The Use of Big Data Analytics in Organizational Decision-Making: A Structured Literature Review

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Abstract

Big Data Analytics (BDA) is playing an increasingly important role in supporting organizational decision-making amid growing data volume, velocity, and variety produced by business activities and the external environment. BDA enables organizations to identify patterns, build predictions, evaluate alternative courses of action, and develop more evidence-based decisions. Yet the availability of analytical technology does not automatically yield high-quality decisions or improved organizational performance. The benefits of BDA depend on an organization's ability to integrate technology, human resources, data quality, decision processes, and managerial capabilities. This article synthesizes the literature on the role of BDA in organizational decision-making, identifies the factors that influence value creation, and formulates an agenda for future research. The study was developed through a structured review of a provided set of references, using a thematic synthesis spanning analytical capability, decision quality, dynamic capabilities, organizational performance, data governance, and implementation challenges. The conceptual synthesis indicates that BDA's contribution to organizational decisions can be understood through the relationships among analytical resources, the ability to turn data into insight, the integration of insight into managerial processes, and organizational follow-through. Analytical capability, information quality, user competence, management support, and the fit between analytics and the decision context are important conditions in this process. The article proposes a research agenda emphasizing the causal mechanisms between BDA use and decision quality, human interpretation, data governance, and differences in benefits across organization types. This synthesis strengthens theoretical understanding and offers practical direction for organizations seeking to use analytics effectively.

Keywords: Big Data Analytics; decision-making; decision quality; analytical capability; organizational performance; literature review

1. Introduction

The development of digital technology has expanded organizations' ability to generate, store, process, and distribute data. Data drawn from customer transactions, operational activities, internal information systems, digital media, sensors, and a range of external sources offer an opportunity to understand organizational conditions more comprehensively. Yet the growing availability of data also brings challenges: the complexity of processing, uncertainty about information quality, and the difficulty of identifying insights relevant to managerial decisions. In this context, Big Data Analytics (BDA) has emerged as an approach that integrates technology, analytical methods, and organizational capability to transform data into information usable for strategic and operational action [1], [2].

BDA is concerned not only with the use of software or analytical algorithms but also with an organization's ability to connect data, analytical methods, professional knowledge, and decision needs. Chen et al. position the development of business intelligence and analytics as a shift from data processing toward the creation of business impact [1]. This perspective underscores that the value of analytics is determined not merely by the volume of available data or the sophistication of the technology, but by an organization's ability to use analytical results to understand problems, evaluate alternatives, and determine action. BDA is therefore best understood as part of a decision-making system that involves both technical and socio-organizational dimensions.

Decision-making is a fundamental organizational process because it determines resource allocation, strategy selection, operational control, responses to environmental change, and the achievement of goals. In a dynamic business environment, decisions are often made under uncertainty, time constraints, and incomplete information. BDA can reduce part of this uncertainty through descriptive, diagnostic, predictive, and prescriptive analysis.

Descriptive analysis helps explain what has happened; diagnostic analysis explores causes; predictive analysis estimates likely future conditions; and prescriptive analysis helps evaluate alternative actions. Although these categories are interrelated, their contribution to a decision depends on the type of problem, the quality of the data, and users' ability to understand the results.

A number of studies have addressed the relationship between BDA and the quality of decision-making and organizational performance. Li et al., for example, specifically examine the impact of BDA use on organizational decision quality [3], while Chatterjee et al. link BDA to decision-making processes, forecasting, and firm performance [4]. Di Berardino and Vona [5] and Torre et al. [6] offer literature reviews of the relationship among big data, analytics, and decision-making. Recent reviews continue to map this growing field, including work on big data decision-making capabilities [7], the influence of BDA on business decision-making within management information systems [8], the integration of BDA and business intelligence in organizational decision-making [9], and the use of big data to support decision-making for sustainable development [10]. This body of work shows that the link between analytics and decisions is an expanding area of research, yet one that still needs to be synthesized with perspectives on organizational capabilities, value creation, managerial change, and the risks of using imperfect information.

