Management Papers

A BIBLIOMETRIC INSIGHT TO MACHINE LEARNING APPLICATIONS FOR DECISION-MAKING

Ivona Serafimovska
Faculty of Economics-Skopje,
Ss. Cyril and Methodius University in Skopje, North Macedonia
ivona.serafimovska@eccf.ukim.edu.mk

Bojan Kitanovikj
Faculty of Economics-Skopje,
Ss. Cyril and Methodius University in Skopje, North Macedonia
bojan.kitanovikj@eccf.ukim.edu.mk

Filip Peovski
Faculty of Economics-Skopje,
Ss. Cyril and Methodius University in Skopje, North Macedonia
peovski@eccf.ukim.edu.mk

ABSTRACT
Using a multi-method bibliometric analysis of published documents from Web of Science and Scopus in the last 34 years, this comprehensive study investigates how machine learning improves advanced decision-making while adhering to the PRISMA guidelines. This study's main goal is to make the methodological patterns, thematic directions, and intellectual structure of research at the nexus of machine learning and decision-making visible. The results show that the U.S., China, India, Germany, and the U.K. are leading a rapidly expanding, cooperative research landscape with a strong emphasis on management, marketing, and finance. Tree-based models, support vector machines, deep learning, reinforcement learning, and explainable artificial intelligence are examples of frequently used algorithms. The field is moving toward applications in big data environments, ethical considerations, and increased interpretability. Digital transformation, competitive intelligence, and strategic planning are highlighted in influential works. This synthesis offers direction for developing more transparent machine learning models and practical frameworks for their use in decision-making, serving both academics and practitioners.

Keywords: *Bibliometric analysis, Decision-making, Machine learning*

JEL classification: *B41, C55*

1. INTRODUCTION

The adaptability of organizations in the complex and dynamic economic environment is mostly influenced by the scope and quality of the decisions being made. While decisions are mostly intuitive among economic agents, it is preferable to base them on data and information, rather than experience and pure common sense. The decision-making process intertwines multiple factors that span across various goals, environments, policies, and even human behavior. Moreover, the exponential growth of data and information implies the necessity of using

10.47063/EBTSF.2025.0015
http://hdl.handle.net/20.500.12188/34495

modern and robust methods that can adequately face such challenges. Machine learning (ML), which has been vastly popularized in recent years, adapts well to the aforementioned aspect and rapidly adapts to the continuous evolution of data landscapes, transcending the most common limitations.

Motivated by this, we specify four operational aims for this study: 1) quantify the temporal evolution of citations and publications of ML-based decision-making based on documents indexed in the Web of Science and Scopus databases between 1990 and 2024; 2) recover the intellectual structure (co-citation/bibliographic coupling) and the main thematic clusters (keyword co-occurrence); 3) classify methodological portfolios by decision context; and 4) summarize sectoral adoption and interpretability/ethics signals to surface actionable gaps for future work. Stemming from this, this research endeavor attempts to answer the following research questions: a) *How have ML for decision-making publications and citations changed from 1990 to 2024 across nations and industries?*; b) *What topics and intellectual groups are revealed by bibliographic coupling and co-citation?*; c) *How do decision contexts (strategic, tactical, and operational; forecasting, classification, and optimization) fit with methodological portfolios (algorithms, interpretability orientation)?;* and d) *Which documented limitations and adoption trends serve as the driving forces behind a focused future research agenda?*

Two important contributions are made in this paper. Through a multi-technique bibliometric analysis, it first provides a theoretical framework that synthesizes influential research on machine learning in organizational decision-making, highlighting both current and emerging trends. Second, it offers a thorough analysis of the literature with useful advice for professionals involved in operational and strategic decision-making, including managers and policymakers.

The paper is structured in the following manner. The bibliometric theory and earlier research are reviewed in Section 2. Following the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) guidelines, Section 3 describes the data and methodology. The results of the bibliometric network are shown in Section 4. Leading machine learning applications in decision-making are methodically covered in Section 5. Section 6 concludes the study.

2. LITERATURE REVIEW

Although their focus deviates from the decision-analytic lens, early surveys present machine learning (ML) as a general-purpose technology for inductive inference (Dietterich, 1996; Jordan and Mitchell, 2015). While Athey (2017) emphasizes integrating predictive models within explicit decision objectives, econometrics-focused contributions (Mullainathan and Spiess, 2017; Athey and Imbens, 2019) contend that prediction enhances causal reasoning in policy settings rather than replacing it. On the other hand, value creation is repositioned toward judgment, supervision, and complementary skills by management-of-work perspectives (Brynjolfsson and Mitchell, 2017; Agrawal *et al.*, 2019). Our review adds value by contrasting these camps. For instance, while decision-first approaches ensure relevance, they run the risk of under-exploiting complex patterns. Approaches where prediction is the primary goal, on the other hand, face interpretability and external validity constraints in high-stakes decisions. Our coding of “decision context” and “interpretability orientation” in the empirical corpus is driven by this nexus.

