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HOW DOES BIG DATA CHANGE MANAGEMENT DECISION-MAKING?

KAKO VELIKI PODACI MIJENJAJU MENADŽERSKO ODLUČIVANJE?

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ABSTRACT

Big data systems enable the transformation of large amounts of raw data from sources into strategic information that transforms sectors such as healthcare, transportation, and finance. In today's uncertain environment, strategic decision-making is a dynamic challenge. Teams of experts need to process and accurately interpret a large amount of heterogeneous information in order to make informed decisions. The more accurate, timely, and in-depth the information, the higher the likelihood of making accurate and effective decisions. With the emergence of big data, traditional reliance on intuition and experience is being transformed by a data-driven approach. This transition allows managers to not only base their choices on empirical evidence but also to uncover hidden patterns, predict future trends, and optimise strategies with remarkable precision. Advances in technology and organisations' increasing ability to analyse data enable opportunities for future research on the long-term effects of big data analytics tools.

The purpose of this paper is to present a review of the literature that analyses the concept of big data and its theoretical framework. The emphasis is on the analytics comparison of traditional data types with big data. This paper highlights the evolving role of managers in a big data environment, emphasising the growing need for analytical literacy, the ability to interpret complex datasets, and close collaboration with data science and information technology teams. While the benefits of big data include faster decision-making, some challenges remain. These include data privacy and security, ethical dilemmas related to algorithmic bias, issues of data quality and reliability, and financial and organisational costs. Ultimately, big data is not merely a technological tool but a transformative strength in management. It requires a cultural shift toward evidence-based decision-making, continuous learning, and responsible data governance. Organisations that successfully integrate big data into their decision-making processes are better positioned to achieve sustainable growth, resilience, and long-term competitive advantage.

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SAŽETAK

Sustavi velikih podataka omogućuju pretvaranje velikih količina sirovih podataka iz različitih izvora u strateške informacije koje mijenjaju sektore poput zdravstva, prometa i financija. U današnjem neizvjesnom okruženju strateško odlučivanje predstavlja dinamičan izazov. Timovi stručnjaka moraju obraditi i ispravno interpretirati veliku količinu heterogenih informacija kako bi donosili utemeljene odluke. Što su informacije točnije, pravodobnije i dublje analizirane, veća je vjerojatnost donošenja ispravnih i učinkovitih odluka. Pojavom velikih podataka tradicionalno oslanjanje na intuiciju i iskustvo sve se više transformira u pristup temeljen na podacima. Ova promjena menadžerima omogućuje da svoje odluke ne temelje samo na empirijskim dokazima, nego i da otkrivaju skrivene obrasce, predviđaju buduće trendove te optimiziraju strategije s iznimnom preciznošću. Napredak tehnologije i sve veća sposobnost organizacija da analiziraju podatke otvaraju prostor za buduća istraživanja o dugoročnim učincima alata za analitiku velikih podataka.

Cilj ovoga rada jest prikazati pregled literature koja analizira koncept velikih podataka i njegov teorijski okvir. Naglasak je stavljen na analitičku usporedbu tradicionalnih vrsta podataka i velikih podataka. Rad ističe promjenjivu ulogu menadžera u okruženju velikih podataka, naglašavajući rastuću potrebu za analitičkom pismenošću, sposobnošću interpretacije složenih skupova podataka te bliskom suradnjom s timovima za podatkovnu znanost i informacijsku tehnologiju. Iako prednosti velikih podataka uključuju brže donošenje odluka, određeni izazovi i dalje ostaju prisutni. Među njima su privatnost i sigurnost podataka, etičke dvojbe povezane s algoritamskom pristranošću, pitanja kvalitete i pouzdanosti podataka te financijski i organizacijski troškovi. U konačnici, veliki podaci nisu samo tehnološki alat, nego transformacijska snaga u menadžmentu. Oni zahtijevaju kulturni zaokret prema odlučivanju utemeljenom na dokazima, kontinuiranom učenju i odgovornom upravljanju podacima. Organizacije koje uspješno integriraju velike podatke u svoje procese odlučivanja imaju bolju poziciju za ostvarivanje održivog rasta, otpornosti i dugoročne konkurentske prednosti.

