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International Journal of Combinatorial Optimization Problems and Informatics, 17(3), 2026, 219-233. ISSN: 2007-1558.
https://doi.org/10.61467/2007.1558.2026.v17i3.1338

Big data in organizations: A systematic review of impact, efficiency, and predictive capacities

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Abstract. The rapid growth of data volumes in organizational environments has accelerated the adoption of Big Data and advanced analytics as key components of digital transformation. However, alongside potential gains in efficiency, innovation, and evidence-based decision-making, significant risks and challenges arise in technological, organizational, ethical, and human-capital domains. This study aims to conduct a systematic review of recent literature on Big Data, artificial intelligence, and machine learning applied to decision-making in business and organizational contexts, to identify their main uses and applications, as well as the benefits, risks, challenges, and factors influencing effective adoption. The review followed PRISMA Statement recommendations for the search, selection, and critical appraisal of studies, applying predefined inclusion and exclusion criteria. The study concludes that responsible adoption of these technologies requires robust infrastructures, solid data governance frameworks, strategic leadership, continuous upskilling, and an organizational culture oriented toward ethics and the critical use of information.

Keywords: Big Data; Advanced Analytics; Organizations; Decision-Making; Machine Learning.

Article information
Received: Feb 9, 2026
Accepted: May 11, 2026

1 Introduction

The accelerated digitalization of productive, financial, educational, and social processes has generated unprecedented volumes of information. In this context, Big Data and advanced analytics have become core pillars of organizations' digital transformation, as they enable the processing and exploitation of large amounts of structured and unstructured data to support strategic, tactical, and operational decision-making. This shift is not merely about having more data, but about developing analytical capabilities such as machine learning, data mining, predictive and prescriptive analytics, and artificial intelligence techniques that enable the conversion of information into actionable knowledge and sustainable competitive advantages.

Current research shows that Big Data and advanced analytics applications span a broad landscape, encompassing finance, energy, logistics, retail, software development, healthcare, and education, among other domains. In this context, organizations seek to improve forecasting accuracy, optimize resources, automate processes, personalize services, and reduce risks through data-driven models. However, these potential benefits coexist with major challenges, ranging from the need for robust technological infrastructure and persistent data quality and integration issues to high implementation costs, data science skill shortages, and, critically, ethical concerns related to privacy and information security, as well as algorithmic bias in automated decision-making.

In addition, the intensive use of personal and sensitive data can give rise to new forms of inequality and discrimination—both direct and indirect—when analytical models reproduce or amplify pre-existing biases in the data on which they are trained. Decisions such as granting credit, selecting candidates for employment, designing marketing strategies, reallocating patients within healthcare systems based on severity, or allocating resources in educational programs may all be influenced by these biases, potentially generating adverse impacts on vulnerable groups. Consequently, the discussion of Big Data and advanced analytics can no longer be confined to their technical and economic potential; it must centrally incorporate ethical, legal, and data-governance dimensions.

There is a growing body of publications on Big Data, artificial intelligence, and machine learning; however, the available evidence is often fragmented by sector or use case, making it difficult to develop an integrated view of the benefits, risks, and challenges associated with their adoption in organizations. From one perspective, studies focus on demonstrating improvements in efficiency and predictive performance, while, on the other, research warns of privacy concerns, discrimination, lack of transparency, and weaknesses in data governance. In this context, there remains a pressing need to systematically synthesize this knowledge with methodological rigor to address key questions about how, under what conditions, and with what implications these technologies are being used across different organizational settings.

Against this backdrop, the present study aims to conduct a systematic review of recent literature on Big Data and advanced analytics applied to business and other organizational domains, following PRISMA guidelines. The specific objectives are to: (a) identify the main uses and applications of Big Data, artificial intelligence, and machine learning in support of decision-making; (b) synthesize the benefits, risks, and challenges reported in the implementation of these technologies; and (c) analyze the technological, organizational, ethical, and human-capital factors that enable or constrain their effective adoption. This study provides a reference framework to guide researchers, executives, and policymakers in the responsible and strategic integration of Big Data and advanced analytics within organizations.

2 Literature review

2.1 Advanced analytics and its relationship with big data

Big Data analytics is defined as the application of advanced analytics techniques to operate on large-scale datasets. In essence, it brings together two distinct domains: Big Data, understood as massive volumes of detailed information, and advanced analytics, which comprises a collection of diverse tools, including those based on predictive analytics, data mining, statistics, artificial intelligence, and natural language processing. By integrating these two concepts, Big Data analytics emerges as a unified approach (Aguilar, 2019).

Advanced analytics goes well beyond merely meeting a company's needs and those of its customers. Accordingly, it is essential to understand who the potential customer is, for whom they require a given product or service, and why—often using dashboards. The data collected and stored are fundamental to advanced analytics applied to Big Data, enabling organizations to become highly competitive in the business marketplace.

Prescriptive analytics responds to the need for innovation and to business objectives by enabling organizations to capitalize on future opportunities and to identify risks they may face ahead. It supports anticipating what is likely to happen and determining what actions the organization should take to mitigate risks. This capability is critical for resource optimization and effective organizational decision-making.

2.2 Factors influencing big data adoption

Technological innovations that emerged from ongoing changes, improvements, and declining costs associated with the Internet of Things have accelerated the generation of massive volumes of data. This has enabled major shifts driven by social media, mobile devices such as smartphones, and cloud computing. Moreover, a primary principle of Big Data adoption is that traditional hardware and software are no longer sufficient to process data at scale, ensure its protection, and support rapid growth, nor to deliver information quickly and efficiently.