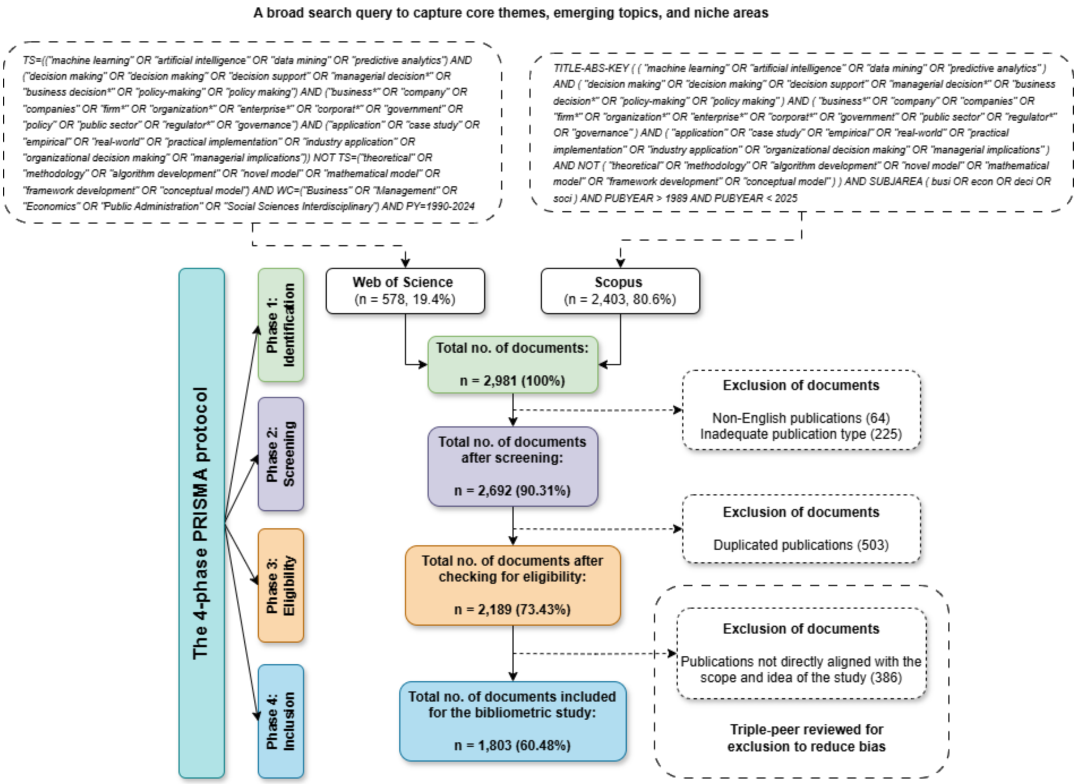
Empirical research is dominated by financial markets. For Brazilian day trading, Paiva *et al.* (2019) combine portfolio theory and support-vector machines, producing better risk-adjusted returns. In his review of reinforcement-learning advances in dynamic allocation and option pricing, Hambly (2023) points out that value-based and policy-gradient approaches perform better under regime changes than traditional stochastic control. By focusing on the most instructive observations, decision-centric active learning (Saar-Tsechansky and Provost, 2007) further lowers data-acquisition costs in credit scoring. Supply-chain and industrial environments both gain in this case, as Chen and Zhou (2020) combine real-time parameter estimation with model-predictive control to stabilize time-varying production systems, while Bertolini *et al.* (2021) document how predictive maintenance and defect detection drive Industry 4.0. Park and Yang (2022), whose interpretable LSTM predicts economic crises with explainable-AI overlays, and Guo *et al.* (2021), who combine neural networks with multi-criteria decision aiding to elicit stakeholder preferences, both address macro-policy and labor perspectives. De Laat (2018) contends that partial explainability, as opposed to complete code disclosure, strikes a balance between accountability and proprietary incentives, but transparency is still a limitation.

Despite the widespread adoption, disparities still exist between sectors. Empirical research is dominated by financial markets (Paiva *et al.*, 2019; Hambly, 2023), while public-sector and emerging-market deployments lag, especially in areas where interpretability and governance are most important (De Laat, 2018; Bücker *et al.*, 2022; Monken *et al.*, 2023). Our comparative synthesis between methods and decision fit and our agenda prioritizing contexts where human-AI complementarity is consequential are motivated by this asymmetry as well as the well-documented trade-off between accuracy and transparency (Kratsch *et al.*, 2021; Makridakis *et al.*, 2023).

3. METHODS AND DATA

Bibliometric analysis tracks conceptual evolution, identifies influential works, and quantifies scholarly output. In quickly expanding fields, it provides reproducible insights and improves literature reviews (Zupic and Čater, 2015) by offering a macro-level perspective (Donthu *et al.*, 2021). Performance analysis evaluates publishing and citation metrics (Lamovšek and Černe, 2023), while the five techniques, such as citation analysis, co-citation, bibliographic coupling, co-author, and co-occurrence analyses, provide insights into the topic (Marzi *et al.*, 2025). We supplemented these methods with a manual classification of each included document by decision context (strategic, tactical, operational), task type (e.g., forecasting, optimization, classification), and human-AI interaction mode in order to go beyond basic clusters and better capture the decision-making dimension. By using a hybrid approach, we were able to understand the networks both as abstract knowledge structures and in terms of the application of machine learning to real world decision-making. To ensure transparency through identification, screening, eligibility, and inclusion, this study uses the PRISMA protocol (Moher *et al.*, 2009; Page *et al.*, 2021). For identification, we use Web of Science Core Collection and Scopus (Baas *et al.*, 2020), while Google Scholar is not used due to noted problems with access and quality (Lim *et al.*, 2024). With an emphasis on practical applications, we review literature combining machine learning and decision-making in public administration, economics, and business and management, with a focus on papers published between 1990 and 2024. Figure 1 visually presents the flow of the process in acquiring and pre-processing data alongside the extensive search queries for both databases.