Ključne riječi: veliki podaci, odlučivanje, analitika, menadžment, odlučivanje temeljeno na podacima

INTRODUCTION

Organisations today operate in a digital environment where most activities leave a trace that can be recorded and analysed – from transactions and web clicks to sensor readings and social media interactions (Šebalj, Živković, & Hodak, 2016). The growing availability of data has contributed to the rise of big data as both a technological and managerial paradigm. Rather than focusing entirely on more data, big data emphasises the ability to process diverse, rapidly changing data sets and convert them into insights that support action (Vinčević & Zajmović, 2021). The period of open information is advancing due to the increasing use of big data, which presents the main activity of organisations to create social knowledge for environmental sustainability.

Traditionally, managerial decision-making has been shaped by bounded rationality. Managers rely on limited information, heuristics, and experience to choose satisfactory options under constraints of time and resources. While this approach can be effective in stable environments, modern competition is now defined by high uncertainty, rapid change, and increasing customer expectations. Customer behaviour evolves quickly due to the generation of feedback on various digital platforms (Kutnjak, 2025). In this context, organisations seek to make decisions that are more timely, evidence-based, and aligned with user needs.

Big data is changing the decision-making process by expanding informational inputs (more sources and formats), accelerating feedback (near-real-time measurement), and enabling advanced analytics that reveal patterns beyond human observation. This type of decision-making improves prediction – what is likely to happen, and planning – what to do next. Consequently, there is a reshaping of the organisational structure, which requires new data architectures, governance, and managerial competencies. (Krajnović, Žilić, & Panjkota, 2022). At the same time, the deployment of big data also introduces various risks. If data is incomplete, outdated, inconsistent, or inaccurate, analytics may produce misleading signs and flawed decisions (Sparling, 2018). As more sensitive information is collected and shared between systems, security and privacy challenges are increasing (Al-Zahrani & Al-Hebbi, 2022).

This paper aims to provide a review of the relevant literature on the concept of big data in the context of analytics and decision-making. The conceptual goals of this paper are to analyse and synthesise existing findings in the field of big data analytics. The paper presents current knowledge about the observed concepts. When systematising knowledge and existing insights, the methods of description, classification, induction, deduction, and generalisation were used. The research questions are aimed at exploring the differences between big data and traditional managerial data. Also, the effects of big data on decisions at strategic, tactical, and operational levels were analysed. The paper discusses the managers' benefits and challenges in data-driven decision-making.

