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Article

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The interplay between business analytics capabilities and decision-making performance in Indonesia's public sector

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ABSTRACT

This study investigates the relationships between data-driven culture, business analytics capability, and decision-making performance, with a focus on the mediating effects of data literacy skills and knowledge management. Additionally, it examines the moderating effects of social capital and perceived uniqueness. A quantitative approach using structural equation modeling (SEM) was utilized to analyze data collected from 330 experienced executives and managers in administrative and supervisory roles within public sector organizations. The results revealed that data literacy skills and knowledge management mediate the relationship between data-driven culture and business analytics capability. Furthermore, the study identifies perceived uniqueness as having a moderating effect on social capital's relationship with business analytics capability and decision-making performance. These findings contribute to addressing a critical gap in the literature by empirically confirming the moderating role of perceived uniqueness in business analytics capability and decision-making performance. The findings offer both theoretical and practical implications with recommendations for future research.

1. Introduction

In today's era of digital transformation, data offers many benefits and potentials, making it a valuable asset for organizations and presenting great opportunities for value creation (Fattah, 2024a; Medeiros & Maçada, 2022; Oesterreich et al., 2022). To harness this potential, organizations recognize the value of data and the importance of making informed decisions, which rely on the availability of relevant, timely data and information. However, to support the decision-making process, this data must be carefully managed, processed, and analyzed (Abdellatif et al., 2024; Ahmed et al., 2022). Business analytics (BA) is critical in this process, serving as a key indicator of successful data-driven decision-making. It enables organizations to make strategic, operational, and tactical decisions more effectively by providing insights and supporting decision-making at all levels (Chatterjee et al., 2024; Chaudhuri et al., 2024; Fattah, 2024b; Shi et al., 2024). Therefore, understanding the value of data and using it effectively is key to success in today's data-driven business environment.

New Vantage Partners (2023) conducted *Big Data and AI Executive Survey*, revealing the development of data analytics in multinational companies. The findings indicate that nearly all (79.8 %) of these companies recognize culture, people, and business processes as key

obstacles to the successful implementation of BA. Although the study did not explore specific challenges related to business processes in data analytics implementation, these findings provide an early indication that leading corporations in the world continue to face classic problems. Therefore, implementing data analytics on a large scale without adequately addressing factors such as people, business processes, and culture may lead to inefficiency and failure.

While the development of analytics has become prominent in the private sector, the public sector has also started to embrace data analytics to gain insights and enhance decision-making processes (Barbala et al., 2024; Fattah, 2024a; Polzer & Li, 2022; Talib et al., 2024). For the public sector, such as the government, effective use of data is hoped to provide benefits in improving and creating the quality of public services, supporting the right decision-making, and providing a better understanding of citizens' needs (Fattah, 2024b; Lega et al., 2024). This growing adoption underscores the critical role of effective data management and analysis in improving the efficiency and effectiveness of public sector operations.

According to the 2024 United Nations *E-Government Report*, prepared by the United Nations Department of Economic and Social Affairs, Indonesia achieved an e-Government Development Index (EGDI) score of 0.7991, placing it in the Very High e-Government Development Index

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(VHEGDI) category (United Nations, 2024). This score reflects a significant improvement in government capabilities related to digital modernization initiatives, aimed at enhancing the quality, efficiency, and accessibility of public services. This progress positions Indonesia as a regional leader in digital transformation, reinforcing the broader trend of digital advancement across Asia. As digital transformation accelerates, the volume of data generated continues to expand. In the digital era, data is now regarded as a resource as valuable as natural commodities like minerals, requiring proper processing and analysis to extract meaningful business insights (Fattah, 2024b).