Figure 1: The conducted PRISMA protocol



(Source: Authors' work)

Combining these large databases through intensive data wrangling (see Koehler *et al.*, 2017), which included standardization and duplicate removal, was a significant challenge. Although Web of Science entries generally have more detailed metadata, Scopus was incorporated into its structure. There are several methods for merging, including open-source tools (Nikolić *et al.*, 2024), a three-step protocol (Caputo and Kargina, 2022), and bibliometrix/biblioshiny in R (Lim *et al.*, 2024). Despite warnings in favor of automation (Kasaraneni and Rosaline, 2024), we chose to manually merge using both full and abbreviated field names (Kumpulainen and Seppänen, 2022). The deduplication of documents under the screening phase was based on repetitive DOIs.

To avoid bias, eligibility was manually evaluated by three separate reviewers in the third phase. Documents (a total of 386 or 12.95% of the original sample) that were judged inappropriate by two or more reviewers were eliminated. Items that mentioned machine learning or decision-making in passing or that didn't have any real-world applications for ML decision-making were eliminated. These fields included healthcare, education, maritime, urban governance, agriculture, meteorology, psychology, and cybersecurity. A total of 1,803 (60.48%) documents were included for analysis beyond phase four.

4. MAIN INSIGHTS

4.1. Cluster analysis of authors' keywords

Using a LinLog/modularity normalization and a minimum occurrence threshold of 10, the author's keyword co-occurrence network offers an empirically supported perspective on the theoretical underpinnings of machine learning applications in decision-making. Three distinct theme clusters were produced when 50 of the 4,826 keywords were judged suitable for inclusion.

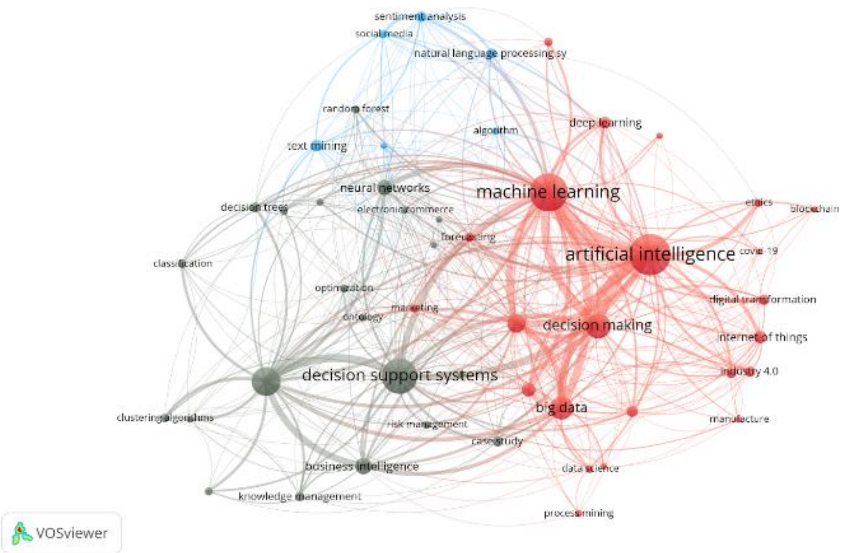
Cluster 1: Core analytics, strategic decision processes, and emerging technologies. The conceptual center of the field is represented by Cluster 1, which consists of 23 keywords and is anchored by three highly recurring terms: “artificial intelligence” (352 occurrences, total link strength: 359), “machine learning” (300 occurrences, total link strength: 354), and “decision making” (135 occurrences, total link strength: 196). To address complex business challenges, such as supply-chain optimization and Industry 4.0 applications, research encompasses deep learning, big-data analytics, and predictive tools. Growing concerns about interpretability, ethics, and long-term socioeconomic impact are reflected in emerging themes like explainable AI, digital transformation, and sustainability. All things considered, this cluster demonstrates how sophisticated analytical techniques meet organizational strategy and governance to tackle modern decision-making issues.

Cluster 2: Foundational decision support, knowledge integration, and established algorithms. Cluster 2 is dominated by methodological and infrastructural constructs that have long supported data-driven decision processes. As conceptual anchors, three keywords stand out: “business intelligence” (58 occurrences, total link strength: 97), “data mining” (179 occurrences, total link strength: 199), and “decision support systems” (257 occurrences, total link strength: 188). By using analytical techniques such as support vector machines, neural networks, decision trees, and classification algorithms integrated into knowledge management and data warehouse platforms, this cluster organizes and leverages structured information to support decision-making. For well-informed decision-making, it makes optimization, predictive modeling, and historical data analysis possible. The enduring significance of these frameworks for effective resource allocation and strategic insights across organizations is demonstrated by domain-specific applications in e-commerce and CRM.

Cluster 3: Linguistic dimensions, content-driven analytics, and cognitive insight. The third cluster, which is composed of six keywords, focuses on using unstructured textual data to extract meaning and structure. The terms “text mining” (31 occurrences, total link strength: 39), “sentiment analysis” (26 occurrences, total link strength: 47), and “natural language processing systems” (21 occurrences, total link strength: 34) are the most prominent examples of this cluster. This highlights a move toward language-based analytics of digital communications, which adds qualitative information to decision-making. Multiple insights into stakeholder preferences, consumer behavior, and public concerns are subsequently obtained by incorporating text analysis into quantitative models. This improves interpretability and directs the creation of policies, user experience design, and reflects in brand management.

We find two empirically supported bridges in the network beyond the three-way structure. For instance, explainable/transparent terms linking “decision support/assurance/governance” have grown since 2019 (Bücker *et al.*, 2022; Monken *et al.*, 2023), and second, there are weak but growing ties between reinforcement learning and optimization, indicating an early convergence of sequential choice and stakeholder-preference modeling (Guo *et al.*, 2021; Hambly *et al.*, 2023). These time-stamped connections support our assertion that the field is moving from purely algorithmic performance to auditable decision benefit, with a focus on interpretability and governance.

