

Ontological Framework for Integrating Predictive Analytics, AI, and Big Data in Decision-Making Systems Using Knowledge Graph

Stanislav Safranek^a and Andrea Zvackova^b

*University of Hradec Kralove, Faculty of Informatics and Management,
Hradecka 1249/6, 50003, Hradec Kralove, Czech Republic*

Keywords: Artificial Intelligence, Big Data, Decision System Support, Knowledge Graph, Knowledge-Based Systems, Predictive Analytics.

Abstract: The rapid development of AI, big data and DSS is changing decision-making processes by enabling the efficient processing of huge volumes of data for strategic and operational decisions. The increasing complexity of data-driven decision making requires the integration of predictive analytics, machine learning and knowledge-based systems. This paper presents an ontological framework that uses a knowledge graph to systematically depict the interrelationships between these technologies and supports transparent, efficient and ethical decision making in the areas of business intelligence, healthcare, public policy and crisis management. It also addresses challenges such as algorithmic bias, ethical considerations and explain ability and highlights the need for responsible AI deployment.

1 INTRODUCTION

In today's fast-paced world, breakthroughs in Artificial Intelligence and Big Data are revolutionizing how organizations make critical decisions—enabling real-time predictions, rapid data processing and effective decision support.


In response to these evolving challenges, we propose an ontological framework that systematically represents the intricate interconnections among Big Data, predictive analytics, Artificial Intelligence, decision support systems and human-system integration. This framework, based on a knowledge graph, provides an approach to understanding how these components interact and support decision-making processes across different systematic domains. Ontology enables organizations to identify patterns, improve decision-making and increase the transparency of AI-based decision support systems.


While the rapid evolution of AI and data analytics fuels groundbreaking capabilities, it also brings to light serious concerns—such as algorithmic bias, ethical pitfalls and challenges in AI explainability. Given the increasing autonomy of intelligent systems, ensuring fairness, transparency and alignment with

human values is more critical than ever. The ontological framework presented in this article also encompasses these ethical aspects, providing a basis for the responsible use of AI in decision-making processes.

This article investigates the role of AI and Big Data in enhancing evidence-based decision-making across various sectors—including public administration, healthcare and business intelligence. By examining applications at both the individual and organizational levels, our study highlights the potential benefits and challenges of integrating these technologies into public sector strategies.

The resulting framework is depicted as a knowledge graph, where thematic clusters illustrate the dynamic interconnections among technologies. This visual representation not only clarifies complex relationships but also aids in uncovering innovation opportunities within decision-making processes. This approach not only allows us to understand current trends and challenges related to the use of AI and big data, but also provides a framework for identifying and developing innovative solutions that can contribute to better decision-making at the individual, organizational and societal levels.

^a  <https://orcid.org/0009-0008-0716-5082>

^b  <https://orcid.org/0000-0002-4092-9522>

2 LITERATURE REVIEW

2.1 Analysis of Current Research in the Field of Decision-Making Systems

Decision-making systems are defined as computer software or information systems designed to support managerial decision-making. The gradual evolution of these systems has led from single manager support to group support systems (GSS), management information systems (MIS), Business Intelligence (BI), knowledge management systems (KMS) and now intelligent DSS (Mombini, 2020). This evolution reflects the increasing complexity of decision-making processes, requiring more advanced analytical tools and AI-driven methodologies. As a result modern decision-making systems integrate large-scale data analysis, machine learning models and predictive analytics to enhance accuracy and efficiency.

While existing literature extensively discusses the technical capabilities of DSS and AI, there remains a gap in understanding how these systems can be ethically aligned with human-centric values. For instance, Dignum (2018) emphasizes the importance of ethical AI frameworks, while Floridi et al. (2018) advocate for AI systems that promote fairness, accountability and transparency. This review extends previous analyses by critically evaluating not only the technical efficiency of decision-making models but also their ethical implications in real-world applications.

2.1.1 Technologies for Ontology-Based Decision Support

Modern decision-making increasingly relies on the integration of Big Data, Artificial Intelligence (AI) and simulation-based models, which form the analytical foundation of ontology-based decision support systems.

