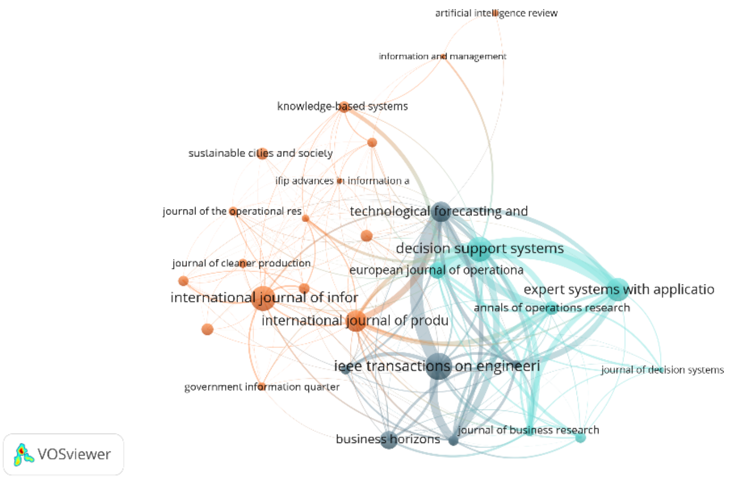
*Cluster 3 (blue) - The role of big data in ML-driven decision making*. Big data analytics is highlighted in this cluster as a crucial facilitator of ML-driven operational and strategic choices. Chen et al. (2021) investigate how organizational and environmental factors impact the adoption of AI in China's telecom industry. The competitive advantage of ML-based social media analytics in services is illustrated by He et al. (2013). Saggi and Jain (2018) highlight issues with data governance and quality while putting forth a strategic roadmap to increase operational efficiency through big data and ML.

*Cluster 4 (yellow) - Interpretable and human-centered ML systems*. The fourth cluster places a strong emphasis on trust, ethics, and transparency in ML integration. Hong et al. (2020) investigate how the adoption of interpretable models is influenced by human perceptions of complexity and clarity. "Transparency by design" is recommended by Felzmann et al. (2020) as a way to incorporate moral protections into automated systems. The main goal is to encourage responsible use by matching ML capabilities with societal values.

*Cluster 5 (violet) - Industry 4.0 and supply chain intelligence*. The role of ML in supply chains of the future is examined in the smallest cluster. In smart factories, Lee and Lim (2021) associate ML with automation, labor transformation, and predictive maintenance. Sharma et al. (2022) link algorithmic decision-making to innovation in Industry 4.0 by highlighting AI's application in risk mitigation and real-time decision-making.

Important publication sources were also identified through bibliographic coupling. Thirty journals satisfied the requirements using fractional counting and thresholds ( papers and  citations); the largest connected set had 29 items (Figure 9).

**Figure 9**. Bibliographic coupling of most influential journals, weighted by normalized citations, method of fractional counting.




Three disciplinary cores in ML-driven decision-making research are revealed by bibliographic coupling of journals. A solid foundation in system-level decision-making and computational optimization is reflected in the light blue cluster, which is anchored by the European Journal of Operational Research and Decision Support Systems (93.98 normalized citations). ML applications in engineering, strategy, and industrial innovation are the focus of the grey cluster, which is centered on IEEE Transactions on Engineering Management (112.44) and Technological Forecasting and Social Change (64.20). The International Journal of Information Management (96.61) and Knowledge-Based Systems (19.41) are at the forefront of the orange cluster, which symbolizes the convergence of information systems, knowledge management, and decision intelligence.