Figure 2: Network of authors' keywords.

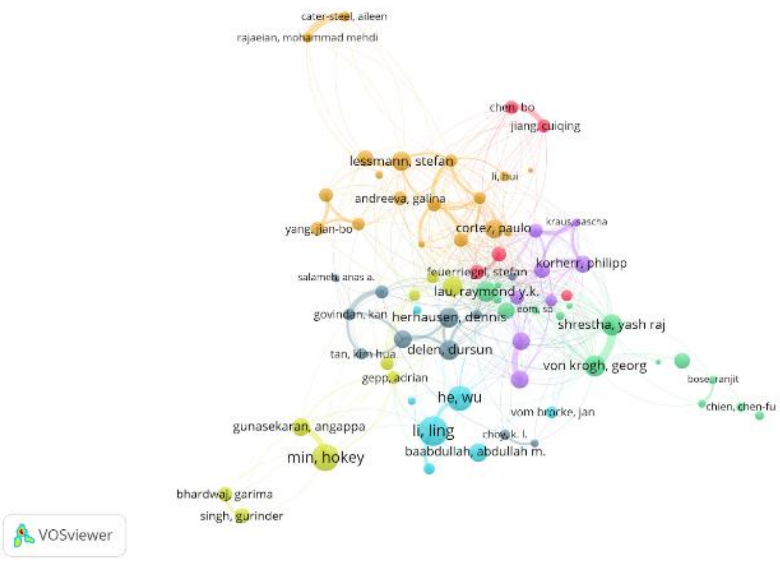


(Source: Authors' work)

4.2. The most prominent authors

The following bibliographic coupling technique focuses on authors, employing fractional counting to measure connections based on shared references, which resulted in the visualization map in Figure 3. The analysis considers authors with a minimum of 2 publications and at least 10 citations per author, narrowing the dataset from 5,597 authors to 121 who meet the threshold for influence and productivity. Among these, the largest connected set consists of 73 authors, further divided into 7 distinct clusters, each with a minimum size of 5 authors. The analysis uses the LinLog/modularity method to optimize clustering, emphasizing relationships within and between groups. Weights are based on normalized citations, ensuring that the scientific impact of authors is equitably represented. The authors highlight topics like operations research, decision-support systems, and machine learning applications by grouping them into seven clusters based on common references. Well-known writers Lessmann (10.52), Cortez (9.36), and Stahlbock (6.26) act as intellectual linkages; their work covers supply-chain management, marketing, and the choice of AI methods (Hoffmann *et al.*, 2020; Lessmann *et al.*, 2021).

Figure 3: Bibliographic coupling of authors

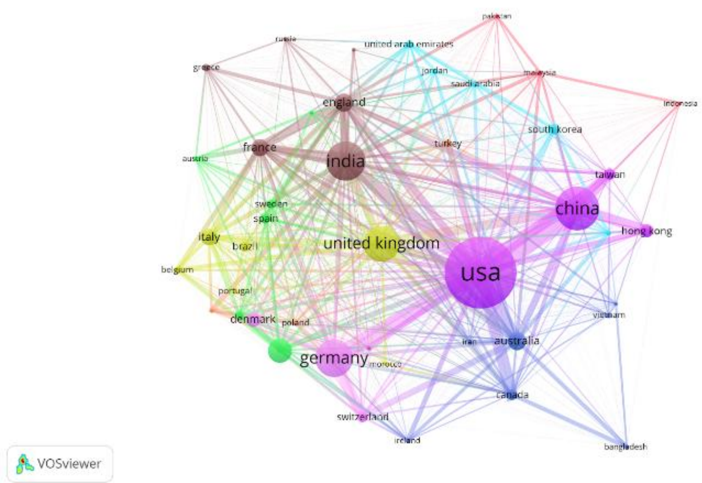


(Source: Authors' work)

4.3. Countries driving the global research

An additional bibliographic coupling technique on involved countries in the research field was conducted, based on shared references in their publications. The analysis includes countries with a minimum of 10 publications and at least 50 citations, reducing the dataset from 114 to 44 countries that meet the threshold for scientific impact and productivity. Using normalized citations as weights, the analysis emphasizes the relative influence of each country's contributions, ensuring fair comparison. The LinLog/modularity normalization method was applied to optimize clustering, resulting in 3 distinct clusters, each with a minimum size of 5 countries. Also, the minimal cluster size is now reduced to 3 countries. This produced 9 clusters presented in Figure 4.

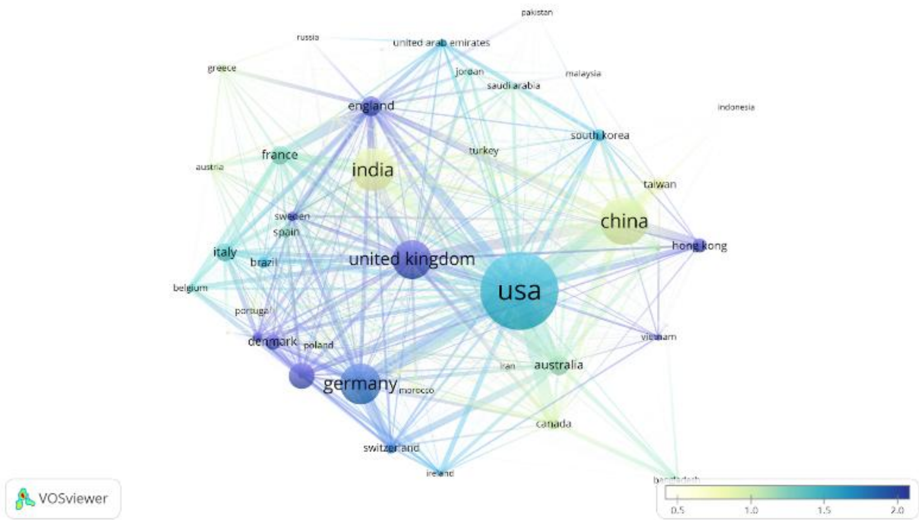
Figure 4: Bibliographic coupling of countries with scaled by normalized citations.