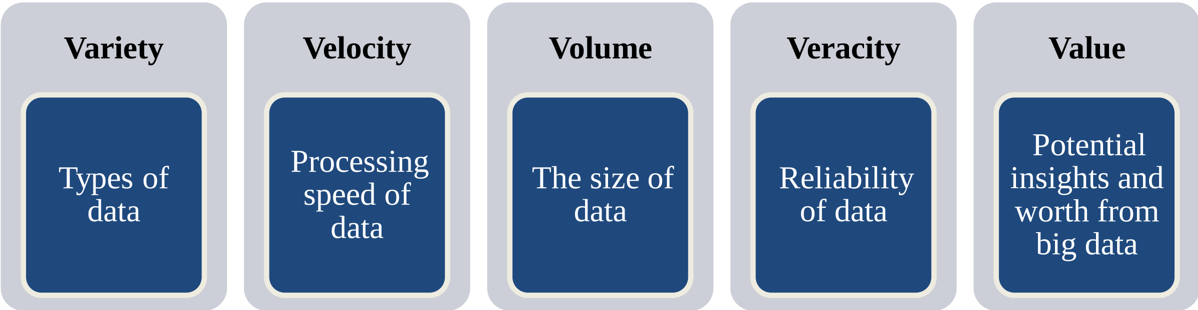
2. LITERATURE REVIEW

2.1. The concept of big data

Big data is commonly described through a set of characteristics often summarised as the "V" dimensions (Figure 1). These elements form a framework for understanding modern digital information management (Mohamed, Najafabadi, Wah, Zaman, & Maskat, 2020). The first characteristic is variety and includes different formats and sources of information. The other characteristic, velocity emphasize the importance of fast processing of data in real time. Next is volume, which describes the vast amount of information collected, measured in extreme units, like gigabytes, terabytes or larger. For the accuracy of the analysis, veracity is emphasised as a measure of the reliability of the source. The value is the useful insight that organisations gain from processing complex data sets. Big data may appear in various formats and forms, which present the core of the variety, the first characteristic of big data (Mohamed et al., 2020).

Structured data is easily processed, while managing unstructured and semi-structured data requires advanced analytics to overcome computing capacity challenges and extract real value.

Figure 1. Characteristics of big data – the five "V-dimensions"



Source: Own source, 2026.

At minimum, big data involves high volume, high velocity, and high variety of data, large quantities, rapid generation and processing, and multiple formats and sources (Šebalj et al., 2016). Many authors add veracity and value as additional dimensions, trustworthiness and the capacity to extract business benefit, respectively (Vinčević & Zajmović, 2021). Managerial relevance follows from the premise that competitive advantage increasingly depends on the ability to transform raw data into actionable knowledge. Research on a big data framework classifies the domain areas of big data, within which each characteristic (such as speed or credibility) manifests itself in a specific way. Specific application areas are divided into the following domains: medical care and health, social networking, economic sector, natural resource management, and government and public sector. Big data in health and medical care refers to the use of massive and rapidly growing sets of clinical data to improve medical decisions, research diseases and ensure patient well-being. It encompasses large amounts of diverse clinical data, such as electronic records and medical images. The application of sensors to monitor vital signs in real-time enables rapid data processing (velocity) to provide valuable insights for medical decision-making (Nguyen et al., 2017). The key challenges in this area remain the integration of complex data and ensuring its veracity and patient privacy. Social network analytics take advantage of the rapid speed of information flow (velocity) to enable personalisation of content and the spread of news in real time, often faster than physical events themselves. Through advanced analysis of interactions and connections, it enables organisations to understand patterns of behaviour to optimise marketing strategies (Castiglione, Colace, Moscato, & Palmieri, 2018). Such processing of unstructured data creates significant value for business, provided that the veracity of the source of information is ensured. The commercial sector represents the most prominent application area of big data analytics, where it is estimated that retailers that fully utilise the power of analytics can increase their operating margins by as much as 60% (Mohamed et al., 2020). Data in the commercial sector is relatively well structured and integrated within closed systems, unlike sectors such as healthcare or the networking and internet sector.

Analytics of big data are used for the integration of supply chains, advertising, and customer relationship management (Ding, Liu, Han, Zhang, & Song, 2017). Retailers process large amounts of structured and multimodal data, such as transactions and customer preferences. The emphasis is not on the data quality, but on developing new analytical methods that would fully utilise the available resources. Improvements in computer data processing have enabled detailed monitoring of environmental changes such as deforestation, melting glaciers and extreme weather events through satellites and sensors. Collecting large amounts of data on carbon footprints and natural resources is critical to developing sustainability strategies and understanding the impact of human activities on the planet (Yuan, Chen, Jiang, & Li, 2017). Although analytics is still in its early stages, it provides the necessary knowledge to find new solutions in the fight against the negative effects of climate change.