Big Data, defined by volume, variety, velocity and veracity (Zhang, 2018), enhances strategic decisions by improving accuracy and enabling dynamic adaptation (Ren, 2022). Techniques like data mining and machine learning extract actionable insights, particularly in customer analytics and fraud detection (K., 2024).

Intelligent Decision Systems (IDMs) combine simulation and neural networks to model complex environments and improve output quality (Wang & Dai, 2024). Transformer-based Foundational Decision Models (FDMs) and Multi-Agent Systems (MASs) add adaptability and distributed reasoning (Wen et al., 2023; Cho et al., 2024).

AI acts as the cognitive layer, with deep learning enabling advanced forecasting (Huang, 2020). Ethical aspects such as explainability and trust are addressed through approaches like Epistemic Quasi-Partnership (EQP) theory (Dorsch & Moll, 2024).

Frameworks like MCDM and SDSS integrate quantitative and qualitative inputs and have proven effective during crises like COVID-19 (Mu, 2023; Sidahmed & Zaraté, 2024). These technologies are embedded in the proposed ontological framework, structured as clusters in a knowledge graph, enabling transparent, adaptive and ethically sound decision-making.

2.2 Applications of AI and Big Data in Decision-Making Systems

The integration of AI and big data into decision-making systems has revolutionized various industries by increasing the efficiency and accuracy of decisions. These technologies enable organizations to process vast amounts of data, gain valuable insights and make informed decisions in real time. The applications of AI and big data in decision-making systems are diverse, examples include:

2.2.1 Business Intelligence and Predictive Analytics

AI-driven predictive analytics are extensively used in business to optimize operations and strategy. For example, the Nigerian National Petroleum Corporation integrates Big Data and machine learning to improve forecasting and decision-making (James et al., 2024).

2.2.2. Public Policy and Evaluation

During the COVID-19 pandemic, data-driven systems enabled scientific policy evaluation, targeted interventions and crisis modelling, improving government responsiveness and legitimacy (Dong et al., 2021; Wong, 2021). Predictive analytics supported decisions on lockdown timing, vaccine distribution and healthcare capacity.

2.2.3 Technological and Ethical Considerations

Machine and deep learning are key in handling the complexity of big data, enabling predictive modelling, anomaly detection and recommendation systems (SCSVMV Deemed to be University, India, a Dr. Saraswathi M., 2024).

The ethical use of data in AI applications is essential to ensure unbiased and fair decision-making. This includes adhering to data ethics principles and ensuring that AI systems are developed and used responsibly (Rhem, 2023).

3 METHODOLOGY

The aim of this paper is to analyse the current issues of Artificial Intelligence, Big Data and Decision-Making in the context of its use by the general public and also to show its benefits in the prediction of phenomena and their impact on everyday life. Specifically, the paper focuses on how Artificial Intelligence and Big Data analytics can be used to support decision-making in the public and private sectors, not only at the individual level, but also at the level of organizations and institutions. The aim is to show how predictive models, based on the analysis of huge amounts of data, can help predict various social, economic and environmental phenomena and thus improve the quality of decision-making.

The outputs of the analysis from the theoretical and practical level are presented in the form of a knowledge graph in basic clusters representing a set of interconnected concepts and the relationships between them. Each cluster represents a specific area of knowledge that is connected based on their interrelationships and interactions. The presentation of the outputs through this graph facilitates the understanding of the complex relationships between technologies and processes that are necessary for the effective use of artificial intelligence and big data in practice. This tool not only clearly depicts the connections between key concepts but also serves as a foundation for further research and development in this dynamic field.

Although we have focused on a rather superficial level of exploration in this article, this chart provides a useful overview of how the different technologies and principles can be linked and what their interdependencies are. The knowledge graph also serves as a basis for further detailed research and analysis that can lead to the identification of new opportunities for improving decision-making processes in different sectors.

This approach not only enables an understanding of current trends and challenges related to the use of AI and big data but also provides a framework for identifying and developing innovative solutions that can contribute to better decision-making at the individual, organizational and societal level.