2.3 Factors leading to discrimination when applying big data technologies in decision-making

Discrimination is understood as the act of treating individuals differently in comparable situations when there are no valid legal grounds that justify differential treatment, thereby forcing individuals to bear the adverse effects of such unequal treatment. In this sense, both direct and indirect discrimination may arise from the processing of personal data (Carreño, 2024).

Data analytics applied to Big Data, as noted, encompasses data-mining and deep-learning techniques that uncover patterns associated with human behavior, enabling decision-making across multiple domains—from approving a loan to processing and tracking a job application. This form of decision-making is intrinsically intertwined with individuals' everyday activities and experiences.

The adoption of Big Data technologies can be a highly useful tool to encourage, counteract, or prevent inequality and discrimination, depending on the interests of the organizations that choose to deploy them within their scope of action and competence. In addition, the importance of legal regulation is underscored to safeguard individuals' confidential information—particularly sensitive data—preventing the exploitation of vulnerability, especially among older adults, and ensuring that such information is not exposed or misused to the detriment of the person

3 Methodology

A systematic review was conducted following the PRISMA Statement recommendations (Page et al., 2021) to identify articles addressing the research questions on Big Data and advanced analytics applied to business. This study involved searching for research outputs in the form of journal articles. The research questions addressed through the systematic review were as follows:

RQ1. What are the uses and applications of Big Data, artificial intelligence, and machine learning in organizations to support decision-making?

RQ2. What benefits, risks, and challenges are reported in the literature regarding the implementation of Big Data and advanced analytics in organizations?

RQ3. What technological, organizational, ethical, and human-capital factors facilitate or constrain the effective adoption of Big Data and advanced analytics?

A literature search was conducted in the Scopus database using the following query: "Big Data" AND "advanced analytics" AND "machine learning" AND "business decision making" AND ("data governance" OR "data management") AND "artificial intelligence" AND "ethics" AND "predictive analytics" AND "Big Data" AND "industry 4.0" NOT "healthcare".

3.1 Inclusion and Exclusion Criteria

Research articles were included if they addressed at least one of the stated objectives. The search was restricted to publications in Spanish and English. Systematic reviews and meta-analyses were excluded (Table 1).

Table 1. Inclusion and exclusion criteria

Inclusion	Exclusion
Publications in English and Spanish.	Studies not published in English or Spanish
Open-access research articles.	Duplicate publications.
	Systematic review articles.
	Non–open-access articles.
	Topics outside the business sector.

3.2 Selection and assessment process

The researcher(s) [UDBA, JFCJ, and MRVA] conducted the study selection process. In the first stage, the records retrieved were screened by title and abstract using the Rayyan tool. In the second stage, full-text screening was performed; articles for which discrepancies persisted were excluded from inclusion.

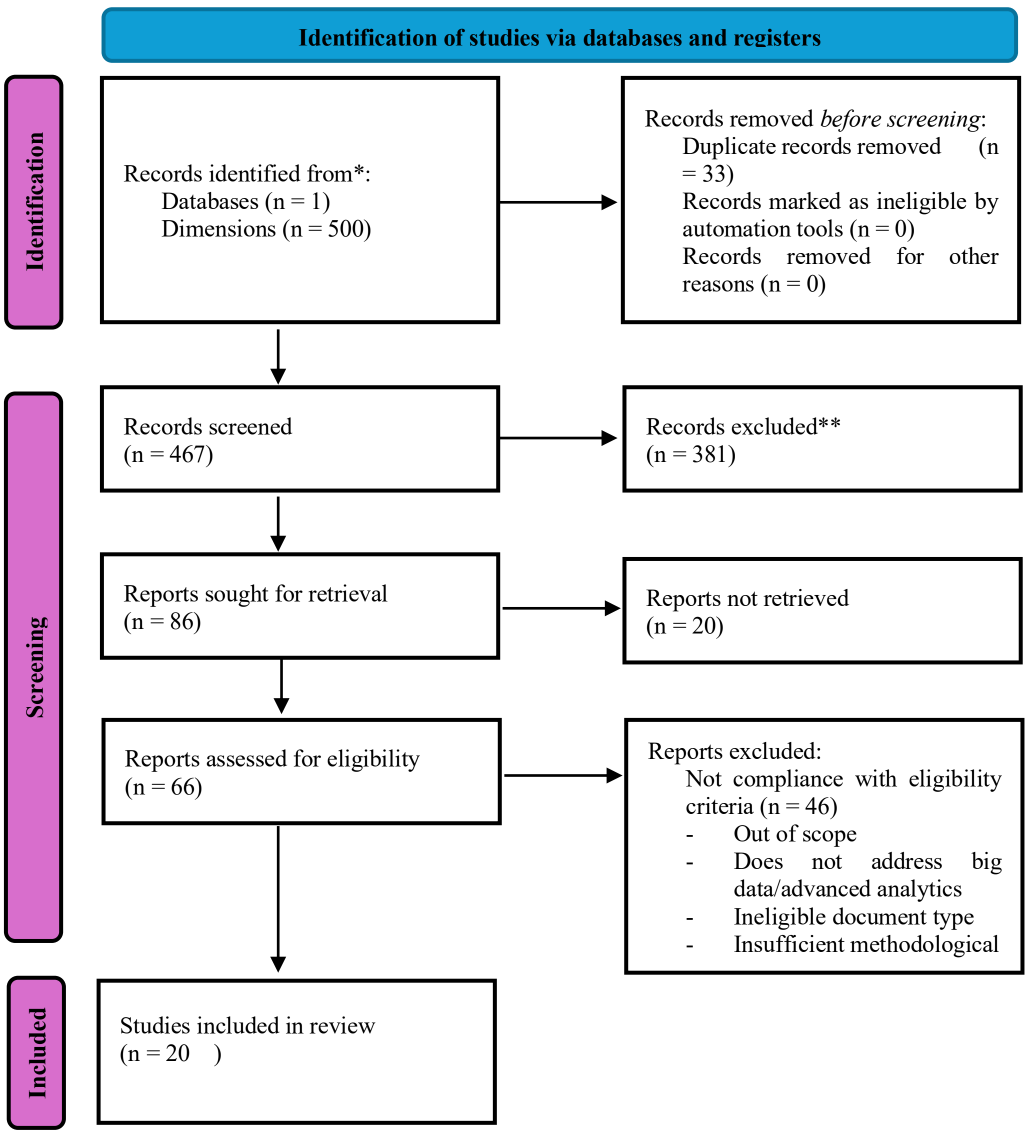
3.3 Risk of bias assessment for individual studies