Analytics in the public sector and environmental management uses big data sets to improve the sustainability, security and efficiency of services through systems such as smart cities and advanced fraud detection (Kousiouris et al., 2018). Public administration faces the challenge of managing enormous amounts of data (volume) generated by citizens, which governments use to develop smart cities. Such cities use electronic sensors and connected devices that monitor traffic, people's routine and pollution in real time (velocity). Also, these systems enable a fast reaction to natural disasters, like floods and earthquakes. Furthermore, it can be used as protection against crime and cyber attacks. Finally, personalisation of public services and an increase in internal transparency create new value for the community.

2.2. Traditional datasets vs. big data

Unlike traditional databases, big data greatly expands the range of information available to organisations for analysis and decision-making. This may be achieved by combining classic transaction reports with behavioural signals from networking, social data from posts, and machine-generated data from sensors. Furthermore, this fundamentally transforms the rate of strategic decision-making. Replacing static reporting cycles with real-time data flow enables faster and more precise performance control. Such a transformation results in “continuous management”, whereby evaluation and decision-making processes take on an iterative character with a high level of adaptability.

In the modern world, big data analytics has become a key factor for improving project management, enabling faster and more accurate decision-making. Traditional planning methods that rely on strictly defined sequences of events are being replaced by new approaches based on machine learning and business analytics. More than 77% of organisations recognise that the use of analytics brings inherent benefits, such as correcting organisational inefficiencies and improving the cost-benefit ratio (Forbes, 2023). According to research from the Project Management Institute (2019), organisations that use advanced analytics tools are 30% more likely to deliver projects within budget and on time. However, implementing big data analytics carries challenges such as a lack of skills among managers, data isolation within departments, and a lack of uniformity in their sharing. An additional obstacle is the high cost of implementing systems and acquiring appropriate technology platforms. Unlike conventional planning, data-driven approaches use predictive modelling to improve yields and predict the outcomes of specific projects. The application of big data analytics is especially effective in complex sectors such as construction, IT, and healthcare, where risks and uncertainties are higher (Sajid, Shah,

& Ahmad, 2024). Ultimately, the ability to leverage data is key to maintaining a competitive advantage in a rapidly changing digital environment.

The differences in decision-making between traditional methods and big data analytics are based on speed, how information is processed, and the predictability of outcomes (Siddiqui, 2025). Traditional decision-making is often based on historical data and periodic reports. In contrast, big data analytics empowers decision-makers to be more proactive, allowing them to anticipate risks and respond quickly to changes. This directly reduces the likelihood of project delays or cost overruns. While traditional systems rely on data generated at a slower rate (e.g., monthly reports), big data analytics enables real-time or near-real-time processing. This is crucial for dynamic decisions such as fraud detection or current customer engagement. Traditional decision-making uses structured, tabular data within limited databases. Big data analytics incorporates large datasets that are often unstructured, such as videos, sensors, and social networks, providing a greater picture for decision-making. Projects that use big data analytics for decision-making achieve better results in budget management and meeting deadlines compared to conventional practices. Stakeholder satisfaction is more stable and consistent with the big data analytics approach. The effectiveness of big data analytics for decision-making is not the same across industries.

Data-intensive sectors like information technology provide greater benefits, while traditional sectors like construction show smaller improvements. While the benefits are clear, sources note that traditional decision-making may be preferred in organisations that face high initial implementation costs, lack of specific skills, or resistance to change. Also, as technology evolves, future decision-making will increasingly rely on artificial intelligence and machine learning that build on the foundations of big data analytics. The true value of big data in a decision-making context comes to light through four distinct analytical approaches. Descriptive analytics provides a summary of past events, while diagnostic analytics investigates the underlying causes behind those events. Looking forward, predictive analytics estimates potential future outcomes, and prescriptive analytics suggests specific actions to take under various constraints. Integrating these tools into dashboards and automated alert systems has a direct impact on decision-making processes, whether conducted by human experts or algorithms. However, experts emphasise that successful implementation within a company does not depend only on technology, but is strongly influenced by organisational factors such as governance, employee skills, and existing corporate culture.