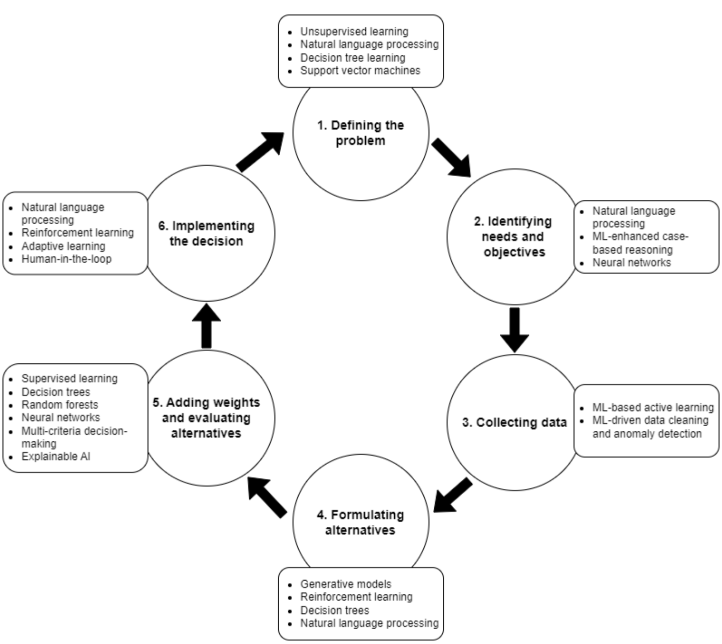
## 5. SYSTEMATIC REVIEW AND DISCUSSIONS

There are two primary contributions made by this article. For the scholarly community, it promotes theory development, advances empirical research on ML applications, and provides information for programmatic studies on organizational decision-making, especially in business settings. It offers practitioners summarized insights to direct organizational operations and strategy. We demonstrate that ML has become essential to data-driven decision-making in both the public and private sectors through a thorough literature review and bibliometric analysis. Organizations can use it to forecast results, spot trends in historical data, and guide strategic choices (Mahdavinejad et al., 2018). In reality, ML facilitates financial, marketing, and policy decision-making through methods like explainable AI, deep learning, and sentiment analysis (Lessmann et al., 2021).

Using algorithms like decision trees, support vector machines, and neural networks, ML improves inventory management, supply chain efficiency, risk mitigation, and resource allocation at the operational level (Sarker et al., 2019). Healthcare, telecommunications, finance, and government are among the industries that benefit from these tools (Sarker, 2021). In order to demonstrate its wide-ranging influence on contemporary organizational decision-making, ML is also spreading into new fields like cybersecurity, smart city management, image and speech recognition, and precision agriculture (Ullah et al., 2020).

Based on empirical findings (Merkert et al., 2015; Pei et al., 2024; Ali et al., 2023), Figure 10 provides a summary of commonly used ML techniques across key stages of strategic and operational decision-making. By identifying patterns and drawing conclusions from textual feedback, unsupervised learning and natural language processing (NLP) take center stage during the problem-definition and needs-identification phases (Merkert et al., 2015). Reinforcement learning, case-based reasoning, and generative deep learning are used to expand solution sets and simulate scenarios during the decision design phase (Alabi et al., 2022). In order to evaluate costs, benefits, and risks, evaluation frequently uses multi-criteria frameworks in conjunction with supervised techniques like decision-tree ensembles, SVMs, and neural networks (Ali et al., 2023). Lastly, implementation makes use of human-in-the-loop systems, reinforcement learning, and anomaly detection for adaptive refinement and real-time monitoring, allowing for continuous learning while the system is being executed (Pei et al., 2024).

**Figure 10**. Decision-making phases and most popular ML-based techniques



Through our multi-technique bibliometric approach, we synthesized the literature into a variety of clusters based on co-authorship, keyword co-occurrence, and bibliographic coupling. Based on this, we can integrate these findings into four summary statements:

1) *The breadth of ML algorithms and paradigms is expanding and emerging*. This expansion covers a wide range of methodologies, from more sophisticated approaches like deep learning, reinforcement learning, and ensemble methods to more conventional ones like decision trees, support vector machines, and Bayesian networks. Modern algorithms are especially useful in dynamic, uncertain environments because they are excellent at complex pattern recognition, optimization, and content generation (Sarker, 2021). On the other hand, traditional ML approaches place more emphasis on efficiency and interpretability, with methods such as regression and decision trees providing clear and understandable decision support (Felzmann et al., 2020).
2) *ML methods are linked to decision types, which flow into larger domains*. While fuzzy logic and explainable AI support strategic decisions in uncertain contexts like digital transformation, deep learning and big data analytics support complex forecasting tasks (Papadakis et al., 2024). Decision trees are used for operational tasks, and genetic algorithms and reinforcement learning allow for real-time analytics. Segmentation is supported by clustering and classification, and insights are extracted from unstructured marketing data using generative AI and natural language processing (Shankar & Parsana, 2022). Fuzzy logic and multi-criteria techniques are combined in hybrid models to provide customized organizational support (Reis et al., 2025).
3) *Healthcare, governments, ICT, finances, marketing, management, and transportation are the primary representative domains*. Because of their emphasis on innovation, high R&D expenditures, and robust data infrastructure, these sectors are crucial in promoting the use of ML in decision-making (Kratsch et al., 2021). Through improved e-commerce, customer relations, human resource management, and social media optimization, their forward-thinking strategy enables them to realize benefits while absorbing implementation costs (Sarker, 2021).
4) *The application of ML algorithms in decision-making processes in organizations is uneven across organizations and industries due to facilitating conditions and affecting determinants/barriers*. Data access, resources, and digital readiness all influence the uneven adoption of ML. Costs, skill shortages, privacy concerns, and ethics are major obstacles (Lee & Shin, 2020). Although recent studies emphasize accessibility and human-centered design to promote more inclusive organizational use, it is still concentrated in tech-mature sectors.