This process was conducted using the CASP critical appraisal tool for mixed-methods studies, observational designs (including cohort and cross-sectional studies), as well as quasi-experimental intervention studies. The assessment was carried out in detail by the researcher(s) [UDBA, JFCJ, and MRVA], who evaluated each study included in this research

Within the review, 10 criteria were used to assess risk of bias: (Q1) Does it have a clearly defined objective? (Q2) Is the stated approach/methodology appropriate for the objective? (Q3) Does it describe a reproducible search strategy? (Q4) Does it specify inclusion/exclusion criteria or the selection process? (Q5) Does it assess the quality/risk of bias of the included sources? (Q6) Does it describe how evidence was extracted/organized? (Q7) Is there an explicit synthesis of how findings are integrated and how conclusions are reached? (Q8) Are the central claims supported by concrete evidence? (Q9) Does it discuss limitations and risks? (Q10) Are the conclusions/implications consistent with the content and do they acknowledge implementation conditions?

4 Results

Study selection (PRISMA flow). The Scopus database search yielded 500 records. After removing 33 duplicates, 467 records were screened by title and abstract. Of these, 381 records were excluded for not addressing the research questions, leaving 86 reports sought for retrieval. Twenty (20) full-text reports could not be retrieved, resulting in 66 reports assessed for eligibility. Following full-text assessment, 46 reports were excluded for predefined eligibility reasons, and 20 studies were included in the final synthesis (Figure 1).



Source: Adapted from Page et al. (2021).

Fig. 1. PRISMA diagram.

4.1 Description of the selected studies

After applying the search, screening, and quality appraisal process in accordance with the PRISMA protocol, 20 studies meeting the established inclusion criteria were included. The Scopus search was restricted to publications from January1, 2014 to December 31, 2025; thematic relevance to Big Data, advanced analytics, and artificial intelligence. These studies reflect a diversity of approaches, methodologies, and applications across different organizational and industrial contexts, enabling a comprehensive overview of the current state of knowledge (Table 2).

Table 2. Summary of findings

No.	Study title	Authors	Study objective	Methodology	Key findings	Limitations
1	Application of Artificial Intelligence and Big Data in Financial Management	Yang (2024)	Improve the efficiency and accuracy of financial decision-making through AI and Big Data to support sustainable development and business innovation	Machine-learning algorithms applied to financial Big Data	AI and Big Data enhance risk identification and increase the accuracy and efficiency of financial management	Traditional methods constrain data mining; privacy concerns and high costs; high complexity of financial data
2	Big Data and Predictive Analytics in Reservoir Engineering: The Future of Dynamic Reservoir Models	Onyebuchi Uchendu et al. (2024)	Enhance predictive accuracy and operational efficiency in hydrocarbon reservoir management and recovery using Big Data and ML	Advanced analytics, predictive models, AI, and digital twins applied to large-scale reservoir datasets	Hybrid models, ML, and digital twins improve prediction accuracy, optimize field operations, and support reservoir characterization decisions	High dependence on Big Data; difficulty handling continuously growing data volumes; diversity of data types, formats, and scales
3	Artificial Intelligence and Big Data Analytics for Advancing Industry 4.0, Industry 5.0, and Society 5.0	N. L. Rane et al. (2024)	Integrate AI and Big Data to improve decision-making and strategies in industry and society through large-scale, high-speed data processing	Review/analysis of academic articles to identify patterns, trends, and correlations via predictive analytics	AI on Big Data detects patterns and trends useful for risk assessment, fraud prevention, healthcare support, and outbreak control	Data must be hosted in the cloud/online; robust computing infrastructure required for advanced industrial applications
4	Leveraging Big Data and AI to Improve Business Decision-Making: Strategies, Challenges, and Future Directions	Tang (2024)	Show how real-time Big Data and AI transform unstructured data into actionable information to optimize operations, enhance customer relationships, and increase profits	Integration of Big Data and AI for real-time predictive analytics using advanced algorithms	Big Data + AI make information more accessible, improve operational efficiency, deepen customer insight, and support business model adaptation	Integration challenges with legacy systems; ethical risks (bias, privacy); cultural resistance to automation
5	Big Data Analytics-Driven Project Management Strategies: Leveraging AI for Dynamic Scheduling, Risk Prediction, and Automated Task Prioritization in Complex Projects	Zahaib Nabeel (2024)	Integrate AI and Big Data in project management to forecast delays/risks in real time and optimize resources and outcomes	ML on historical data and project metrics to assess risks and dynamically adjust schedules and resources	AI-driven dynamic scheduling enables real-time plan/task adaptation under change and complexity, improving decisions in complex projects	Data volume exceeds traditional systems; data quality/availability issues; incomplete/inaccurate data lead to unreliable forecasts