Several government agencies in Indonesia have utilized data to improve critical incident management and responses to natural disasters such as drought, epidemics, and large-scale accidents. Additionally, data analytics has been applied to areas such as preventing money laundering and fraud, mitigating cyber threats, monitoring the workforce, and analyzing mass and social media to capture public sentiment (Kominfo, 2022). Ideally, greater data availability will encourage better policy formulation and decision-making. From the perspectives of affordability and digital actualization, big data (BD) analytics projects can be developed (Fattah, 2024b; Malik et al., 2024) and applied to various high-impact applications such as e-government (Di Vaio et al., 2022). In Indonesia, 85 % of government institutions report readiness for data analytics adoption. However, several challenges remain, particularly concerning data quality, skills, knowledge, technology infrastructure, information systems, analytics teams, organizational culture, collaboration, and management support (Sulistyowati et al., 2021).

Recognizing the importance of BA, the public sector must manage it as this capability to facilitate digital transformation (Davidson et al., 2023; Malik et al., 2024; Shipilov & Gawer, 2020). In the context of BA, organizations need to interpret data and extract a wealth of business information to answer questions and gain insights into business performance (Abdellatif et al., 2024; Fattah, 2024b; Yalcin et al., 2022). This approach utilizes statistical models, algorithms, and other analytical techniques to analyze data and uncover hidden patterns, correlations, trends, and insights (Fattah, 2024b). These processes can impact the decision-making performance (DMP) of organizations (Abdellatif et al., 2024; Chatterjee et al., 2023; Fattah, 2024b) and ultimately drive their success (Chatterjee et al., 2024). However, this understanding is not easy due to the highly unstructured nature of data, which may require multiple mechanisms to capture value from a variety of structured and unstructured data. It also requires certain efforts and capabilities within the organization to ensure the quality of the resulting decisions (Ahmed et al., 2022; Fattah, 2024b).

Creating business value from BD is a complex and dynamic process involving socio-technical factors and multidimensional and hierarchical value-creation mechanisms (Dremel et al., 2020; Farouk et al., 2025; Malik et al., 2024; Oesterreich et al., 2022). From a technical perspective, BD analytics encompasses advanced techniques with different levels of intelligence, including descriptive, predictive, and prescriptive analytics, each contributing to varying levels of organizational performance (Chatterjee et al., 2023; Fattah, 2024b). Beyond its technical aspects, BD analytics is considered a socio-technical concept that requires the integration of social factors such as organizational culture, individual expertise, knowledge, governance, collaboration, access, and supportive management practices to maximize its effectiveness (Oesterreich et al., 2022). Social capital (SC) is a non-generic complementarity (Malik et al., 2024), which is used to mobilize appropriate resources and knowledge and facilitate collaboration among various organizational stakeholders to enhance BD analytics capabilities. Specifically, BD analytics capabilities are conceptualized as socio-technical artifacts consisting of technologies and technical tasks to generate BD (Farouk et al., 2025; Oesterreich et al., 2022).

Maximizing BA requires addressing resource dependency challenges, including access to BD, control over data platforms, and collaboration among data providers. These dependencies create barriers to developing a robust BA framework. Additionally, SC—the collaboration and

relationships among individuals involved in data collection, processing, analysis, and decision-making—can be leveraged to mitigate these challenges. Integrating SC with BA offers analytical solutions from both technological and skills perspectives. This integration requires deeper collaboration across cross-functional teams, including business, process, and other users—not just technology teams. These teams must align their thinking, language, terminology, and concepts to ensure effective communication and data analysis. Since BA challenges extend beyond typical technology issues, they require a holistic approach that incorporates people, processes, and cultures to drive success (Hagen & Hess, 2021; Heubeck et al., 2024; Malik et al., 2024). By addressing these factors, organizations can enable data-driven decision-making, leading to more effective and informed business strategies.