2.3. Big data and changes in decision-making across management levels

Scientific data on big data emphasise the importance of how information is transmitted and used within companies (Fanelli, Pratici, Salvatore, Donelli, & Zangrandi, 2023). The main goal of analytics in this process is to minimise errors and narrow the range of data so that decisions are as accurate as possible. This section describes big data's effect on strategic, tactical, and operational decision-making. Regardless of differences in scope or timeframe, big data influences all of them by increasing informational richness, improving timeliness, and enabling more advanced forms of analysis. Table 1 shows the characteristics of management decision-making levels.

2.3.1. Conceptual framework for big data analytics

Big data analytics increases the efficiency of knowledge application by improving organisational learning, which plays a key role in knowledge management. Also, it contributes to the creation of valuable knowledge resources that are difficult to imitate, which ultimately leads to sustainable competitive advantage (Ghasemaghaei, 2019). The ability of a company to make effective decisions is ingrained in its learning capacity. Big data plays a crucial role in decision-making in large groups (Large-Scale Decision-Making, LSDM). It represents a fast-growing research field that deals with situations in which more than 20 members participate in solving complex problems. LSDM also includes participants from entire industrial clusters, which is crucial when solving problems such as the scarcity of natural resources. Also, it offers adequate insights to find optimal solutions and overcome the uncooperative behaviour of key decision makers (Ding et al., 2020). The introduction of big data analytics enables the transition from conventional decision-making to data-driven decision support systems for large groups.

Although leading organisations are increasingly adopting this approach, science is only beginning to explore in more detail how big data tools can be specifically applied in LSDM situations to solve the most complex challenges facing modern organisations (Awan, Shamim, Khan, Zia, Shariq, & Khan, 2021). Big data analytics and business intelligence and analytics capabilities are positively associated with the quality of decision-making. This impact is even more pronounced when manufacturers actively use data-driven insights. The research of Awan et al. (2021) showed that big data analytics capabilities directly drive decision-making quality, while business intelligence and analytics affect it indirectly, precisely through the generation of these insights. These findings serve as a reference point for managers to develop strategic insights within the circular economy paradigm. Big data analytics has been recognised as a key tool for developing smart manufacturing systems. Organisations are ready to invest significantly in big data analytics tools to improve forecasting and decision-making processes, thereby ensuring greater operational efficiency. This type of analytics transforms various forms of raw data into meaningful information that helps reduce uncertainty in decision-making. According to the Theory of the resource-based view, companies primarily rely on their internal resources, which must be valuable, rare, inimitable, and non-substitutable (VRIN) (Mithas et al., 2013). However, the mere presence of VRIN resources does not guarantee success in an unstable market, but organisations must also have the ability to activate and adapt these resources through analytical tools in order to gain an advantage (Pisano, 2015). The Theory of dynamic capability complements the resource-based view by focusing on how organisations actively adapt their resources and skills to market challenges. The dynamic capability view is defined as a set of high-level routines that provide management with options for producing meaningful results in a changing environment (Winter, 2003). Successful implementation of big data analytics requires the synchronisation of internal VRIN resources with external opportunities, which is a direct combination of the resource-based view and dynamic capability view concepts.

Dynamic capabilities driven by big data analytics tools help companies cope with uncertainty and improve financial performance (Wang, Xu, Zhang, & Zhong, 2022). Big data analytics combined with artificial intelligence enables companies to reduce production costs and mitigate market risks. The resource-based view concept is further visible through the specific IT skills and analytical competencies that form the knowledge base of the modern company. Through the dynamic capability view, companies develop the ability to quickly configure new practices needed to adapt to new business paradigms. Research confirms that the capabilities enabled by big data analytics directly affect the operational and financial performance of companies. Despite numerous studies, there is still a gap in the literature in understanding how big data analytics simultaneously improves all aspects of organisational performance. The integration of internal VRIN capabilities and dynamic routines through big data analytics is crucial for long-term competitiveness in a technologically advanced world.