Literature sources and studies were selected to create the ontological framework based on four criteria's - relevance of the thematic framework, expert quality and currency, domain diversity and ethics. The knowledge graph presented in this study was constructed using semantic web technologies, specifically leveraging the Resource Description Framework (RDF) and Web Ontology Language (OWL) to define and categorize relationships among key concepts. RDF Data sources included peer-reviewed journals, industry reports and real-world case studies from sectors such as healthcare, public policy and business intelligence. To validate the framework, expert reviews were conducted with professionals from both academic and industry backgrounds, focusing on the model's applicability, clarity and ethical robustness (Berners-Lee et al., 2001). RDF was used to provide a basic representation of the Subject-Predicate-Object assertion that defines the relationships between concepts. Based on the selected resources, a conceptual model was created and distributed into clusters. In the knowledge graph, each cluster contains the key concepts identified by the literature. The thematic clusters are designed to depict the interactions and connections between the key areas of this paper. For ensuring the accuracy and fluency of the translations the text was partially processed using DeepL – an advanced tool based on artificial intelligence for machine translation.

4 RESULTS AND DISCUSSION

Jamarani's (2024) taxonomy of predictive analytics applications in big data provides the foundation for a coherent ontology model, essential in navigating the growing volume and complexity of data. This model enables effective integration of AI and Decision Support Systems (DSS), improving decision accuracy and relevance. A knowledge graph based on this ontology visually maps key relationships—including predictive analytics, AI, DSS and human-system integration—facilitating intuitive exploration, revealing patterns and supporting innovation, research and strategic decision-making (Chen, 2020).

AI applications span multiple domains: optimizing supply chains, enhancing e-commerce recommendations, supporting strategic decisions, improving healthcare diagnostics, advancing precision agriculture and enabling smart city planning. Through the integration of AI, Big Data and DSS, organizations can enhance decision-making, efficiency and adaptability.

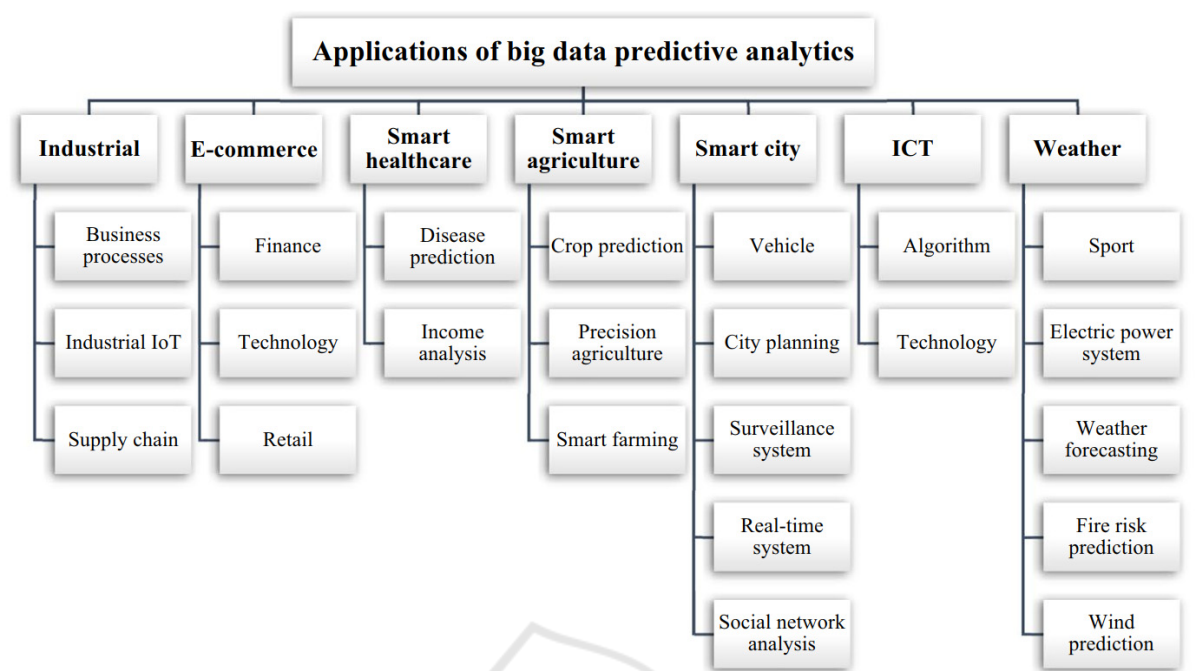


Figure 1: Taxonomy of prediction analysis applications in big data (Jamarani, A., 2024).