6	Application of Data Analytics for Management Decision-Making in Retail	Makarov (2024)	Use data analytics as a strategic tool to improve decision-making and competitiveness in retail firms	Use of Big Data, AI, and retail widgets, supported by IoT growth, to analyze sales and customer behavior	Widget-based product analytics optimizes assortment, removes low-profit/seasonal products, and increases profitability	High dependence on IoT; limited connected users reduce Big Data/AI potential and hinder small retailers' growth
7	Using Data Mining Principles to Implement Predictive Analytics Across Different Domains	Asgarova et al. (2024)	Examine big-data-based technologies to improve management and reduce costs using data mining for research purposes	Massive data collection and data-mining algorithms to extract information and describe data characteristics	Resource allocation and big-data processing algorithms improve operational efficiency and patient satisfaction in healthcare	Clear goals are essential; even accurate algorithms yield low utility if objectives are poorly defined
8	Leveraging Big Data to Inform Strategic Decision-Making in Software Development	Patrick Azuka Okeleke et al. (2024)	Use Big Data to make better-informed decisions, optimize operations, and improve productivity in software development	Multifaceted approach combining data governance, collaboration, infrastructure, and continuous improvement	Performance analytics (load times, errors, transactions) revealed poor server data management; improvements increased software quality and user experience	Privacy/security challenges; volume/variety management; data quality/accuracy; regulatory compliance (e.g., GDPR); ethical implications
9	Solving Supply Chain Management Problems with AI and Big Data Analytics for Future Operational Efficiency	Angela Omozele Abhulimen & Onyinye Gift Ejike (2024)	Provide an overview of AI and Big Data analytics use in supply chain management and associated challenges	Converting transactional data into structured data; using AI and advanced data management systems to support proactive decisions	AI + Big Data improves demand forecasting, risk management, operational efficiency, and sustainability, enabling competitive advantage	Demand variability, disruptions, inefficiencies; data quality/integration issues; constraints in converting data to structured formats
10	Leveraging Big Data for Agile Transformation in Tech Companies: Implementation and Best Practices	Simpson & Johnson (2024)	Combine Big Data analytics with agile methods to drive innovation and improve decision-making in tech companies	Integrating IoT data into decision processes via agile approaches (e.g., blockchain, rapid/adaptive iterations)	IoT + Big Data enable real-time monitoring of assets/conditions, process optimization, and rapid response to changes/opportunities	Privacy and regulatory compliance risks; need robust data-protection frameworks; ethical guidelines required
11	On the Introduction of Digital Technologies in Accounting and Financial Analysis	Novichenko et al. (2024)	Integrate digital technologies to manage large data volumes and increase accounting firms' efficiency and competitiveness	AI chatbots/virtual assistants, cloud analytics, and Big Data to support accounting tasks and real-time reporting	Big Data analytics combines statements, market trends, and consumer behavior to support better financial decisions	High adoption/maintenance costs; infrastructure upgrades and training; SME constraints; cybersecurity risks for sensitive financial data
12	Online Education, Big Data Management, and Smart-Technology-	Zhang (2024)	Apply AI, Big Data, and ML to design more effective online teaching strategies (e.g., VR-based English learning)	Case studies and experimental evaluations of an online-education framework integrating Big Data, data	VR-based online learning improves retention and engagement, boosts performance, reduces errors, and enables	Large volumes of platform-generated data create challenges for data management and effective use

	Based Data Mining			mining, and smart technologies	personalized learning	
13	Effective Decision-Making Through Data Analysis	Khan (2024)	Explain how data analytics improve decision-making, resource allocation, and risk mitigation	Data mining, clustering, and neural networks on historical and current data to derive trends and predictive models	Data analytics optimizes resources, streamlines operations, improves customer experience, and drives innovation	Privacy/ethics risks; algorithmic bias; need responsible data use, data literacy, and a collaborative culture
14	Business Intelligence in the Big Data Era: A Review of Analytical Tools and Competitive Advantage	Adebunmi Okechukwu Adewusi et al. (2024)	Describe BI evolution to leverage Big Data and generate a competitive advantage	Review of BI tools from traditional reporting to advanced analytics and ML in Big Data business environments	BI + Big Data improves consumer understanding, profiling, segmentation, and personalization, strengthening decisions	Data quality/security issues; shortage of professionals with required competencies
15	Internet of Things: An Analysis of Emergence, Components, and Challenges	Hooda et al. (2023)	Explain how Industry 4.0 transforms manufacturing into an end-to-end smart supply chain	IoT, cloud computing, Big Data analytics, and ML applied to manufacturing and supply-chain processes	Factories become intelligent units with automated, scalable processes that improve efficiency, quality, and competitiveness	Network/cloud security risks; need security standards to ensure confidentiality and availability
16	Cloud-Based Data Analytics for Business Intelligence	Dashora (2023)	Improve data analysis and decision-making through cloud-based analytics for BI, data science, and research	Cloud platforms to manage and analyze structured/unstructured data, overcoming on-prem limitations	Cloud analytics and visualizations generate insights that support growth and more informed business decisions	Data integration complexity, security uncertainty, and cost-management challenges during cloud migration
17	Improving Big Data Storage for Efficient, Integrated, and Advanced Analytics	Santos et al. (2019)	Improve organizational performance through better Big Data storage and management practices	ML-enabled broker to manage, profile, label, and track data in Big Data Warehousing systems	Flexible visualizations and code reuse create a decision-support environment with more efficient, integrated analytics	Weak data governance; skills gaps; high implementation costs; difficulties processing growing volumes and data types
18	Predictive Analytics: Its Role in Big Data	Sharma (2019)	Improve decision-making by applying predictive analytics to massive data from social media, e-commerce, surveys, etc.	Conceptual discussion of predictive analytics using descriptive analytics and data mining	Predictive analytics anticipate human trends and buying behavior, providing a fuller market view	Poorly built predictive models reduce visibility and the ability to reach potential customers
19	Reality Mining and Predictive Analytics for Building Smart Applications	Asri et al. (2019)	Predict lifestyle patterns using real-time Big Data and ML from mobile-device data	Mobile/sensor data collection within a Big Data framework processed with prediction algorithms	In healthcare, real-time analytics enables efficient predictions that can help prevent risks and save lives	Unsupervised learning: hard to achieve high accuracy and select the right number of clusters; requires validation
20	HOLMeS: eHealth in the Big Data and Deep Learning Era	Amato et al. (2019)	Present HOLMeS, a Big Data platform supporting eHealth applications via online medical suggestions	Chatbots and deep learning to analyze clinical data and provide preventive recommendation	ML identifies patterns in clinical data, supporting medical decision-making and enabling	Large-scale medical data processing under time constraints, high computational cost, and privacy risks for clinical data