Another important issue is that the success of BDA cannot be explained through the use of technology alone. Gupta and George discuss the development of BDA capability as a combination of resources and competencies that an organization must build [11]. Mikalef et al. examine the role of dynamic and operational capabilities in the relationship between BDA capability and competitive performance [12], and Wamba et al. likewise treat dynamic capabilities as a relevant factor in explaining the link between BDA and firm performance [13]. These perspectives suggest that analytics creates value when an organization can convert analytical results into process change, strategic response, and action suited to environmental conditions.

At the same time, the use of BDA faces challenges related to data quality, system integration, analytical competence, interpretation of results, privacy, security, and governance. Sivarajah et al. highlight the diverse challenges of big data and the analytical methods used to address them [2]. Günther et al. emphasize that realizing value from big data is a broader matter than technology adoption, because it involves how organizations understand and use data [14]. In the health sector, Orlu et al. examine the sustainability of decision-making when the available information is imperfect [15]. This shows that an increase in analytical capacity does not remove the need for professional judgment, risk control, and contextual consideration.

Furthermore, the use of BDA can affect business models, work structures, and relationships among organizational units. Acciarini et al. review how organizations can leverage big data to innovate their business models [16], while Sahut et al. synthesize the impact of big data on decision-making, processes, and organizational change [17]. These perspectives broaden the understanding that BDA is not merely an instrument to support existing decisions but can also drive changes in how an organization creates value, organizes processes, and interacts with its environment.

Although the literature on BDA, firm performance, and decision-making has grown, a synthesizing framework is still needed to explain how analytical resources are translated into decision quality, how those decisions are followed through, and the conditions that determine their success or failure. A review that treats performance as the sole end outcome risks overlooking the mechanisms between analytics use and organizational attainment. Conversely, a review focused only on technology may neglect interpretive ability, the culture of decision-making, and the implementation process.

In light of these problems, this article aims to (1) synthesize the literature on the role of BDA in organizational decision-making; (2) identify the dimensions of capability and organizational conditions that influence the use of analytical results; (3) explain the conceptual relationships among BDA, decision quality, organizational capabilities, and performance; and (4) formulate an agenda for future research. Its main contribution is a thematic synthesis that connects technology, information, people, the decision process, and organizational value creation within a single conceptual framework.

2. Method

Research Design

This article uses a structured literature review with a conceptual-synthesis orientation. This approach was chosen to integrate research that addresses BDA in decision-making, analytical capability, organizational performance, and managerial change. A literature review allows the identification of major themes, the comparison of theoretical perspectives, and the formulation of relationships among concepts that can be developed in subsequent research.

The study uses the provided reference list as its initial corpus. The references include systematic reviews, structured literature reviews, bibliometric analyses, empirical studies using quantitative or mixed methods, and conceptual-synthesis articles. This diversity of publication types makes it possible to discuss BDA from the level of technology through to its organizational consequences. However, because the study was compiled from a

provided reference list without independent documentation of database searching, it does not claim to be a systematic literature review that meets all the requirements of PRISMA or other systematic protocols.

Scope of the Literature

The scope of the literature is directed at five main themes. The first is the concept and development of BDA within the context of business intelligence and information systems. The second is the effect of BDA use on decision quality, forecasting, and the decision-making process. The third is the organizational capabilities that support the conversion of analytics into value, including operational and dynamic capabilities. The fourth is the relationship of BDA to firm performance, business-model innovation, and organizational change. The fifth concerns implementation challenges, including data quality, information limitations, analytical methods, and governance needs.

References addressing organizations in general are used to build a cross-context synthesis. Research focused on particular sectors—such as healthcare [15], [18] or public policy [19]—is used as a contextual perspective to show that the use of BDA can be shaped by the characteristics of the decision, the level of risk, and institutional conditions.

Analytical Procedure

The synthesis was carried out through a thematic reading of the research focus reflected in the titles and bibliographic information provided. References were then grouped by their substantive theme—BDA capability, decision quality, organizational capability, performance and innovation, and challenges and governance. These themes were used to develop a comparative narrative connecting research questions, core concepts, and managerial implications.