The table below presents the key concepts that are divided into clusters based on their role in knowledge analysis. Each cluster represents a specific domain that is essential for the interconnection between different domains such as predictive analytics, artificial intelligence, big data, decision support systems and human systems integration. The goal is to show how these concepts work together to support decision-making processes in modern informatics.

Table 1: Roles of Key Concepts Across Clusters in Knowledge Analysis.

Class	Role in Analysis
Predictive Analytics	Central concept linking AI, Big Data and decision-making processes.
Regression Analysis & Classification	Combination of two main techniques in predictive analytics, providing the foundation for many decision-making processes.
AI (Artificial Intelligence)	Key element in informatics, encompassing various techniques to support predictive analytics and DSS.
ML & DL (Machine Learning & Deep Learning)	Combination of two critical AI technologies, enabling advanced analytical capabilities.
Algorithmic Bias & Ethics in AI	Critical ethical issues combined into one node, focused on fair and responsible AI usage.

Big Data	Fundamental source for AI and predictive analytics, essential for model training.
Data Quality & Data Governance	Combination of two aspects that are key to ensuring data is accurate and used responsibly.
DSS	Practical application of AI and predictive analytics in real-world decision-making processes.
Knowledge-Based & Rule-Based Systems	Combination of two approaches in DSS that utilize rules and knowledge for decision support.
Transparency & Accountability	Critical factors for trust in decision-making processes, ensuring that decisions are clear and justifiable.
Human-Systems Integration	Ensures that technologies are usable and user-friendly for end-users.
Usability Testing & Human Factors	Combination of two key aspects focused on system design and usability for users.

4.1 Structure and Relationships Between Key Components of Decision-Making Systems: Knowledge Graph Visualization

The graph below is the result of a detailed examination of the dependencies between predictive analytics, artificial intelligence and decision support systems, highlighting the importance of including human-system integration. It consists of five