				s supported by Big Data	prevention/monitoring	
21	Big Data Analytics in General Education: Opportunities and Concerns	Lyu & Feng (2018)	Develop analytics approaches to predict performance and improve students' knowledge retention	Big Data to collect, store, analyze, and apply educational data; interpretable predictive models	Enables teachers to adapt instruction, improve efficiency, and promote personalized learning	Data fragmentation and security risks; need policies/laws; vulnerability to hacking and information leaks
22	Big Data, Advanced Analytics, and the Future of Comparative Effectiveness Research	Berger & Doban (2014)	Adopt Big Data and Advanced Analytics to improve treatment research and development in healthcare	Predictive analytics on longitudinal data to identify risks, opportunities, and likely outcomes	Predictive analytics exploits historical patterns to explain outcomes and support clinical and research decisions	Advanced analytics is accessible to a limited number of specialists

Given that Table 3 provides study-level detail, we additionally present a domain-level synthesis to improve readability and highlight cross-sector patterns. Table X aggregates the included studies by application domain and summarizes typical uses, benefits, and risks reported across each domain.

Table 3. Domain-level synthesis of Big Data

Domain	*n*	Typical uses (RQ1)	Recurring benefits (RQ2)	Risks/Challenges (RQ2–RQ3)	Example studies
Finance / Accounting	2	Financial management, accounting analysis, decision support, risk	Risk prediction, efficiency in reporting and decision-making	Privacy, costs, cybersecurity, complexity	Yang (2024); Novichenko et al. (2024)
Supply chain / Logistics / Industry	2	Demand forecasting, disruption management, operational optimization	Efficiency, resilience, sustainability, proactive decisions	Data integration, variability, conversion of unstructured data	Abhulimen & Ejike (2024); Hooda et al. (2023)
Retail / Marketing / Customers	2	Sales analytics, segmentation, widgets/IoT, personalization	Profitability, assortment decisions, and personalization	IoT dependence, data coverage, bias in profiling	Makarov (2024); Adewusi et al. (2024)
Project management	1	Dynamic scheduling, prediction of risks and delays	Resource optimization, real-time adaptation	Data quality, unstable forecasts	Nabeel (2024)
Software development / Tech firms	1	Performance analytics (errors, transactions), strategic decisions, agile transformation	Software quality, productivity, rapid response	Privacy, compliance, data governance	Okeleke et al. (2024)
Energy / Reservoirs	1	Digital twins, hybrid models, operational prediction	Predictive accuracy and operational optimization	Infrastructure dependence, data heterogeneity, and scaling challenges	Onyebuchi Uchendu et al. (2024)
Education / e-learning	2	Learning analytics, personalization, educational data mining	Retention, performance, and personalization	Data fragmentation, security, and large-scale data management	Lyu & Feng (2018); Zhang (2024)
Healthcare / eHealth	4	Clinical platforms, chatbots, prediction, decision support	Prevention/monitoring, efficiency	Privacy, computational cost, bias	Amato et al. (2019); Asri et al. (2019); Berger & Doban

				(2014); Asgarova et al. (2024)
Conceptual / 5 cross-cutting (BI, cloud, predictive analytics, Industry 4/5)	Conceptual frameworks, BI, cloud analytics, predictive/prescriptive analytics	Integrative approach, implementation guidelines	Lack of empirical evidence, cloud dependence, and security	Dashora (2023); Santos et al. (2019); Sharma (2019); Rane et al. (2024); Tang (2024)

To move from a sector-by-sector reporting approach to a systematic comparison, a cross-context synthesis was developed based on two key axes: small and medium-sized enterprises (SMEs) versus large corporations and regulated versus non-regulated sectors. Table 4 summarizes the most common benefits, barriers, risks, and success conditions by context, along with the main sources of divergence identified in the existing literature.

Table 4. Cross-context synthesis matrix

Comparative context	**Typically reported benefits**	**Dominant barriers**	**Dominant risks**	**Success conditions**	**Sources of divergence/contradiction**
SMEs – Non-regulated sectors	Rapid operational efficiency	Limited budget; integration with legacy systems; low data quality	Vendor dependence, reactive security, and unmonitored bias	Pragmatic cloud adoption; narrowly scoped use cases	High vs. rapid, depending on digital maturity; limited adoption
SMEs – Regulated sectors	Improved control and traceability; error reduction; analytics for compliance and risk management	Compliance costs; audits; need for formal controls; scarce talent	Privacy and penalties; security breaches; unacceptable model opacity	Strong governance from the outset; privacy by design; interpretable models	Rapid innovation vs. slow implementation due to regulatory burden and mandatory audits
Large enterprises – Non-regulated sectors	Analytics scaling; automation; large-scale optimization; advanced innovation and personalization	Integration complexity; silos; cultural resistance across departments; technical debt	Reputational risk; bias at scale; dependence on cloud/IoT platforms	Robust architecture + MLOps; KPI-to-process alignment; cross-functional teams	More data = better models vs. more data = noise when data veracity is lacking
Large enterprises – Regulated sectors	Advanced risk management; prediction with controls; more consistent decisions; efficiency with compliance	Complex governance; long approval cycles; extensive documentation, and traceability	Critical privacy/security; bias and discrimination; need for explainability	Data and model governance (auditability); bias assessment; access control; advanced security	Powerful models vs. acceptable models (explainability is prioritized over pure performance)

4.2 What are the uses and applications of Big Data, artificial intelligence, and machine learning in organizations to support decision-making?