(Source: Authors' work)

Global ML research is led by the US, China, India, the UK, and Germany, and these countries frequently collaborate and have a high citation impact (see Figure 5). In addition to cross-regional ties between China, India, and the US, regional clusters include European alliances (Germany, Italy, France) and Asian-Middle Eastern ties (South Korea, Saudi Arabia, India). Emerging niches are reflected in peripheral contributors such as Greece and Bangladesh. While Taiwan, Germany, the US, and the UK dominated earlier work, bibliographic coupling reveals recent (post-2020) growth from the UAE, Saudi Arabia, Jordan, and India. Southeastern Europe, Latin America, and Africa are underrepresented regions that should be the focus of future studies.

Figure 5: Bibliographic coupling of countries by average normalized citations.



(Source: Authors' work)

5. SYSTEMATIC REVIEW AND DISCUSSION

The maps suggest a straightforward narrative. Uneven adoption across sectors can be explained by the fact that work in information systems and operations research is still only tangentially related to text-centric analytics. The rapid growth of studies that focus on interpretability after 2019 and their increased connections to decision support and assurance topics are indicators of growing governance concerns (De Laat, 2018; Bücker *et al.*, 2022; Monken *et al.*, 2023). While auditable and naturally interpretable approaches are more important in public sector contexts, application-driven strands in finance and logistics tend toward deep models (Makridakis *et al.*, 2023; Pugliese *et al.*, 2021). These trends can be inferred from the timing of links that connect clusters as well as from the composition of bibliographic coupling and co-citation communities. Using Table 1, we expand on the previous analysis by demonstrating how machine learning techniques are linked to decision-making contexts in the literature. The table shows how these approaches are frequently combined with neighboring approaches and how these combinations occur across various domains, rather than treating them as a strict taxonomy. This facilitates a clearer understanding of the types of techniques that are most frequently used in particular decision-making contexts and where their effects have been most noticeable.

This has two-fold implications relating to the scientific communities interested in exploring the applications of machine learning and those investigating how decision-making in organizations can be enhanced, particularly in a business context, and practitioners' communities, whose members can embed the findings in organizational and unit-based strategies, policies, and activities on an operational level.

A fundamental application of machine learning is the use of data-driven predictive analytics to make intelligent decisions by forecasting by utilizing the relationships between predictors and outcomes (Mahdavinejad *et al.*, 2018). Financiers, marketers, and policymakers use algorithms such as deep learning, sentiment analysis, explainable AI, and natural language processing (NLP) to forecast trends and comprehend behavior (Lessmann *et al.*, 2021; Monken *et al.*, 2023). Decision-making across sectors, including government and nonprofits, is improved by techniques like support vector machines (SVMs), decision trees, decision support systems (DSS), and neural networks, which optimize inventory, logistics, risk management, resource allocation, and strategy (see Sebastião *et al.*, 2020). Beyond traditional domains, ML supports context-aware computing, image/speech recognition, cybersecurity, digital attack prevention, IoT-based smart city traffic and energy management, and sustainable agriculture (Saba *et al.*, 2023), indicating future ML trajectories.

Table 1: Decision-making areas of global research and machine learning applications

Machine Learning Concepts	Decision-Making Areas	Key Domains
Core AI/Analytics Deep learning, neural networks, SVM, decision trees, random forests, explainable AI, generative AI, NLP, text mining, sentiment analysis	Forecasting and classification; sentiment/content analysis; strategic decision support; innovation management	Finance, marketing, and brand strategy, policy and public opinion, social media, and consumer behavior
Optimization and planning Genetic algorithms, fuzzy logic, multi-criteria decision making, time-series and predictive analytics, big data, and IoT analytics	Supply-chain and resource optimization; sustainability planning; digital-transformation strategy; real-time automation	Supply-chain management and Industry 4/5.0; smart cities; sustainable development; healthcare; project management
Decision support and risk Decision-support systems, data mining, clustering, expert systems, simulation, reinforcement, and unsupervised learning	Organizational decision support, CRM and e-government, risk assessment and crisis management, ERP and resilience	Cybersecurity and financial markets, e-commerce, agriculture, information systems, and engineering education
Human-Centric and contextual ML Adversarial ML, supervised learning, multi-objective optimization, automated decision frameworks	Human-in-the-loop support; UX and stakeholder preference elicitation; scenario simulation; robustness testing	Virtual/augmented reality; digital education; human-machine collaboration; HR management; emerging digital platforms

(Source: Authors' work)

The bibliometric approach employed yielded a multi-level insight into how decisions are formed based on applications of machine learning algorithms. For instance, we can highlight several key points.