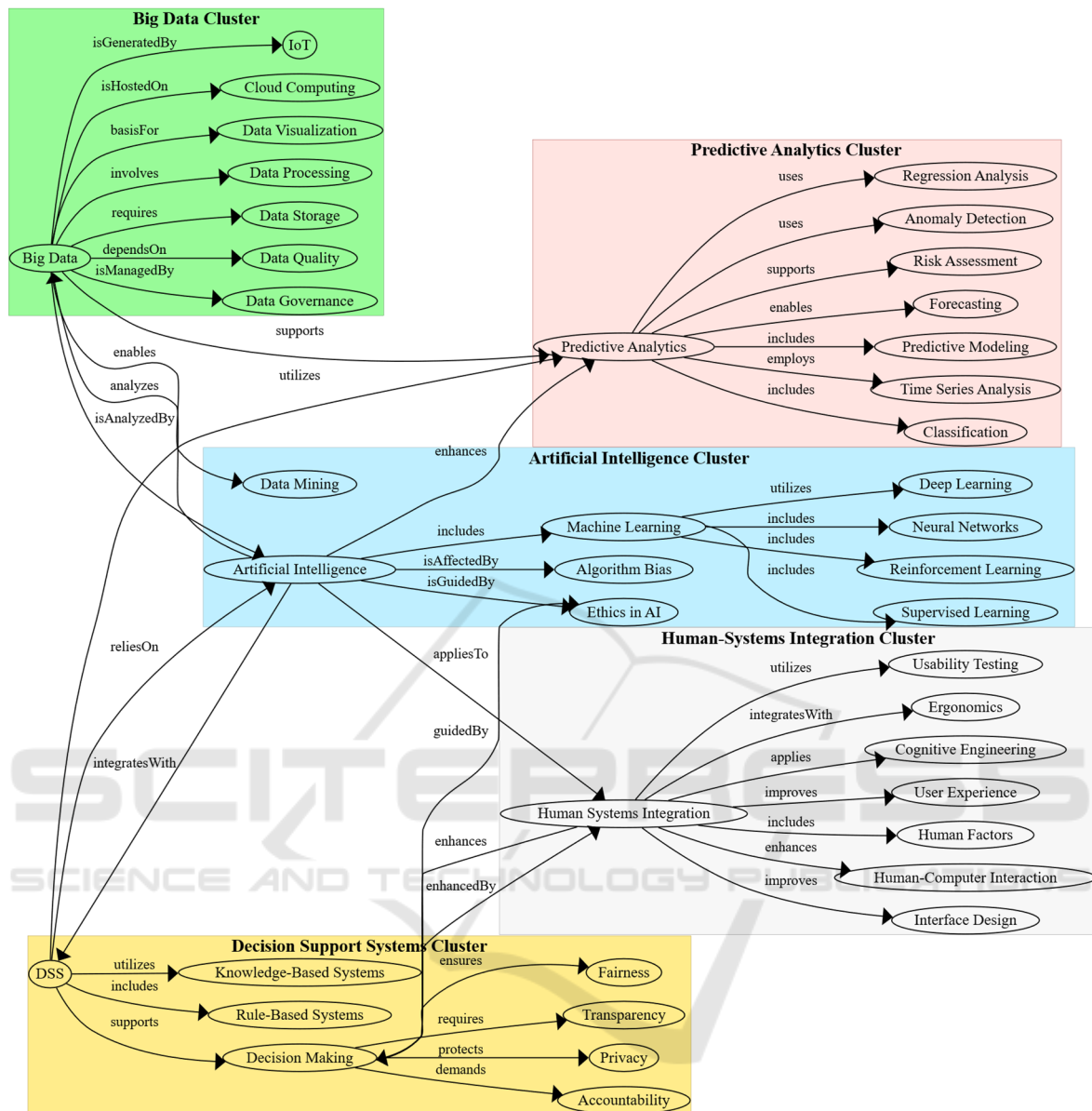


Figure 2: Knowledge Graph of Predictive Analytics and AI in Decision-Making.

interconnected clusters representing key domains of modern informatics and technology.

The Big Data Cluster focuses on foundational concepts of data processing for modern decision-making. Technologies such as IoT and Cloud Computing support data acquisition and management, with Data Processing and Data Visualization playing essential roles. While Cloud Computing and Data Storage are related, the former includes broader services such as application management.

The Predictive Analytics Cluster includes techniques like regression, time series analysis and

anomaly detection to anticipate trends and risks. Predictive analytics uses historical data, algorithms and machine learning to build models that support informed decision-making (McCarthy, 2022). These principles are captured within the knowledge graph.

Artificial Intelligence Cluster are concepts like Data Mining bridge AI and Big Data. Data Mining uses AI techniques (e.g., neural networks) to identify useful patterns in large datasets (Kantardzic, 2011; Han, 2022). The cluster also includes Algorithm Bias and Ethical AI, emphasizing fairness and responsible AI practices.

The Human-System Integration Cluster focuses on the interaction between users and technologies, including User Experience (UX), Ergonomics and interface design. It draws from psychology, engineering and design to ensure that systems are intuitive, safe and efficient.

The Decision Support System Cluster includes Knowledge-Based Systems, Rule-Based Systems and Decision-Making processes, all linked with ethical principles such as fairness, transparency, privacy and accountability.