By leveraging all available data and information, organizations can make more timely and informed decisions (Fattah, 2024b; Shi et al., 2024). The benefits of this approach include greater efficiency, the creation of new opportunities, and increased productivity and performance (Griffin & Holcomb, 2023a; Merhi & Bregu, 2020). However, these potential benefits can only be fully realized if the ability to leverage data is embedded in the organizational culture (Fattah, 2024a). Despite the growing interest in fostering a data-driven culture (DDC), the literature has not clearly distinguished between public and private sector organizations, which require different approaches to implementing data-driven strategies. Prior research highlighted that public sector organizations fundamentally differ from private sector organizations in terms of access to resources, objectives, and economic and political constraints (Barbala et al., 2024). Furthermore, data-driven initiatives within the public sector often face greater complexity and unique challenges than those in the private sector, making their implementation more difficult.

Several studies have demonstrated the power of using data in generating actionable insights that foster DDC (Almazmomi et al., 2022; Barbala et al., 2024; Fattah, 2024a; Karaboga et al., 2023; Wamba et al., 2024). DDC can determine the success or failure of strategic initiatives such as BA, as DDC underpins an organization's ability to execute strategic plans effectively (Griffin & Holcomb, 2023a). Additionally, a strong DDC enables organizations to implement top-down strategic DDC across a broad set of data-driven principles, leading to better decision-making and greater innovation (Barbala et al., 2024; Fattah, 2024a; Oliver et al., 2024). However, while DDC is important, its effectiveness depends on balancing the usage and data flow perspectives to facilitate effective analysis. This includes processing, exploring, and interpreting BD to extract information, which involves employing data literacy skills (DLS). DLS is an essential component of data analysis and analytical behavior, which enables individuals to identify, understand, use, reflect, and communicate data to obtain quality data (Abuzaid, 2024; Banasiewicz, 2023; Gartner, 2022; Griffin & Holcomb, 2023b). It encompasses the processes, methods, interpretations, and analytical techniques necessary to interpret BD, derive insights that promote strategic initiatives, and capitalize on innovative opportunities with data (Fattah, 2024b; Griffin & Holcomb, 2023b; Tamm et al., 2022).

Beyond its core analytical capabilities, BA not only uncovers hidden data patterns but also offers significant opportunities for knowledge management (KM). Individual knowledge and experience play a critical role in determining where to collect data, which algorithms to employ for analysis, and how to apply the insights across operational, tactical, or strategic areas (Goswami et al., 2024; Thakral et al., 2024). KM refers to an organization's ability to acquire, share, create, store, and effectively utilize knowledge to drive strategic decision-making (Goswami et al., 2024). By integrating KM with BA, organizations can enhance knowledge creation and capture, conduct ethical data analysis, and manage data responsibly, ultimately leading to greater value creation (Goswami et al., 2024; Makhouloufi et al., 2023; Rehman et al., 2024; Schaefer & Makatsaria, 2021).

While numerous studies have theoretically explored BA outcomes at the organizational level, recent research emphasizes the need for more

empirical evidence on its practical implications and benefits. A recent study in the public sector by [Talib et al. \(2024\)](#) identified BD management capabilities as a crucial factor in achieving optimal DMP. Effective data-driven decision-making extends beyond management practices (e.g., infrastructure, personnel) and necessitates a series of BD activities, including data collection, preparation, analysis, and decision execution ([Fattah, 2024b](#); [Shamim et al., 2020](#)). Each stage requires different resources and managerial capabilities. This research assumes resources are arranged and used effectively to achieve the desired performance results. However, the integration of resources across different stages of BD activities and the promotion of organizational innovation through BA solutions are often overlooked ([Mikalef et al., 2020](#); [Shamim et al., 2020](#); [Yoshikuni et al., 2023](#)). The instrumental role of resources in BA business value remains a subject of ongoing discussion in management literature ([Mikalef et al., 2020](#)). This issue requires further development and presentation in the literature, highlighting potential areas for impactful research. For both practitioners and academics, BD analytics continues to gain research attention due to the complexity and impact of data-related problems in decision-making processes within business organizations, especially the public sector ([Di Vaio et al., 2022](#)). Accordingly, this study explores how BA enhances DMP by leveraging BD within the Indonesian public sector, addressing these critical research gaps. To establish this perspective, this research aims to empirically explore and validate the relationships among culture, skills, knowledge, analytics, social networks, and performance. Specifically, the study seeks to address the following research questions (RQs) to deepen the understanding of these interactions.