While classical models sacrifice raw accuracy for auditability and small-sample stability, deep models are sensitive to drift and can leak target information in the absence of robust pipelines (Kratsch *et al.*, 2021; Makridakis *et al.*, 2023). Compared to models that are naturally interpretable, post-hoc explainers may not always meet accountability requirements in regulated settings (De Laat, 2018; Bücker *et al.*, 2022). Furthermore, decision quality depends not only on predictive fit, which is a problem that has been identified in the corpus but is rarely

10.47063/EBTSF.2025.0015
http://hdl.handle.net/20.500.12188/34495

operationalized, but also on matching learning objectives with cost-sensitive losses and constraints.ML techniques correspond with different types of decisions. For instance, explainable AI and fuzzy logic are used for policy ambiguities in strategic and policy decisions, while big-data analytics and deep learning are used for complex forecasting (Makridakis *et al.*, 2023). For routine tasks, operational decisions employ decision trees and random forests; for dynamic scheduling, they employ genetic algorithms and reinforcement learning (Pallathadka *et al.*, 2023). In DSS and business intelligence (BI), organizational support employs data mining, regression, and clustering. Moreover, the industries that drive innovation through significant budgets and data availability include healthcare, government, ICT, finance, marketing, management, and transportation (Kratsch *et al.*, 2021). Through improved decision-making, they optimize social media, customer relationship management (CRM), e-commerce, human resources, and resource management, proving that benefits outweigh costs. Although the field is dominated by tree-based models, explainable artificial intelligence, deep learning, reinforcement learning, and support vector machines, each has unique trade-offs. Deep learning is less appropriate for controlled or high-stakes situations because it frequently lacks transparency and is susceptible to data drift, despite its high accuracy. Support vector machines and tree-based ensembles, on the other hand, are simpler to validate but have the potential to oversimplify intricate decision environments. Although reinforcement learning promises flexibility, its actual application is constrained by the volume of data and the challenge of matching learning signals to actual decision-making goals. Even useful explainable AI tools occasionally provide post-hoc explanations instead of true interpretability.

The application of ML algorithms in decision-making processes in organizations is uneven across organizations and industries due to facilitating conditions and affecting barriers. Data quality, computing power, expertise, and digital readiness facilitate the adoption of machine learning in decision-making, but privacy, ethics, resistance, skill gaps, and costs impede its use in small and medium enterprises and under-resourced industries (Burggräf *et al.*, 2024). The goal of new accessible, humanized machine learning trends is to make their use more accessible to all. The post-2018 corpus clearly shows the rise of interpretability and ethical considerations, as keywords like “explainable AI,” “transparency,” and “accountability” become more common and occur alongside terms related to decision support. This temporal pattern suggests that, concurrent with the technical drive toward explainable models, conversations about ethical and governance issues are becoming more popular.

It is important to recognize several limitations, even though this bibliometric analysis offers valuable insights into the domain of machine learning and decision-making. First, by using a limited set of keywords, the study might have missed new or specialized fields. Second, references that are cited to criticize rather than support specific findings can distort the metrics used to measure citation impact, making them less representative of true scholarly influence. Third, there is potential for different interpretations of the data due to the subjective nature of the process of grouping important terms and assigning themes. Last but not least, the study mostly used keywords that the authors themselves supplied, which may have combined different ideas or missed minute differences that could have revealed other important patterns in ML-driven decision-making.

6. CONCLUSION

Following PRISMA guidelines, we conducted a multi-technique bibliometric review of Scopus and Web of Science documents to investigate how machine learning aids in decision-making, pinpoint research hotspots, and suggest future directions. The United States, the United

Kingdom, India, Germany, and China are the top contributors to the growing publication trends. Although machine learning has shown great promise in automating and redefining decision-making processes, applications are still dispersed, which could lead to a gap between research and practice.

Classification algorithms help with segmentation, fraud detection, and prioritization, while predictive models dominate forecasting and diagnostics, providing strategic and operational insights. Techniques based on optimization improve efficiency and resource allocation (Sarker *et al.*, 2019). These approaches address both particular problems and cross-functional goals, and they cover a wide range of industries, including healthcare, government, ICT, finance, marketing, management, and transportation. We identified two main research concepts: a domain-driven focus on contextual constraints like ethical and regulatory considerations, and a technology-driven focus on algorithmic features (complexity, scalability, and interpretability). It is still difficult to integrate these viewpoints; research frequently uses a single technique in a limited domain (such as genetic algorithms for supply chains or deep learning for clinical imaging) without synthesizing the entire machine learning ecosystem.

Limits of the study focus on four frictions, such as alignment of decision losses with predictive targets, accountability transparency, robustness to drift and scarce labels, and external validity under domain shift and governance. The following are the methodological priorities: preference-aware reinforcement learning, prediction under uncertainty, cost-sensitive and constrained learning as well as causal machine learning for counterfactual decision support (Athey and Imbens, 2019; Makridakis *et al.*, 2023; Hambly *et al.*, 2023). We provide a framework for choosing the best approaches and identifying uncharted territory by mapping popular approaches, deep learning, neural networks, decision trees, text mining, sentiment analysis, natural language processing, and explainable AI, to their respective application domains. Both researchers and practitioners can benefit from this synthesis, since researchers can look into why particular algorithms perform well in particular situations, and practitioners can use machine learning more strategically, for example. Consequently, additional research questions can be derived from here. Compared to black boxes that are explained after the fact, do models that are inherently interpretable lead to better regulatory outcomes? When labels are limited, can human-in-the-loop active learning provide better decisions than end-to-end deep models? In what circumstances do hybrid ML and MCDM systems perform better on stakeholder satisfaction than pure ML optimizers? By doing this, the field can transcend disjointed applications and create a cohesive body of knowledge that connects advancements in algorithms with real-world enhancements in decision outcomes.