5 ETHICAL AND SOCIETAL IMPLICATIONS OF AI AND BIG DATA IN DECISION-MAKING SYSTEMS

As AI-driven systems become increasingly autonomous, ethical considerations such as algorithmic bias, data privacy and decision transparency become paramount. These systems influence critical areas such as criminal justice, healthcare, finance and public policy, where biased or opaque decisions can have severe societal consequences. Algorithmic bias occurs when AI models produce systematically prejudiced outcomes due to biased data or flawed model design. For example, the COMPAS algorithm used in the U.S. judicial system has faced criticism for racial bias in recidivism predictions, disproportionately affecting minority groups (Angwin et al., 2016). Addressing such biases requires diverse datasets, transparent algorithm design and continuous model evaluation. With the proliferation of Big Data, concerns about data privacy and security have intensified. AI systems rely on vast datasets, often containing sensitive personal information. Frameworks like the General Data Protection Regulation (GDPR) emphasize data minimization, user consent and transparency to safeguard individuals' privacy. Explain ability in AI refers to the ability to understand and interpret how decisions are made. Black-box models, particularly in deep learning, pose challenges in this regard. Implementing explainable AI (XAI) techniques enhances accountability and fosters trust among users and stakeholders (Floridi et al., 2018). The European Union's AI Act (European Commission, 2021) and IEEE's guidelines on ethically aligned design provide frameworks for responsible AI development. These guidelines promote human oversight, accountability and ethical risk assessments throughout the AI lifecycle. Moreover, AI systems can exacerbate social

inequalities if not designed with inclusivity in mind. Ethical AI development should prioritize human well-being, ensuring technologies enhance societal benefits without marginalizing vulnerable populations (Dignum, 2018).

6 FUTURE RESEARCH DIRECTIONS

Future research in the field of Artificial Intelligence (AI), Big Data and Decision Support Systems (DSS) should focus on several key areas in light of rapid technological advancements. The integration of emerging technologies such as quantum computing and blockchain holds the potential to revolutionize data security, processing speed and decision-making accuracy (Tang, 2024). A critical direction is the development of Explainable AI (XAI), which enhances the transparency of decision-making processes and fosters user trust (Das, Zhang, & Kiszka, 2024). Further research should investigate adaptive algorithms capable of continuous learning in real-time without explicit human intervention (Elhaddad & Hamam, 2024). Understanding the impact of AI and DSS in different cultural and organizational contexts through comparative studies is also essential, as it can reveal how socio-economic factors influence the effectiveness of these systems (Ramachandran et al., 2023). Additionally, interdisciplinary collaboration is crucial, fostering comprehensive approaches to the implementation of AI and DSS across sectors such as healthcare, public policy and education (Sharma et al., 2023). The future of AI, Big Data and DSS thus lies in the development of systems that are not only technologically advanced but also ethically sustainable, adaptable and inclusive across diverse domains and cultures.

7 CONCLUSION

The integration of Artificial Intelligence (AI), Big Data and Decision Support Systems (DSS) presents transformative opportunities for enhancing decision-making across various domains. This paper has introduced an ontological framework based on knowledge graphs, providing a structured representation of the complex interrelationships between predictive analytics, AI, DSS and human-system integration. The framework facilitates not only more informed and efficient decision-making

but also emphasizes ethical considerations, transparency and accountability in AI applications.

Our findings highlight the critical role of predictive analytics in anticipating trends and risks, the importance of ethical AI to ensure fairness and reduce algorithmic biases and the value of human-system integration for user-centric technology design. By visualizing these interconnections, the knowledge graph aids in identifying patterns, fostering innovative solutions and supporting data-driven strategies.

The proposed framework has practical implications for sectors such as healthcare, finance, and public policy—enhancing patient risk assessment, improving fraud detection and enabling real-time social trend monitoring. By supporting structured data integration and analysis, it helps organizations improve decision accuracy, efficiency, and ethical compliance.

Looking ahead, future research should focus on advancing explainable AI, adaptive algorithms and interdisciplinary collaborations to address emerging challenges. The ontological framework presented here offers a foundation for further exploration, ensuring that the evolution of AI and Big Data technologies contributes to responsible, effective and sustainable decision-making at individual, organizational and societal levels.

ACKNOWLEDGMENT

The research has been partially supported by the Faculty of Informatics and Management UHK specific research project 2108 Addressing Current Challenges in the Field of Smart Cities and Cybersecurity.