The studies focused on the impact of Big Data and artificial intelligence on financial management and on the optimization of business processes. Yang (2024) shows how machine learning algorithms contribute to improving the accuracy of financial decision-making, while acknowledging limitations related to data privacy and high implementation costs. Complementarily, Tang (2024) outlines strategies for transforming unstructured data into actionable information, highlighting ethical challenges associated with algorithmic bias and cultural resistance to change.

For Industry 4.0 and 5.0, Paramesha et al. and Rane et al. (2024) analyze the role of predictive and prescriptive analytics in risk prevention and strategic decision-making, emphasizing the need for robust computing infrastructure. Onyebuchi Uchendu et al. (2024) explore the use of hybrid models and digital twins in reservoir engineering, underscoring the importance of advanced analytics for improving operational efficiency in the energy sector. Likewise, Zahaib Nabeel (2024) proposes a framework for managing complex projects based on dynamic programming and AI-enabled automated prioritization, highlighting how these technologies can anticipate risks and adjust resources in real time.

In the retail sector, Makarov (2024) explains how integrating widgets, IoT, and Big Data strengthens firms' competitiveness, although reliance on internet access constitutes a limitation. Jahani et al. (2023) provides an in-depth analysis of Big Data applications in supply chain management and logistics, identifying several methodological gaps and underscoring the need for more structured and systematic approaches. Asgarova et al. (2024) argue that data mining can optimize customer service, whereas Patrick Azuka Okeleke et al. (2024) maintain that integrating analytics into strategic decision-making is essential for software development, while noting challenges related to data privacy, quality, and accuracy.

4.3 What benefits, risks, and challenges are reported in the literature regarding the implementation of Big Data and advanced analytics in organizations?

The systematic review indicates that Big Data improves decision-making and predictive capability by forecasting demand, delays, risks, and failures. As a result, decision-making becomes faster, evidence-based, and increasingly real time, supported by predictive models and machine learning. Operational efficiency and resource optimization also facilitate tasks such as schedule planning, inventory management, routing, workforce allocation, and infrastructure utilization, thereby reducing costs and improving service quality.

Among the risks identified are concerns related to data privacy, security, and misuse, including the possibility of cyberattacks, hacking, data breaches, and vulnerabilities in cloud and IoT environments. In addition, biased models may lead to discriminatory outcomes or unfair decisions, while the lack of transparency and explainability in AI and machine learning makes it difficult to audit automated decisions. Another major risk involves technological and infrastructural dependence, whereby critical systems rely on cloud services, connectivity, or large external platforms; infrastructure failures or poor integration can disrupt or even paralyze key organizational processes.

Asgarova et al. (2024) point out that even with advanced algorithms and extensive databases, analytics outputs have limited value if analysis objectives are not defined in advance. Without a clear goal, processing large volumes of data can produce fragmented, low-utility, or even contradictory information for decision-making. Moreover, Big Data processing requires substantial infrastructure, time, and financial investment. If an organization does not clearly specify what it seeks to achieve (e.g., optimizing sales, forecasting risks, improving customer service), it risks wasting resources on analytics that lack strategic impact (Tang, 2024).

A major challenge concerns data quality, governance, and integration, which require clear governance policies, data lineage, profiling, standards, and access control. Another key barrier is the skills gap and data literacy deficit, reflected in shortages of professionals with competencies in data science, machine learning, data engineering, and AI ethics, as well as a limited data-driven culture among executives and operational staff and overall low data literacy. In addition, integrating AI and Big Data is complex and time-consuming, often requiring the redesign of processes, organizational structures, and roles; it is not merely a technological shift, but also a managerial and cultural transformation.

4.4 What technological, organizational, ethical, and human-capital factors facilitate or constrain the effective adoption of Big Data and advanced analytics?

From a technological standpoint, effective adoption requires robust data infrastructure, including cloud platforms, data lakes/warehouses, and scalable storage, with the capacity to process massive datasets in real time. It also depends on advanced analytical tools such as machine learning and deep learning algorithms that enable predictive and prescriptive analytics. Regarding data integration and quality, processes such as data cleansing, profiling, labeling, and lineage tracking require architectures capable of combining structured and unstructured data.

Regarding organizational factors, effective adoption requires a clear leadership strategy, with top management committed to evidence-based decision-making and an explicit vision of how Big Data and AI create value through efficiency gains, innovation, and new services. In terms of data governance and policy, defined roles and formal policies are needed to regulate data access, use, security, and quality. In addition, fostering a culture of innovation and continuous improvement promotes openness to experimentation, pilot initiatives, and the iterative use of analytical models, supported by cross-functional collaboration among business units, IT, and analytics teams.

Paramesha et al. (2024) and Rane et al. (2024) note that the success of Industry 4.0 and 5.0 depends on robust platforms that ensure interoperability, security, and scalability. Achieving this requires a solid infrastructure capable of integrating IoT sensors, cloud-based data, and real-time analytics systems. Tang (2024) similarly warns that the lack of seamless integration between AI and legacy systems hinders strategic decision-making, as many organizations still rely on manual processes or outdated systems that do not support machine learning algorithms or advanced analytics techniques.