REFERENCES

Agrawal, A., Gans, J.S. and Goldfarb, A. (2019) “Artificial intelligence: The ambiguous labor market impact of automating prediction”, *Journal of Economic Perspectives*, Vol. 33 No. 2, pp. 31-50. https://doi.org/10.1257/jep.33.2.31

Athey, S. (2017) “Beyond prediction: Using big data for policy problems”, *Science*, Vol. 355 No. 6324, pp. 483-485. https://doi.org/10.1126/science.aal4321

Athey, S. and Imbens, G.W. (2019), “Machine learning methods that economists should know about”, *Annual Review of Economics*, Vol. 11 No. 1, pp. 685-725. https://doi.org/10.1146/annurev-economics-080217-053433

Baas, J., Schotten, M., Plume, A., Côté, G. and Karimi, R. (2020), “Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies”, *Quantitative Science Studies*, Vol. 1 No. 1, pp. 377–386. https://doi.org/10.1162/qss_a_00019

Bertolini, M., Mezzogori, D., Neroni, M. and Zammori, F. (2021), "Machine Learning for industrial applications: A comprehensive literature review", *Expert Systems with Applications*, Vol. 175, p. 114820. https://doi.org/10.1016/j.eswa.2021.114820

Brynjolfsson, E. and Mitchell, T. (2017), "What can machine learning do? Workforce implications", *Science*, Vol. 358 No. 6370, pp. 1530-1534. https://doi.org/10.1126/science.aap8062

Bücker, M., Szepannek, G., Gosiewska, A., and Biecek, P. (2022), "Transparency, auditability, and explainability of machine learning models in credit scoring" *Journal of the Operational Research Society,* Vol. 73 No. 1, pp. 70-90. https://doi.org/10.1080/01605682.2021.1922098

Burggräf, P., Steinberg, F., Sauer, C. R. and Nettesheim, P. (2024), "Machine learning implementation in small and medium-sized enterprises: Insights and recommendations from a quantitative study", *Production Engineering,* Vol. 18, pp. 751-764. https://doi.org/10.1007/s11740-024-01274-2

Caputo, A. and Kargina, M. (2022), "A user-friendly method to merge Scopus and Web of Science data during bibliometric analysis", *Journal of Marketing Analytics*, Vol. 10 No. 1, pp. 82-88. https://doi.org/10.1057/s41270-021-00142-7

Chen, Y. and Zhou, Y. (2020), "Machine learning based decision making for time varying systems: Parameter estimation and performance optimization", *Knowledge-Based Systems*, Vol. 190, p. 105479. https://doi.org/10.1016/j.knosys.2020.105479

De Laat, P.B. (2018), "Algorithmic decision-making based on machine learning from big data: can transparency restore accountability?", *Philosophy and Technology*, Vol. 31 No. 4, pp. 525-541. https://doi.org/10.1007/s13347-017-0293-z

Dietterich, T. (1996), "Machine learning", *ACM Computing Surveys*, Vol. 28 No. 4es, p. 3. https://doi.org/10.1145/242224.242229

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N. and Lim, W. M. (2021), "How to conduct a bibliometric analysis: An overview and guidelines", *Journal of Business Research*, Vol. 133, pp. 285-296. https://doi.org/10.1016/j.jbusres.2021.04.070

Guo, M., Zhang, Q., Liao, X., Chen, F.Y. and Zeng, D.D. (2021), "A hybrid machine learning framework for analyzing human decision-making through learning preferences", *Omega*, Vol. 101, p. 102263. https://doi.org/10.1016/j.omega.2020.102263

Hambly, B., Xu, R. and Yang, H. (2023), "Recent advances in reinforcement learning in finance", *Mathematical Finance*, Vol. 33 No. 3, pp. 437-503. https://doi.org/10.1111/mafi.12382

Hoffmann, N., Stahlbock, R. and Voß, S. (2020), "A decision model on the repair and maintenance of shipping containers", *Journal of Shipping and Trade*, Vol. 5 No. 1, p. 22. https://doi.org/10.1186/s41072-020-00070-2

Jordan, M. I. and Mitchell, T. M. (2015), "Machine learning: Trends, perspectives, and prospects", *Science*, Vol. 349 No. 6245, pp. 255-260. https://doi.org/10.1126/science.aaa8415

Kasaraneni, H. and Rosaline, S. (2024), "Automatic merging of Scopus and Web of Science data for simplified and effective bibliometric analysis", *Annals of Data Science*, Vol. 11 No. 3, pp. 785-802. https://doi.org/10.1007/s40745-022-00438-0

Koehler, M., Bogatu, A., Civili, C., Konstantinou, N., Abel, E., Fernandes, A. A. A., Keane, J., Libkin, L. and Paton, N. W. (2017), "Data context informed data wrangling", *2017 IEEE International Conference on Big Data (Big Data)*, pp. 956-963. https://doi.org/10.1109/BigData.2017.8258015

Kratsch, W., Manderscheid, J., Röglinger, M. and Seyfried, J. (2021), "Machine learning in business process monitoring: A comparison of deep learning and classical approaches used for outcome prediction", *Business and Information Systems Engineering,* Vol. 63, pp. 261-276. https://doi.org/10.1007/s12599-020-00645-0

Kumpulainen, M. and Seppänen, M. (2022), "Combining Web of Science and Scopus datasets in citation-based literature study", *Scientometrics*, Vol. 127 No. 10, pp. 5613-5631. https://doi.org/10.1007/s11192-022-04475-7

Lamovšek, A. and Černe, M. (2023), "Past, present and future: A systematic multitechnique bibliometric review of the field of distributed work", *Information and Organization*, Vol. 33 No. 2, 100446. https://doi.org/10.1016/j.infoandorg.2022.100446