The next stage was conceptual synthesis. Here, the relationship between BDA and performance was not treated as automatic but was analyzed through intermediate mechanisms—information quality, interpretation of results, decision quality, and implementation capacity. This approach allowed the article to build a framework explaining how analytics can deliver benefits and why the results obtained can differ across organizations.

Because no database searching, exhaustive full-text examination, recording of the number of articles found and excluded, or formal appraisal of study quality was undertaken, the findings should be understood as a preliminary conceptual synthesis. Should the manuscript be submitted as a systematic literature review, the search procedure, inclusion–exclusion criteria, deduplication process, eligibility assessment, and record of the selection outcome would need to be added on the basis of a search actually conducted.

3. Results

The Development of BDA as Decision Support

The literature shows that BDA has evolved from the use of data for reporting and monitoring toward more complex analytics that support prediction, the evaluation of alternatives, and strategic decisions. Chen et al. situate business intelligence and analytics within a trajectory that connects data to business impact [1]. Through a bibliometric analysis of BDA applications in information management, Ardito et al. draw attention to the relationship among analytics use, operational efficiency, and decision-making [20]. Batistič and van der Laken likewise map the evolution of big data and analytics research and its relationship to organizational performance [21].

This development shows that the value of BDA is not limited to producing faster reports. Analytics can help an organization detect shifts in demand, monitor processes, identify anomalies, estimate risk, and formulate alternative actions. However, the more complex the analytical output, the greater the need for organizational ability to understand the assumptions, limitations, and relevance of those results for a particular decision.

Di Berardino and Vona [5] and Torre et al. [6] make the relationship among big data, BDA, and decision-making the focus of their literature reviews. Both are useful for recognizing that this field studies not only analytical technology but also how the information produced relates to the decision process. In this synthesis, the development of BDA is understood as a shift from an orientation toward data collection to an orientation toward using insight to support organizational action.

BDA and the Quality of Decision-Making

One central theme in the literature is BDA's contribution to decision quality. Li et al. specifically examine the impact of BDA use on the quality of organizational decision-making [3]. This focus treats decision quality as an outcome distinct from the mere intensity of technology use. An organization may use analytical systems extensively, yet the benefit still depends on whether the results are relevant, accurate, timely, and suited to the problem at hand.

Chatterjee et al. link BDA to decision-making processes, forecasting, and firm performance [4]. In that context, analytical capability can support decisions by broadening the information base used and helping an organization assess likely future conditions. Nonetheless, decision quality also depends on how managers interpret the results, set priorities, and weigh the consequences of alternative actions.

Conceptually, decision quality can be understood through several dimensions. The first is the appropriateness of the decision to the problem faced. The second is timeliness—the ability to produce a decision while the information is still relevant. The third is the consistency and transparency of the basis for judgment. The fourth is the ability to weigh risk and uncertainty. The fifth is the fit of the decision with organizational goals and constraints. These dimensions form an analytical framework used in this article, not a claim that every study reviewed uses the same measures.

BDA can strengthen these dimensions by processing broader data and recognizing patterns difficult to identify manually. Even so, analytical results do not always remove bias or uncertainty. Unrepresentative data, ill-suited indicators, imprecise models, or mistaken interpretation can produce misleading recommendations. The use of BDA therefore needs to be accompanied by an evaluation of data quality, analytical assumptions, and the relevance of the results to the decision context.

BDA Capability as an Organizational Resource

The literature indicates that the use of BDA should be understood as an organizational capability rather than merely a technology investment. Gupta and George develop a BDA-capability perspective that stresses the importance of a combination of resources enabling an organization to carry out analytics [11]. This approach helps explain why organizations with relatively similar access to technology can obtain different benefits.

Conceptually, BDA capability encompasses the availability of infrastructure and data, technical expertise, analytical ability, business knowledge, and coordination mechanisms that allow analytical results to be used in work processes. These elements are complementary. Adequate infrastructure will not deliver optimal value if an organization lacks the competence to design analyses or has no mechanism to apply the results. Conversely, professional ability can be hampered when data are fragmented, systems are not integrated, or access to information is inadequate.