REFERENCES

- Angwin, Julia, Jeff Larson, Surya Mattu, a Lauren Kirchner. 2016. „Machine Bias". ProPublica.
- Berners-Lee, Tim, James Hendler, a Ora Lassila. 2001. „The Semantic Web". *Scientific American*.
- Brynjolfsson, Erik, a Andrew McAfee. 2017. *Machine, Platform, Crowd: Harnessing Our Digital Future*. W. W. Norton & Company.
- Creswell, John W. 2018. *Research Design: Qualitative, Quantitative and Mixed Methods Approaches*. Sage Publications.
- Davenport, Thomas H., a Rajeev Ronanki. 2018. „Artificial Intelligence for the Real World". *Harvard Business Review* 96(1): 108–16.
- Das, Bandan, Yang Z. Zhang, a Jan Kiszka. 2024. „State-of-the-Art and Future Directions". *Journal of Current Trends in Computer Science Research*. doi:10.33140/jctcsr.03.02.06.
- Dignum, Virginia. 2018. „Ethics in artificial intelligence: Introduction to the special issue". *Ethics and Information Technology* 20(1): 1–3.
- Ding, Sizhe. 2023. „Application of Big Data Technology in Intelligent Decision-Making of Public Policy". *Highlights in Science, Engineering and Technology* 61: 260–65. doi:10.54097/hset.v61i.10731.
- Dong, Jiancheng, Huiqun Wu, Dong Zhou, Kaixiang Li, Yuanpeng Zhang, Hanzhen Ji, Zhuang Tong, Shuai Lou, a Zhangsuo Liu. 2021. „Application of Big Data and Artificial Intelligence in COVID-19 Prevention, Diagnosis, Treatment and Management Decisions in China". *Journal of Medical Systems* 45(9): 84. doi:10.1007/s10916-021-01757-0.
- Elhaddad, Malek, a Sara Hamam. 2024. „AI-Driven Clinical Decision Support Systems: An Ongoing Pursuit of Potential". *Cureus* 16. doi:10.7759/cureus.57728.
- European Commission. 2021. „Proposal for a Regulation on a European Approach for Artificial Intelligence".
- Floridi, Luciano, Josh COWLS, Monica Beltrametti, a others. 2018. „AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles and Recommendations". *Minds and Machines* 28(4): 689–707.
- Han, Jiawei, Micheline Kamber, a Jian Pei. 2012. *Data Mining: Concepts and Techniques*. 3rd ed. Amsterdam Boston: Elsevier/Morgan Kaufmann.
- Huang, Xinyu, Peng Wang, Xinjing Cheng, Dingfu Zhou, Qichuan Geng, a Ruigang Yang. 2020. „The ApolloScape Open Dataset for Autonomous Driving and Its Application". *IEEE Transactions on Pattern Analysis and Machine Intelligence* 42(10): 2702–19. doi:10.1109/TPAMI.2019.2926463.
- Chen, Xiaojun, Shengbin Jia, a Yang Xiang. 2020. „A Review: Knowledge Reasoning over Knowledge Graph". *Expert Systems with Applications* 141: 112948. doi:10.1016/j.eswa.2019.112948.
- Cho, Young-Min, Raphael Shu, Nilaksh Das, Tamer Alkhoul, Yi-An Lai, Jason Cai, Monica Sunkara, a Yi Zhang. 2024. „RoundTable: Investigating Group Decision-Making Mechanism in Multi-Agent Collaboration". doi:10.48550/arXiv.2411.07161.
- J. Rhem, Anthony. 2023. „Ethical Use of Data in AI Applications". In *Ethics - Scientific Research, Ethical Issues, Artificial Intelligence and Education* [Working Title], IntechOpen. doi:10.5772/intechopen.1001597.
- Jain (Deemed to be University)- Center for Management Studies, Bengaluru, a Ms. Sunitha B.K. 2024. „The Impact of Data Analytics and Mining in Transforming the Decision-Making System". *International Journal of Scientific Research In Engineering And Management* 08(03): 1–5. doi:10.55041/IJSREM29708.
- Jamarani, Amirhossein, Saad Haddadi, Raheleh Sarvizadeh, Mostafa Haghi Kashani, Mohammad Akbari, a Saeed Moradi. 2024. „Big Data and