RQ1. How do DDC, DLS, and KM influence BAC directly and indirectly, with DLS and KM acting as mediators?

RQ2. How does BAC affect DMP considering the moderating effect of SC?

This study draws inspiration from the dynamic capabilities view (DCV) and social capital theory (SCT) to establish links between DDC, DLS, KM, and SC with business analytics capability (BAC) and DMP. These theoretical perspectives serve as critical lenses for exploring these interactions. The research follows a structured approach, beginning with a discussion of data utilization in the public sector, data infrastructure, data governance, and the regulatory environment, followed by theoretical foundations, conceptual definitions, and research model development. It then presents the research methods, data analysis, results and discussions, conclusions, and implications.

2. Literature review and hypotheses development

2.1. An empirical study on big data utilization in the public sector

The term BD was first used by [Mashey \(1999\)](#), referring to the handling and analysis of very large datasets. Furthermore, this term was further strengthened in the early 2000s by [Laney \(2001\)](#), which became the basis for the development of technology and applications that handle BD to date. BD is defined as a concept that refers to very large, complex, and continuously growing dynamic data sets that are difficult to handle with traditional computing methods and tools ([Gupta & George, 2016](#); [Klievink et al., 2017](#)). This concept focuses on how such data is organized, accessed, and used to generate business insights and better decision-making. In addition, the term BD is often used to describe massive, complex, and real-time streaming data that requires sophisticated management, analytical, and processing techniques to extract insights ([Fattah, 2024b](#); [Gupta & George, 2016](#)).

In the literature and discussions about BD, there are five basic characteristics known as the “5Vs”, namely: (1) Volume: refers to the amount, size, and scale of data. In the future, as the amount and size of data and the number of different application domains increase, these systems will need to adapt to optimize the use of specific analysis tools. Larger data volumes provide the opportunity to discover more complex and deeper relationships; (2) Velocity: refers to the speed at which data is generated and how quickly it needs to be processed. Data needs to

flow quickly and as close to real-time as possible, which allows organizations to be more agile and responsive in the decision-making process; (3) Variety: refers to data heterogeneity, including type, format, semantics, and volume. This means that data can be sourced from various relevant entities within the business ecosystem which requires different approaches in processing and analysis to gain more comprehensive and innovative insights; (4) Veracity: refers to the accuracy and quality of the data used. This relates to bias, noise, and anomalies in the data. The reliability of any analysis process is highly dependent on the truthfulness of the source data and carries a certain level of confidence; and (5) Value: refers to the benefits that can be obtained from data analysis. This is the ultimate goal of BD analysis—producing useful insights for organizations or businesses to support better decision-making, improve efficiency, and even create new business models, products, and services.

According to [Klievink et al. \(2017\)](#), qualifying the use of data in the public sector as the use of BD is based on several distinguishing characteristics. These include the use of multiple large datasets from various sources, both external and internal to the organization, the combination of structured (traditional) and less structured or unstructured (nontraditional) data in analytical activities, the use of incoming data streams in real-time, the development and application of advanced analytics and algorithms, distributed computing, and the innovative use of existing datasets and/or data sources. Furthermore, BD activities encompass processes such as data collection, integration, analysis, and utilization, with applications evaluated based on the added value they generate, such as decision-support information, new insights, or an enriched understanding of reality.

In public sector applications, BD represents a revolutionary tool for unlocking potential benefits. It enables more effective decision-support information, more informed policy-making, a faster and richer understanding of evolving circumstances, and enhanced services based on better insights into citizen needs and demands ([Fattah, 2024b](#); [Klievink et al., 2017](#)). By effectively leveraging the potential of BD, organizations can identify new opportunities, optimize operations, and improve service delivery ([Fattah, 2024b](#); [Medeiros & Maçada, 2022](#)).