Mikalef et al. discuss the relationship between BDA and firm performance through a mixed-method approach [22], while Mikalef et al. explore the relationship between BDA capability and competitive performance via the roles of dynamic and operational capabilities [12]. Wamba et al. likewise emphasize the relevance of dynamic capabilities in the relationship between BDA and firm performance [13]. Taken together, these studies provide a basis for viewing analytical capability as a resource whose value depends on an organization's ability to integrate, develop, and use it. Related evidence from healthcare further frames BDA as a capability whose benefits must be actively realized [18].

BDA capability therefore explains not only an organization's ability to generate analytical information but also its ability to make that information part of managerial processes. This conversion requires coordination among information technology units, analysts, and decision-makers so that analytical results do not stop at a technical report.

The Relationship Among BDA, Organizational Capabilities, and Performance

Organizational performance is an important theme in BDA research, but the relationship between analytics and performance cannot be treated as invariably direct. Maroufkhani et al. present a systematic review of BDA and firm performance [23]. Mikalef et al. [22] and Müller et al. [24] also examine the analytics–performance relationship, with attention to empirical approaches and industry characteristics. This literature underscores the importance of examining the conditions under which analytics use yields organizational benefits.

One relevant mechanism is the enhancement of operational capability. Analytics can help an organization identify process bottlenecks, optimize resource use, improve forecasting, and strengthen coordination. Another mechanism is dynamic capability—the ability to read environmental change, identify opportunities, and reconfigure resources and processes. In this framing, BDA provides information that can help an organization understand change, while organizational capability determines whether that insight can be turned into appropriate action [12], [13].

Grover et al. offer a research framework on creating strategic value from BDA [25]. This perspective is relevant because the benefits of analytics can be measured not only through efficiency but also through the ability to support innovation, strategic change, and business-model development. Acciarini et al. specifically review how organizations leverage big data for business-model innovation [16]. The outcomes of BDA can thus take varied forms, from improvements in routine decisions to more fundamental strategic change.

Müller et al. treat industry characteristics as a consideration in analyzing the relationship among big data, analytics, and firm performance [24]. This indicates that the benefits of BDA must be interpreted in light of the organizational environment. Organizations operating with structured data and repeated decisions may obtain benefits different from those facing high-risk decisions, strict regulation, or an intensive need for professional interpretation.

Business-Model Innovation and Organizational Change

The use of BDA can drive change that extends beyond improving individual decisions. Acciarini et al. examine the role of big data in business-model innovation [16], while Sahut et al. synthesize the impact of big data on decision-making, processes, and organizational change [17]. Both perspectives affirm the relevance of BDA to changes in how an organization creates and delivers value.

At the operational level, analytics can support workflow improvement, performance monitoring, and resource allocation. At the tactical level, BDA can help develop forecasts, set priorities, and evaluate internal policies. At the strategic level, data-driven insight can support the recognition of market opportunities, the adjustment of value propositions, and the development of products or services. These differences in decision level show that the value of BDA must be assessed by the fit between analytical capability and the purpose of its use.

Organizational change also requires adjustments to work culture and the distribution of authority. An organization seeking to use analytics effectively needs to build practices that allow data-based results to be considered critically without disregarding professional experience and contextual knowledge. Günther et al. frame the realization of value from big data as a matter involving a range of organizational considerations [14]. The implementation of BDA may therefore require changes in work processes, patterns of coordination, and the way decisions are accounted for.

Challenges in Implementing BDA

Despite its considerable potential, the implementation of BDA faces a number of challenges. Sivarajah et al. critically discuss the challenges of big data and its analytical methods [2]. One fundamental issue is data quality. Data that are incomplete, inconsistent, delayed, or unrepresentative of the relevant conditions can reduce the accuracy of analytical results. Using large volumes of data does not automatically improve decision quality if those data contain errors or do not fit the analytical question.

A further challenge is the integration of data and systems. Organizations often use different information systems for operational, financial, marketing, human-resource, and customer-service functions. If data cannot be integrated adequately, the analysis risks producing a partial picture. In addition, technical ability needs to be matched by business competence so that analytical models address the questions genuinely relevant to the organization.