2.3.2. Strategic decision-making

Strategic decision-making is a key business process for selecting the best course of action to achieve long-term goals. It shapes the long-term direction of the market, including positioning, business model design, investment priorities, partnerships, and innovation. Also, it goes beyond simply selecting options and involves making informed and considered decisions aligned with the organisation's vision, such as entering new markets, developing products, or allocating resources. Effective strategic decision-making directly impacts business performance, with profitability being one of the primary metrics affected by these decisions (Haessler, 2020). Hence, investment based on careful research in new technology can significantly increase efficiency and reduce operating costs. In addition, strategic decisions in supply chain management and workforce optimisation are crucial for eliminating inefficiencies and achieving operational excellence.

Big data contributes to strategy by enabling organisations to detect shifts in customer behaviour, emerging market niches, and competitive threats earlier. User activities across digital channels generate large datasets that can reveal needs and expectations, supporting customer-centric strategy formation (Kutnjak, 2025). In addition, big data supports scenario-based strategic planning. When organisations integrate external signals (e.g., macro indicators, social trends, and supply network events) with internal performance data, they can develop richer scenarios and stress-test assumptions. This can increase strategic agility, an organisation's ability to revise strategy as conditions change, while maintaining coherence and focus. However, big data can also create strategic blind spots if decision-makers over-trust models or optimise for short-term measurable outcomes at the expense of long-term value. This risk highlights the need for strategic governance and human oversight, ensuring that analytics is aligned with purpose and ethics (Krajnović et al., 2022). Traditional models of strategic decision-making in marketing primarily rely on structured market research, competitive analysis, and the planning phases – situation analysis, formulation, implementation, and evaluation (Mikalef, Boura, Lekakos, & Krogstie, 2020). However, big data and analytics are fundamentally redefining these models. The introduction of data-driven insights increases the accuracy of market analyses and the effectiveness of strategic plans.

2.3.3. Tactical (middle-management) decision-making

Middle management includes managers below top management and above the operational level. Regardless of how well a strategy is formulated, middle managers are crucial to its implementation. Although change can be initiated "from the top", it requires that employees understand its intent and implications (Hortovanyi, Szabo, & Fuzes, 2021). Middle managers interpret the strategy in the context of daily business, identify the necessary steps and communicate them to subordinates, acting as a link in accepting changes that they did not design themselves. Tactical decisions operate as the essential bridge that translates a broad strategy into specific resource allocations and process designs. The success of large systems depends on the cooperation of all levels of management. Lower-level managers encourage organisational changes, while the active participation of middle management is crucial for survival in conditions of strong market competition (Volberda, 2017). Managed primarily by middle managers, these decisions cover a wide range of operational areas, including budgeting, pricing adjustments, campaign targeting, and procurement plans. Nonaka (1994) emphasises that middle managers, because of their unique position, influence strategy by mediating vertically between the top and the bottom of the organisation. Complex and geographically dispersed organisations cannot be managed by a few individuals. They require distributed and interactive leadership.

Middle managers can also have opportunistic motives. They sometimes may distort reports and overemphasise successes or cover up failures, to focus top management's attention on specific areas (Wickenberg, 2013). If a strategy is unpopular, middle managers may form coalitions against it, create administrative obstacles, or even sabotage it to prove that the decision was wrong. Passive resistance, such as giving low priority to implementation, can seriously compromise its quality and timeliness. The implementation of big data significantly enhances this process by providing a higher level of granularity in measurement, which allows for much more precise segmentation of customers, products, and operations. In the field of customer relationship management, the integration of classic records with behavioural data allows managers to abandon broad categories in favour of micro-segmentation and detailed customer lifecycle management. This data-rich environment encourages an experiment-based approach to management (Korayim, Chotia, Jain, Hassan, & Paolone, 2024). However, the effectiveness of such decisions can be compromised by inconsistent metrics used by different departments. For big data to deliver real tactical value, organisations must prioritise strong data governance. This includes establishing common definitions, shared quality standards, and active cross-functional collaboration to ensure all participants are aligned.