Resistance to change often stems from fears of job loss due to limited digital skills. To mitigate this concern, organizations should invest in training and reskilling programs aimed at enabling employees to develop competencies in data analysis, the use of digital tools, and the interpretation of AI-driven results.

Organizations should communicate the objectives of automation transparently, emphasizing that its purpose is not to replace workers but to enhance productivity and free up time from repetitive tasks so employees can focus on higher-value activities. Involving employees in Big Data or AI pilot projects helps them experience the benefits firsthand, fostering ownership of the change and reducing resistance.

5 Discussion

The studies analyzed converge on the view that Big Data and advanced analytics have become cross-cutting technologies with impacts across multiple sectors, including financial management (Yang, 2024; Novichenko et al., 2024), reservoir engineering (Onyebuchi Uchendu et al., 2024), Industry 4.0/5.0 and Society 5.0 (Rane et al., 2024; Hooda et al., 2023), project management (Nabeel, 2024), retail (Makarov, 2024), software development (Okeleke et al., 2024), supply chain and logistics (Jahani et al., 2023; Abhulimen & Ejike, 2024), health and eHealth (Amato et al., 2019; Asgarova et al., 2024), as well as online education and learning analytics (Lyu & Feng, 2018; Zhang, 2024). This diversity of applications supports the argument advanced in the theoretical framework that "data-driven" organizations are not confined to a single sector; rather, they represent a management paradigm grounded in the exploitation of large-scale data and the capacity to transform it into actionable knowledge.

Regarding the reported benefits, the findings confirm Davenport and Harris's view of analytics as a lever for competing and achieving competitive advantage: across virtually all studies, improvements are observed in decision-making (faster, evidence-based, and more predictive), gains in operational efficiency (optimization of schedules, inventories, routes, human resources, and technological assets), and greater personalization of products and services (customer segmentation, enhanced user experiences, and more targeted interventions in healthcare and education).

Studies by Tang (2024), Khan (2024), and Adewusi et al. (2024), for example, show how combining Big Data, business intelligence, and predictive models enables organizations not only to understand what is happening, but also to anticipate scenarios and adapt strategies proactively. These findings align with the conceptualization of Big Data through its "V's" (volume, velocity, variety, veracity, and value), insofar as the ability to capture massive data streams in real time and process them through machine learning algorithms translates into better-informed decisions and the creation of new business opportunities.

However, the review also highlights a substantial gap between theoretical potential and practical implementation. While the benefits are consistently reported, their magnitude appears strongly contingent on the technological and organizational context. In sectors such as healthcare, reservoir engineering, and Industry 4.0—where robust infrastructures and high computational capacity are in place—successful cases are more readily observable (Amato et al., 2019; Hooda et al., 2023; Onyebuchi Uchendu et al., 2024).

In the context of small and medium-sized enterprises, or organizations with limited resources—such as those examined in studies on accounting, retail, or cloud adoption (Dashora, 2023; Makarov, 2024; Novichenko et al., 2024)—the costs associated with infrastructure, maintenance, and staff training become a major barrier. This tension between promise and practical feasibility clearly indicates that the adoption of Big Data and advanced analytics is not merely a technical challenge, but fundamentally a socio-technical one, in which financial capacity, strategic vision, and organizational culture are decisive.

Regarding risks and challenges, the findings reveal a recurring pattern: benefits are often achieved at the cost of greater complexity and increased exposure to new types of vulnerabilities. On the technical side, persistent issues arise around data quality, integration, and governance—such as siloed, incomplete, or inconsistent data; difficulties in combining heterogeneous sources (IoT sensors, transactional records, and clinical, educational, or online behavioral data); and the absence of systematic processes for data profiling, lineage, and access control (Santos et al., 2019; Lyu & Feng, 2018). In this regard, the reviewed studies confirm that data veracity and governance—beyond sheer volume—are critical conditions for advanced analytics to produce reliable and actionable outcomes.

From an ethical and regulatory perspective, the literature shows growing concern about privacy, security, and algorithmic bias. Studies in healthcare, education, and financial services warn that handling sensitive data entails risks of hacking, data leakage, and misuse, particularly when organizations depend on cloud infrastructures and IoT devices (Amato et al., 2019; Lyu & Feng, 2018; Novichenko et al., 2024). Other works point to the potential for discriminatory decisions arising from models trained on non-representative data, as well as the opacity of certain deep-learning algorithms, which undermine explainability and accountability (Khan, 2024; Simpson & Johnson, 2024). These findings reinforce the need—already established in the theoretical framework—to advance toward ethical data-governance frameworks that combine external regulations (personal data protection) with internal policies promoting transparency, fairness, and responsible AI use.

Finally, with respect to human capital, the review highlights a skills gap that recurs across virtually all sectors: there is a shortage of specialists in data science, data engineering, cybersecurity, and AI ethics, alongside low data literacy among middle management and operational staff. Several studies agree that, without internal capabilities to frame analytical problems, interpret results, and translate insights into decisions, organizations become dependent on external consultants or “black-box” tools that are not fully integrated into their processes (Jahani et al., 2023; Jamarani et al., 2024). This finding has direct implications for the educational context in which this study is situated: programs such as the bachelor’s degree in information technologies are expected to train professionals who can not only use Big Data and advanced analytics tools but also understand their organizational and ethical implications and lead data-driven transformation processes

5.1 Integrative conceptual model for the responsible adoption of Big Data and advanced analytics in organizational decision-making.