The human dimension also shapes implementation outcomes. Decision-makers need to understand the meaning, assumptions, limitations, and uncertainty of analytical results. Without that understanding, model recommendations may be accepted uncritically or ignored despite their relevance. Conversely, excessive reliance on intuition can also diminish the benefit of analytics when available evidence is not adequately considered. The use of BDA therefore requires a balance among quantitative evidence, contextual knowledge, and professional judgment.

In the health sector, Orlu et al. highlight the challenge of sustaining decision-making when information is imperfect in the big data era [15]. This context shows that data issues are not only technical but also bound up with decision risk and its consequences for stakeholders. In high-risk organizations, analytics-based decisions require mechanisms for validation, oversight, and clear accountability.

Other challenges include privacy, security, regulatory compliance, and the potential for analytical bias. Although these aspects are not always the primary focus of every study listed, they are important implications of using data in organizational processes. Governance of BDA therefore needs to regulate data access, management responsibilities, information protection, model validation, and the monitoring of decision outcomes.

Thematic Synthesis of the Literature

Based on the groups of literature reviewed, the conceptual synthesis can be presented in the five main themes shown in Table 1.

Table 1. Thematic Synthesis of the Literature on BDA in Organizational Decision-Making

Theme	Main focus	Conceptual implication
BDA capability	Infrastructure, data, expertise, and analytical skills	Provides the foundation for turning data into insight
Decision quality	Relevance, timeliness, evaluation of alternatives, and management of uncertainty	Serves as a key mechanism linking analytics to action
Organizational capability	Process integration, operational capabilities, and dynamic capabilities	Determine the ability to apply insight and respond to change
Performance and innovation	Efficiency, competitive performance, business-model innovation, and value creation	Represent outcomes that can emerge through different mechanisms and conditions
Challenges and governance	Data quality, competence, system integration, risk, privacy, and accountability	Determine the reliability, acceptability, and sustainability of BDA use

Note. Source: Authors' conceptual synthesis based on the reviewed literature.

The synthesis shows that the relationship between BDA and organizational performance is layered. Analytical capability is the foundation, decision quality is one of the intermediate mechanisms, and an organization's implementation capacity helps determine whether decisions produce the expected change. Data quality, user competence, industry characteristics, and governance can act as conditions that strengthen or constrain this relationship.

4. Discussion

BDA as an Integrated Decision-Support System

The synthesis indicates that BDA is best understood as an integrated decision-support system rather than a stand-alone technology. Chen et al.'s view of the evolution of business intelligence and analytics helps explain the shift from data processing toward the creation of business impact [1]. Creating that impact, however, requires integration among data sources, analytical methods, human interpretation, and organizational action.

In practice, an analytical system can produce predictions or recommendations, but the final decision still requires judgment about goals, resources, risks, and likely consequences. The success of BDA therefore cannot be measured by the volume of data processed, system speed, or the number of reports produced. A more substantive measure considers whether analytical information is used, whether it improves the quality of judgment, and whether the resulting decisions produce relevant change.

This perspective broadens the understanding of decision quality that is the focus of Li et al. [3] and Chatterjee et al. [4]. Decision quality is shaped not only by the technical capability of a model but also by the fit of the analytical question to the organizational problem, users' ability to understand the results, and the decision process employed. In other words, BDA offers the potential to improve decision quality, but realizing that potential depends on the design and use of the system as a whole.

Mechanisms for Converting Analytics into Organizational Value

One important implication of this synthesis is the need to distinguish among analytical capability, decision quality, decision implementation, and performance. The four are related but not identical. Analytical capability describes an organization's ability to process and analyze data. Decision quality concerns the soundness of the process and the choices produced. Decision implementation refers to the ability to turn choices into action. Performance, meanwhile, reflects broader consequences such as efficiency, productivity, or competitiveness.