2.3.4. Operational decision-making

In the conditions of transformation of managerial functions, the importance of information-analytical support is growing. This allows a deep understanding of economic processes and an assessment of their impact on the effectiveness of decisions. A key part of this process is expert analytics, which is specialised research involving experts to assess specific objects and phenomena. It identifies essential parameters and structural features of the studied object, providing systematised recommendations for its improvement. In operational management, expert analytics overcomes the shortcomings of traditional accounting information that is often used as a basis for decision-making (Zaika, Hridin, & Sahachko, 2024).

Operational decisions concern day-to-day execution, like scheduling, inventory replenishment, anomaly handling, customer support actions, maintenance planning, and process control. On this level, big data has a direct impact because operational contexts frequently involve streaming data and time-critical decisions. The quality of asset management decisions can be compromised when equipment condition data is incomplete or out of date. Managers in such systems face the challenge of making critical asset replacement decisions using data that often does not reflect the real situation (Sparling, 2018). In such settings, big data tools can improve monitoring, but only if data quality is actively managed and validated.

Organisations can further integrate artificial intelligence into their activities, and in specific situations, even completely exclude the human factor from the process in order to fully exploit the value of data. Various organisations have already implemented advanced technologies to achieve high levels of efficiency and gain a strategic advantage (Akhtar, Frynas, Mellahi, & Ullah, 2019). In this process, artificial intelligence is taking centre stage, attracting the attention of both the scientific community and industry (Balog, 2020).

Generally, operational analytics can also automate decisions, such as routing, alerts, or threshold-based interventions, reducing reaction time. Still, automation increases the importance of “human-in-the-loop” oversight. Managers should ensure that automation rules reflect operational realities and that exceptions are handled appropriately (Krajnović et al., 2022). Some organisations base their operational decisions entirely on statistics. Technology is key to this approach, although many still mistakenly believe that the human brain processes all the raw data. In reality, data only becomes information after systems process it and prepare it in a form that humans can understand.

Table 1. Decision-making at management levels

Level	Charactereistics	Goals and orientation	Accountable for implementation
Strategic decision-making	Policies and direction Mission and vision Multi-year forecasts	Long-term Direct, high impact	Top management
Tactical decision-making	Specific departments of the organisation Quarterly forecasts	Medium-term Implementing strategy, allocating resources	Middle management
Operational decision-making	Specific outcomes Weekly forecasts	Short-term Daily tasks, rule-based	Employees or lower management

Source: Own source, 2026.

2.4. Big data in risk management and crisis decision-making

Modern organisations confront interconnected risks such as supply disruptions, cyber threats, market volatility, and reputational crises. Big data can enhance risk management by improving visibility across networks and enabling earlier detection of weak signals. In supply networks, advanced risk management requires timely information flows and the ability to assess disturbances rapidly (Bischof & Wilfinger, 2019). By connecting data from the logistics chain, sensors (IoT) and market movements, big data enables the creation of systems for early detection of risks, which significantly accelerates management response.

Risk management can be mapped to phases of identification, assessment, mitigation, and monitoring. Big data supports each phase by expanding the evidence base (identification), enabling quantitative scoring models (assessment), optimising response options (mitigation), and supporting continuous tracking (monitoring). In crises, this can shorten decision cycles and improve coordination.

Nevertheless, the benefits depend on trustworthy data and secure infrastructures. If data is compromised or manipulated, decisions can become systematically wrong. Privacy and trust issues are central in big data environments, and inaccurate or misleading data may lead to invalid interpretations that harm outcomes (Al-Zahrani & Al-Hebbi, 2022). Effective crisis decision-making, therefore, requires both analytics capability and robust governance.