- Predictive Analytics: A Systematic Review of Applications". *Artificial Intelligence Review* 57(7): 176. doi:10.1007/s10462-024-10811-5.
- James, Gabriel Gregory, Oise G P, Chukwu E G, Michael N A, Ekpo W F, a Okafor P E. 2024. „Optimizing Business Intelligence System Using Big Data and Machine Learning". *Journal of Information Systems and Informatics* 6(2): 1215–36. doi:10.51519/journal isi.v6i2.631.
- Kantardzic, Mehmed. 2011. *Data mining: concepts, models, methods and algorithms*. 2nd ed. Hoboken, N.J: John Wiley : IEEE Press.
- McCarthy, Richard V., Mary M. McCarthy, a Wendy Ceccucci. 2022. „Introduction to Predictive Analytics". In *Applying Predictive Analytics*, Cham: Springer International Publishing, 1–26. doi:10.1007/978-3-030-83070-0_1.
- McKinsey Global Institute. 2021. „*The State of AI in 2021*".
- Mombini, Haadi; TULU, Bengisu. *A systematic review of decision-making theories used in decision support systems research*. 2020.
- Mu, Enrique. 2023. „Multicriteria Decision Making as Interdisciplinary Research". *International Journal of the Analytic Hierarchy Process* 14(3). doi:10.13033/ijahp.v14i3.1080.
- OECD. 2020. *AI Principles and Recommendations*".
- Ramachandran, K., K. K. K, Amit Semwal, Sardar Parminder Singh, A. Al-Hilali, a M. Alazzam. 2023. „*AI-Powered Decision Making in Management: A Review and Future Directions*". In 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), 82–86. doi:10.1109/ICACITE57410.2023.10182386
- Ren, Shaomin. 2022. „Optimization of Enterprise Financial Management and Decision - Making Systems Based on Big Data" ed. Miaochao Chen. *Journal of Mathematics* 2022(1): 1708506. doi:10.1155/2022/1708506.
- SCSVMV Deemed to be University, India, a Dr. Saraswathi M. 2024. A Novel Study on Machine Learning Algorithms for Big Data". *International Journal of Scientific Research In Engineering and Management* 08(03): 1–5. doi:10.55041/IJSREM29690.
- Sharma, Annu, Gaurav Kumar, Mansoor Farooq, Manish Kumar Gupta, Saranya Raj, a Ashok Kumar Rai. 2023. „*Unleashing the Power of Big Data: A Comprehensive Analysis and Future Directions*". In 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), 828–32. doi:10.1109/IC3I59117.2023.10397810.
- Sidahmed, Elandalousi, a Zaraté Pascale. 2024. „Strategic Support Systems for Crisis Management: A Literature Review". *Foundations and Trends® in Information Systems* 8(1): 1–65. doi:10.1561/29000000025.
- Tang, Nyusifan. 2024. „Leveraging Big Data and AI for Enhanced Business Decision-Making: Strategies, Challenges and Future Directions". *Journal of Applied Economics and Policy Studies* 11(1): 25–29. doi:10.54254/2977-5701/11/2024098.
- Wang, Yan, a Peihui Dai. 2024. „Simulation Driven Intelligent Business Data Analysis and Decision-Making". In *Frontiers in Artificial Intelligence and Applications*, ed. Yalan Ye a Patrick Siarry. IOS Press. doi:10.3233/FAIA240153.
- Wen, Ying, Ziyu Wan, Ming Zhou, Shufang Hou, Zhe Cao, Chenyang Le, Jingxiao Chen, et al. 2023. „On Realization of Intelligent Decision Making in the Real World: A Foundation Decision Model Perspective". *CAAI Artificial Intelligence Research*: 9150026. doi:10.26599/AIR.2023.9150026.
- Zhang, Qingchen, Laurence T. Yang, Zhikui Chen, a Peng Li. 2018. „A Survey on Deep Learning for Big Data". *Information Fusion* 42: 146–57. doi:10.1016/j.inffus.2017.10.006.