This distinction aligns with the literature's attention to BDA capability and firm performance [13], [22], [23]. If research measures only BDA capability and performance, the mechanism linking the two may not be clearly identified. Including decision quality and implementation as intermediate mechanisms, by contrast, allows researchers to explain why similar capabilities can produce different results.

Conceptually, the value-creation process can be formulated as follows: BDA resources and capabilities enable data to be processed into insight; relevant insight can improve the decision process; sound decisions must be implemented through operational and dynamic capabilities; and that implementation can produce organizational benefits. This sequence is not a causal model tested in the present article but a synthesizing proposition that can serve as a basis for empirical research.

Dynamic Capabilities and Organizational Context

Dynamic capability is an important perspective for understanding how BDA contributes to an organization's ability to adapt. Mikalef et al. examine the role of dynamic and operational capabilities in the relationship between BDA capability and competitive performance [12]. Wamba et al. likewise treat dynamic capabilities as a relevant element in the relationship between BDA and firm performance [13].

From this perspective, data and analytics help an organization recognize patterns of change, but the organization still needs the ability to interpret signals, determine responses, and reallocate resources. Analytics may detect a shift in demand, for example, but the benefit is realized only when the organization can adjust inventory, production capacity, services, or marketing strategy. Analytical capability and organizational capability must therefore be seen as complementary.

Industry context also needs to be taken into account. Müller et al. show the relevance of industry characteristics in studying the relationship among big data, analytics, and performance [24]. An organization facing routine decisions with structured data may need different mechanisms from one managing strategic decisions under high risk or substantial uncertainty. This difference suggests that future research should avoid assuming that models of BDA use apply uniformly across sectors.

Organizational Change and a Data-Driven Culture

BDA can change how an organization allocates attention, sets priorities, and accounts for decisions. Moving toward a data-driven culture, however, requires more than technology investment. An organization also needs to develop the ability to question the quality of evidence, understand uncertainty, and combine analytical results with professional knowledge.

Günther et al. frame the realization of value from big data as a matter requiring attention beyond the technical [14]. Acciarini et al. broaden this discussion by linking big data use to business-model innovation [16], while Sahut et al. highlight the relationship of big data to decision-making processes and organizational change [17]. This literature supports the view that implementing BDA can be part of an organizational transformation rather than merely a modernization of analytical tools.

A data-driven culture should also not be taken to mean uncritical acceptance of algorithmic output. An analytically mature organization needs mechanisms to evaluate model assumptions, test the consistency of results, and consider the impact of decisions on stakeholders. Effective decision-making is the product of interaction among evidence, competence, contextual judgment, and accountability.

Practical Implications for Organizations

For practitioners, this synthesis suggests that BDA investment is best begun with the identification of the decision problem to be improved. An organization needs to determine whether its primary need is to improve forecasting accuracy, speed operational response, identify risk, or support strategic innovation. A clear objective helps determine the relevant data, analytical methods, and measures of success.

The next step is to build data quality and governance. Data need consistent definitions, traceable sources, and adequate maintenance procedures. An organization also needs to determine who is responsible for access, validation, security, and use of data. Without this foundation, the sophistication of an analytical model can produce confidence out of proportion to the quality of the underlying evidence.

Developing competence is another important step. Analysts need to understand the business context, while managers need data literacy to interpret results critically. Cross-functional collaboration helps ensure that analysis addresses relevant problems and that recommendations can be applied. In addition, evaluating success should measure not only technical output but also the use of insight, changes in decision quality, the implementation of recommendations, and organizational outcomes.

Finally, an organization needs to match its use of BDA to the level of decision risk. High-risk decisions, or those with a direct impact on individuals, require stronger validation, oversight, and accountability. The use of analytics should be accompanied by explanation of the limitations of the data and model, correction mechanisms, and human involvement where the decision context calls for professional judgment.

Agenda for Future Research

The literature synthesis points to several lines of research that can be developed. First, testing the mechanisms of the relationship between BDA and decision quality. Future research should examine how BDA capability influences decision quality and whether information quality, data literacy, trust in analytics, or system integration act as mediators or moderators. Such testing can clarify the mechanisms linking analytics use to decision outcomes, moving beyond the measurement of a direct relationship between technology and performance.