Findings from Canada confirm that effective implementation of analytical methods enables companies to better manage risks and more accurately predict future opportunities (Saleh, Marei, Ayoush, & Abu Afifa, 2023). The use of big data technology enhances accounting reporting and professional judgment by providing professional insights. Their respondents point out that efficient analytics achieve better business results, which includes customized products, simpler processes and a significantly more effective risk control system.

2.5. Challenges and limitations of big data-driven decision-making

A common limitation in the application of modern technologies is data quality. Even the most sophisticated analytics cannot compensate for incomplete, inconsistent, or inaccurate input information. The key dimensions of data quality, completeness, timeliness, validity, consistency, and accuracy demonstrate how weaknesses in any of these aspects reduce confidence in condition assessments and maintenance decisions (Sparling, 2018). To ease this challenge, organisations typically implement data governance practices, which include clearly defined data ownership, standardisation, validation rules, and ongoing monitoring. However, governance itself needs to be supported by the organisational culture. Employees need to understand the importance of accurate data entry and consistent definitions. Without this awareness, systems remain empty structures, and the quality of information remains dependent on the human factor at the source.

Big data systems frequently aggregate sensitive information from multiple platforms, which creates various security risks such as unauthorised access, data leakage, and integrity attacks throughout the stages of storage, processing, and transmission. Privacy concerns are especially prominent in customer-centric analytics where personal data is utilised to enhance experiences and personalise offerings. These security and privacy challenges directly influence organisational decision-making by constraining the types of data that can be collected and utilised, while also affecting stakeholder trust and creating potential legal or reputational consequences. Consequently, managers need to integrate security-by-design principles, access controls, encryption, and auditability into their big data projects. Additionally, the use of ethical guidelines and compliance frameworks is necessary to ensure that data is handled responsibly.

Big data adoption requires organisational capabilities such as data architecture, analytical talent, and managerial data literacy. This type of data is associated with transformational rather than incremental change, implying that organisations must adjust mindsets, structures, and processes, not merely add a new tool (Krajnović et al., 2022). Similarly, user-oriented digital transformation emphasises that data must be managed and used to align organisational activities with changing user needs (Kutnjak, 2025). The use of big data analytics enables smarter decision-making and more accurate forecasting, which significantly increases the level of efficiency of the entire company (Chatterjee, Chaudhuri, Gupta, Sivarajah, & Bag, 2023).

Without such capabilities, organisations risk accumulating data without converting it into actionable decisions. Training, interdisciplinary teams, and leadership commitment are therefore central to realising value. Big data initiatives are key to transforming traditional organisational decision-making into data-driven decision-making. Previous information systems research has neglected the impact of big data analytics on decision quality. The study of Li, Lin, Ouyang and Luo (2022), based on dynamic capabilities theory, confirms their strong relation. A survey of agricultural companies in China found that the use of analytics positively impacts decision quality, with analytical capabilities being a key mediator.

CONCLUSION

Big data analytics reshapes management decision-making by expanding informational inputs, accelerating feedback loops, and enabling advanced analytics that support predictive and proactive management. Across strategic, tactical, and operational levels, it improves decision timeliness and can enhance decision quality, especially where organisations integrate customer data to support user-oriented transformation and where risk management requires early detection and rapid response. However, big data also introduces critical challenges. Decisions can be distorted by poor data quality, and organisations face heightened security and privacy risks. To realise benefits, organisations must build capabilities in data governance, analytics, and managerial data literacy, while maintaining human oversight and ethical accountability. Overall, Big Data should be understood not merely as a technological upgrade but as an organisational and managerial transformation that changes how evidence is produced, interpreted, and used in decision-making. Therefore, companies should not only encourage the use of analytics but also actively work to strengthen their own data processing capabilities to gain a competitive advantage. In conclusion, there is a necessity to adopt predictive analytics to achieve sustainable growth and competitive advantage in today's data-driven business environment.

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