Lessmann, S., Haupt, J., Coussement, K. and De Bock, K. W. (2021), "Targeting customers for profit: An ensemble learning framework to support marketing decision making", *Information Sciences*, Vol. 557, pp. 286-301. https://doi.org/10.1016/j.ins.2019.05.027

Lim, W. M., Kumar, S. and Donthu, N. (2024), "How to combine and clean bibliometric data and use bibliometric tools synergistically: Guidelines using metaverse research", *Journal of Business Research*, Vol. 182, 114760. https://doi.org/10.1016/j.jbusres.2024.114760

Mahdavinejad, M. S., Rezvan, M., Barekatain, M., Adibi, P., Barnaghi, P. and Sheth, A. P. (2018), "Machine learning for Internet of Things data analysis: A survey", *Digital Communications and Networks*, Vol. 4 No. 3, pp. 161-175. https://doi.org/10.1016/j.dcan.2017.10.002

Makridakis, S., Spiliotis, E., Assimakopoulos, V., Semenoglou, A. A., Mulder, G. and Nikolopoulos, K. (2023), "Statistical, machine learning and deep learning forecasting methods: Comparisons and ways forward", *Journal of the Operational Research Society,* Vol. 74 No. 3, pp. 840-859. https://doi.org/10.1080/01605682.2022.2118629

Marzi, G., Balzano, M., Caputo, A. and Pellegrini, M. M. (2025), "Guidelines for Bibliometric-Systematic Literature Reviews: 10 steps to combine analysis, synthesis and theory development", *International Journal of Management Reviews*, Vol. 27 No. 1, pp. 81-103. https://doi.org/10.1111/ijmr.12381

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., and The PRISMA Group (2009), „Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement", *PLoS Medicine*, Vol. 6 No. 7, e1000097. https://doi.org/10.1371/journal.pmed.1000097

Monken, A., Ampeh, W., Haberkorn, F., Krishnaswamy, U. and Batarseh, F. A. (2023), "Assuring AI methods for economic policymaking", In *AI Assurance*, Academic Press, pp. 371-427. https://doi.org/10.1016/B978-0-32-391919-7.00025-1

Mullainathan, S. and Spiess, J. (2017), "Machine learning: an applied econometric approach", *Journal of Economic Perspectives*, Vol. 31 No. 2, pp. 87-106. https://doi.org/10.1257/jep.31.2.87

Nikolić, D., Ivanović, D. and Ivanović, L. (2024), "An open-source tool for merging data from multiple citation databases", *Scientometrics*, Vol. 129 No. 7, pp. 4573-4595. https://doi.org/10.1007/s11192-024-05076-2

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021), "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews", *Systematic Reviews*, Vol. 10 No. 1, p. 89. https://doi.org/10.1186/s13643-021-01626-4

Paiva, F.D., Cardoso, R.T.N., Hanaoka, G.P. and Duarte, W.M. (2019), "Decision-making for financial trading: A fusion approach of machine learning and portfolio selection", *Expert Systems with Applications*, Vol. 115, pp. 635-655. https://doi.org/10.1016/j.eswa.2018.08.003

Pallathadka, H., Ramirez-Asis, E. H., Loli-Poma, T. P., Kaliyaperumal, K., Ventayen, R. J. M. and Naved, M. (2023), "Applications of artificial intelligence in business management, e-commerce and finance", *Materials Today: Proceedings,* Vol. 80, pp. 2610-2613. https://doi.org/10.1016/j.matpr.2021.06.419

Park, S. and Yang, J.-S. (2022, "Interpretable deep learning LSTM model for intelligent economic decision-making", *Knowledge-Based Systems*, Vol. 248, p. 108907. https://doi.org/10.1016/j.knosys.2022.108907

Pugliese, R., Regondi, S. and Marini, R. (2021), "Machine learning-based approach: Global trends, research directions, and regulatory standpoints", *Data Science and Management,* Vol. 4, pp. 19-29. https://doi.org/10.1016/j.dsm.2021.12.002

Saar-Tsechansky, M. and Provost, F. (2007), "Decision-centric active learning of binary-outcome models", *Information Systems Research*, Vol. 18 No. 1, pp. 4-22. https://doi.org/10.1287/isre.1070.0111

Saba, T., Rehman, A., Haseeb, K., Bahaj, S. A. and Lloret, J. (2023), "Trust-based decentralized blockchain system with machine learning using Internet of agriculture things", *Computers and Electrical Engineering,* Vol. 108, 108674. https://doi.org/10.1016/j.compeleceng.2023.108674

Sarker, I. H., Kayes, A. S. M. and Watters, P. (2019), "Effectiveness analysis of machine learning classification models for predicting personalized context-aware smartphone usage", *Journal of Big Data,* Vol. 6 No. 1, pp. 1-28. https://doi.org/10.1186/s40537-019-0219-y

Sebastião, H. M. C. V., Godinho, P. M. C. and Westgaard, S. (2020), "Using Machine Learning to Profit on the Risk Premium of the Nordic Electricity Futures", *Scientific Annals of Economics and Business,* Vol. 67 (SI), pp. 1-17. https://doi.org/10.47743/saeb-2020-0024

Zupic, I. and Čater, T. (2015), "Bibliometric methods in management and organization", *Organizational Research Methods*, Vol. 18 No. 3, pp. 429-472. https://doi.org/10.1177/1094428114562629

10.47063/EBTSF.2025.0015
http://hdl.handle.net/20.500.12188/34495