Second, integrating the perspectives of dynamic capabilities and the decision-making process. Research could explore how organizations turn analytical insight into responses to market change, supply-chain disruption, and customer needs. This would extend the discussion by Mikalef et al. [12] and Wamba et al. [13] by examining the organizational processes that explain when BDA capability genuinely produces competitive advantage.

Third, comparison across sectors and organization sizes. The characteristics of data, regulation, resources, and risk differ across industries. Comparative research could assess whether the determinants of BDA success in large organizations also hold for small and medium-sized enterprises, public bodies, health organizations, and manufacturing. Research could also test how digital maturity shapes the relationship among BDA, decision quality, and performance.

Fourth, governance, ethics, and analytical accountability. Future research should examine how data quality, privacy, algorithmic bias, transparency, and oversight mechanisms affect trust in analytics-based decisions. This focus is especially important when analytical results are used for decisions with significant consequences for customers, employees, patients, or the public.

Fifth, the interaction between people and analytical systems. There is a need to study how managers interpret algorithmic recommendations, when they follow or reject them, and how professional experience shapes decision quality. Qualitative approaches, experiments, and longitudinal studies can help reveal processes not easily captured by survey measurement alone.

Sixth, measuring the benefits of BDA over the long term. Research could develop indicators that distinguish technical output, decision quality, process change, and organizational performance. Longitudinal studies are needed to assess whether initial benefits persist, how implementation costs evolve, and whether the use of BDA produces sustained changes in capability.

Seventh, the relationship of BDA to business-model innovation and organizational transformation. Drawing on Acciarini et al. [16] and Grover et al. [25], research could examine how analytical insight changes value propositions, customer relationships, revenue structures, or patterns of coordination among partners. This focus helps broaden the measure of BDA's benefits from operational efficiency toward strategic value creation.

These agendas can be summarized in a single research direction: developing a more contextual explanation of how, through what mechanisms, and under what conditions BDA improves decision quality and creates organizational value.

5. Conclusion

This article synthesizes the literature on the use of Big Data Analytics in organizational decision-making by treating analytical capability, decision quality, organizational capability, performance, and governance as interrelated themes. The synthesis shows that BDA offers organizations the opportunity to turn data into insight, strengthen forecasting, evaluate alternative actions, and respond to environmental change in a more informed way. These benefits, however, do not occur automatically simply because an organization adopts analytical technology. BDA's contribution to decisions depends on data quality, analytical ability, user competence, the fit of results to the problem context, and an organization's ability to integrate insight into work processes. Decision quality becomes an important mechanism linking analytical capability to action, while operational and dynamic capabilities help determine whether that action produces organizational benefit. The relationship between BDA and performance is therefore best understood as a multi-stage process rather than a direct link that applies uniformly.

Theoretically, this article offers a synthesis connecting BDA resources, decision quality, implementation, and value creation. Practically, organizations are advised to begin implementation from a clear decision need, to strengthen data quality and governance, to develop analytical literacy, and to evaluate benefits in terms of changes in decisions and organizational outcomes. The use of BDA should also be accompanied by validation, oversight, and ethical consideration, particularly in high-risk decisions.

The agenda for future research includes testing the causal mechanisms between BDA capability and decision quality, integrating the dynamic-capabilities perspective, conducting cross-sector studies, examining analytical governance and ethics, studying human interaction with systems, measuring long-term benefits, and assessing BDA's contribution to business-model innovation. Empirical research using longitudinal designs, mixed methods, and cross-context comparison can deepen understanding of the conditions under which BDA delivers sustained benefits.

This study is limited in that the synthesis was developed from a provided reference list and does not yet include an independently documented process of database searching and study selection. Its results should therefore be treated as a preliminary structured literature review. For publication requiring a systematic literature review, further work should complete the search protocol, inclusion–exclusion criteria, selection process, study-quality appraisal, and documentation of the synthesis based on full texts.

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Data Availability. This study is a literature-based review. The sources used in the conceptual synthesis are listed in the reference section, together with their corresponding bibliographic information and DOI links.

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