Although the literature reviewed agrees that Big Data, artificial intelligence, and machine learning paradigms enhance predictability and operational efficiency, it also shows that these benefits do not materialize immediately. In practical terms, outcomes are shaped by socio-technical factors that link infrastructure and data, organizational capabilities, human capital, and ethical governance practices. Drawing on the synthesis of results (RQ1–RQ3), this study proposes an integrated conceptual model called TOEH-G (Technological–Organizational–Ethical–Human + Governance). The aim is to clarify the value-creation process enabled by Big Data and advanced analytics, the requirements for effective adoption, and the mechanisms that foster the mitigation of risks related to privacy protection, security, bias, and algorithmic opacity (figure 2).

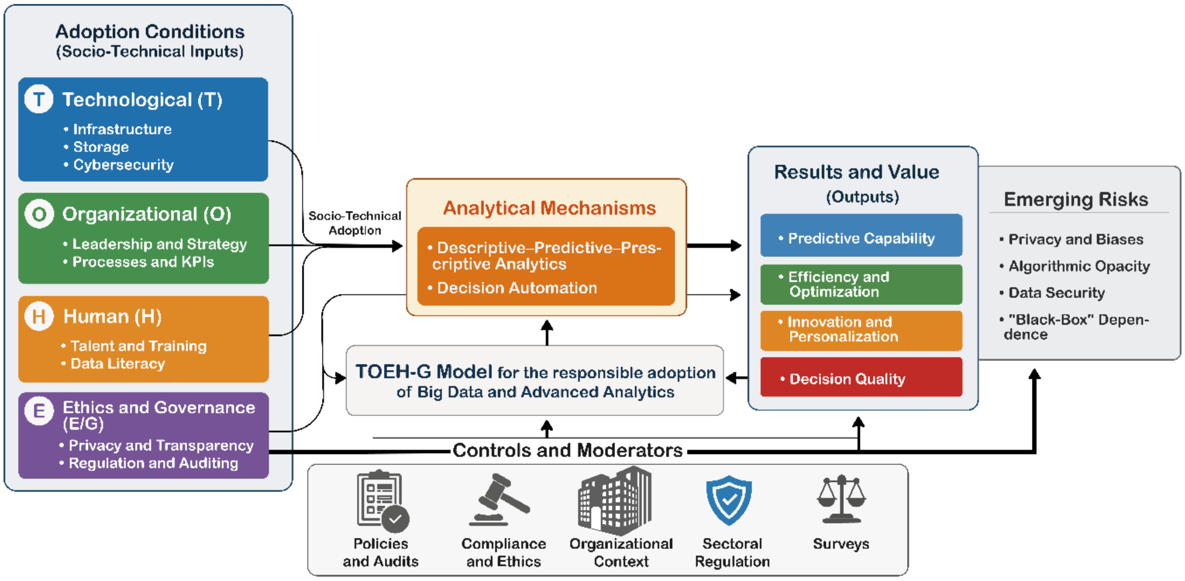


Fig. 2. TOEH-G Model for Responsible Adoption

The model is organized into five main components: (a) the technological dimension, which includes scalable infrastructure, storage, data pipelines, interoperability, and system integration; the evidence shows that the ability to handle volume, velocity, and variety is closely tied to the availability of computing resources, connectivity, processing platforms, and robust architecture. (b) The organizational dimension encompasses executive leadership, strategic clarity, prioritization of use cases, and alignment with performance indicators; the studies indicate that analytics delivers impact when there is an explicit vision of how models are embedded in decision-making processes and operational routines, avoiding fragmented initiatives disconnected from organizational goals. (c) The human dimension focuses on specialized talent and identifies a recurring skills gap that constrains sustained adoption and increases dependence on external consulting or off-the-shelf tools. (d) The ethical and governance dimension includes privacy, data protection, audits, and assessments of algorithmic risk; the literature review highlights that intensive use of personal data and complex models increases exposure to vulnerabilities and biased decisions.

This study demonstrates three important contributions: (a) socio-technical and responsible integration, providing evidence for the TOEH-G framework, which explains adoption as a socio-technical and ethical phenomenon by linking infrastructure, human capital, and governance as fundamental conditions for transforming Big Data into value-driven decisions; (b) clarification of mechanisms and effectiveness conditions, specifying how value is created through analytical mechanisms and under what conditions the benefits materialize; and (c) actionable theory through testable propositions, advancing theoretical propositions that can be empirically examined, offering a clear agenda for future research and a practical framework to guide governance policies, training programs, and responsible adoption strategies.

6 Conclusions

Overall, the reviewed studies confirm that Big Data and advanced analytics are essential tools for digital transformation, delivering significant benefits in terms of efficiency, innovation, and data-driven decision-making. However, they also highlight recurring limitations, including insufficient technological infrastructure, high adoption costs, the complexity of managing massive datasets, privacy risks, and ethical challenges associated with algorithmic bias.

This landscape provides a solid basis for interpreting the results of the systematic review and for formulating recommendations aimed at the responsible and effective integration of these technologies across different organizational contexts.

Actionable recommendations for managers: (a) Start with decision-centric use cases; (b) Establish a minimum viable data governance baseline before scaling; (c) Invest in data quality and integration as a first-order capability; (d) Adopt Responsible-by-design analytics; (e) Build human capability through a tiered data literacy program; (f) Operationalize analytics through MLOps and continuous monitoring; (g) Select architecture pragmatically and manage vendor dependency.

6.1 Future research

To advance the field beyond fragmented sectoral evidence, future research should prioritize the following specific directions: (a) Explainable AI governance frameworks for organizational decision-making; (b) Data literacy maturity models and measurement instruments; (c) Bias auditing protocols and fairness–performance trade-offs across contexts; (d) Socio-technical adoption pathways; (d) Model lifecycle risk management; (e) Cross-context comparative evidence SMEs vs large, regulated vs non-regulated

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