### 5.1. Future research agenda

ML is still changing how decisions are made in many different industries, despite persistent research gaps. Consequently, four priorities are identified by our bibliometric analysis: (1) accelerating the adoption of ML in the public sector in the face of ethical and financial constraints; (2) addressing explainability and trust in high-stakes domains such as public administration and finance (Felzmann et al., 2020; Ranjan & Foropon, 2021); (3) moving from basic analytics to strategic ML through structured methodologies; and (4) analyzing socio-technical and ethical impacts, such as workforce changes, accountability, and cultural shifts, to ensure responsible use.

### 5.2. Research limitations

There are a few limitations to be aware of, even though this bibliometric analysis provides insightful information about ML and decision-making. Firstly, results are sensitive to threshold selections for repetitions and citations, and relying solely on a predetermined set of keywords may exclude new or specialized topics. Secondly, references may be cited critically rather than supportively, which distorts the perceived impact of the references and makes citation metrics deceptive. Thirdly, different interpretations are possible because clustering and theme labeling entail subjective judgment. Finally, combining disparate ideas could mask other significant developments in ML-driven decision-making.

## 6. CONCLUSION

This study used a multi-technique bibliometric approach to review 1,803 articles from Web of Science and Scopus to investigate how ML aids in decision-making, pinpoint research hotspots and trends, and suggest future lines of inquiry.

The results indicate a distinct upward trend in publications, which can be attributed to the increasing relevance and accessibility of ML technologies. China, India, Germany, the United States, and the United Kingdom are the most common research contexts. Even though ML is well known for improving, automating, and even changing decision-making, its global application is still dispersed. Because decision-makers might find it difficult to match suitable ML techniques to particular scenarios, this fragmentation runs the risk of widening the gap between research and practice. Predictive models aid in forecasting and diagnostics, classification supports segmentation and fraud detection, while optimization models improve resource allocation and process efficiency (Sarker et al., 2019).

Two primary streams influence ML research: a technology-driven approach that emphasizes algorithmic characteristics like interpretability, and a domain-driven approach that concentrates on decision contexts and ethics. Integration between the two is still restricted, though. With minimal consideration for wider methodological alignment, the majority of studies apply particular ML techniques to discrete domains. Although our analysis identifies common ML techniques and decision domains, such as healthcare, finance, and policy, it also raises questions about which approaches are most appropriate for particular kinds of decisions. This synthesis provides direction for future study and real-world application by mapping well-known tools like neural networks, decision trees, natural language processing, sentiment analysis, and explainable AI to decision functions.

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## MAŠINSKO UČENJE ZA STRATEŠKO I OPERATIVNO DONOŠENJE ODLUKA: BIBLIOMETRIJSKA PERSPEKTIVA

**SAŽETAK**

Mašinsko učenje, iako često spominjano kao moderna fraza, svakim danom nalazi nove primjene u organizacijskim procesima donošenja odluka. Kako bismo razjasnili njegove strateške i operativne uloge, mapiramo intelektualnu strukturu, tematsku evoluciju i domene primjene kroz bibliometrijsku analizu 1.803 članaka iz Web of Science-a i Scopusa (1990–2024). Analiza koautorstava, ko-pojavljivanja ključnih riječi i bibliografskog spajanja otkriva šest klastera koji obuhvaćaju modeliranje rizika, prediktivnu analitiku, stratešku inteligenciju na čovjeka usmjerenu umjetnu inteligenciju. Dobiveni rezultati pokazuju fragmentiran, ali metodološki raznolik krajolik, pri čemu se usvajanje algoritama razlikuje prema vrsti odluke i industriji. Povezujući ML metode (npr. duboko učenje, obradu prirodnog jezika i objašnjivu AI) s funkcijama odlučivanja (npr. prognoziranje, optimizaciju i klasifikaciju), identificiramo situacije u kojima ML ima najveći utjecaj. Integracijom konceptualnih i praktičnih uvida nadilazimo puko deskriptivno nabrajanje.

**Ključne riječi:** *mašinsko učenje; donošenje odluka; bibliometrijska analiza.*

**JEL:** B41, C55, C88.