Researchers have observed that the utilization of BD significantly contributes to the public sector in both developed and developing countries. For instance, in the United States, BD is employed in intelligence analysis and cybercrime monitoring ([Admass et al., 2024](#)). In China, it supports disease tracking, public health surveillance, and policy design ([Zhang et al., 2024](#)). The United Kingdom's Transport for London (TfL) uses BD to optimize traffic flow and public transportation systems ([Kandt & Batty, 2021](#)). South Korea applies BD in smart city projects aimed at enhancing energy efficiency and quality of life ([Kim et al., 2023](#)). The Netherlands leverages BD for social service enforcement, criminal investigations, and promoting government transparency ([van Veenstra et al., 2020](#)). In India, BD is used to improve public administration and drive the growth of the digital economy ([Mittal et al., 2021](#)). Similarly, Singapore utilizes BD to monitor traffic, predict infrastructure needs, and promote environmental sustainability through its smart city initiatives ([Jiang et al., 2023](#)). Each country, including Indonesia, has developed unique BD projects and initiatives. The utilization of BD varies based on the type of project, its application, and the data sources involved ([Ram & Desgourdes, 2024](#)).

In summary, BD utilization and analysis are important in the public sector for informed decision-making, operational efficiency, resource optimization, and transparent, accountable public service delivery. Organizations can mitigate BD utilization challenges by implementing appropriate technologies to process datasets and transform them into actionable insights ([Barbala et al., 2024](#); [Chatterjee et al., 2023](#); [Fattah, 2024b](#)). Therefore, a comprehensive academic study of BD utilization, particularly within the context of BA, is needed across developed and developing countries. This research aims to provide insights into how the public sector can enhance decision-making, improve performance, and deliver better public services.

2.2. Data infrastructure, data governance, and Indonesia's regulatory environment

Indonesia's data center industry is experiencing rapid growth, projected to accelerate through 2025, driven by government-led digital transformation and increased Artificial Intelligence (AI) adoption via the "Making Indonesia 4.0" program. This program aims to position Indonesia among the top ten global economies by 2030 through the digital technology implementation, which subsequently increases demand for data center services. Projections indicate a 14 % compound annual growth rate (CAGR) for the Indonesian data center sector from 2023 to 2028, with market value raising from \$2.06 billion in 2023 to \$3.98 billion in 2028. This growth has attracted major international cloud service providers such as Amazon Web Services, Google, Microsoft, and Alibaba to establish data centers in Indonesia (Omadata, 2024).

In Indonesia, the government's demand for accountable, high-quality, and accessible data is paramount and is used as the foundation for development planning, implementation, monitoring, evaluation, and control. This demand aims to enhance transparency and optimize data utilization to support data-based development. Accurate data not only improves decision-making but also facilitates future government and development improvements and strategic changes (Fattah, 2024b).

Presidential Regulation No. 95 of 2018 concerning the Electronic-Based Government System (SPBE) mandates the establishment of a National Data Center (PDN) comprised of data centers managed by the Ministry of Communication and Information and/or central and regional governments that meet certain requirements. In the rapidly evolving digital era, PDN is crucial for the Indonesian government. PDN acts as a technology infrastructure for centralized storage, management, and security of government data. Effective e-government, reliant on digital transformation, necessitates robust data infrastructure. Thus, PDN enables public service digitalization, inter-institutional coordination, and data-driven policy planning and implementation. PDN is crucial in e-government and serves as a data centralization hub for integrated public services (efficient and structured), data security (high-security standards), interoperability and integration (enhancing public service efficiency), and support for data-based decision-making (targeted and structured policies), aligning with the Industry 4.0 program. Moreover, PDN offers layered information security protection for central and regional governments, starting from physical facilities, networks, servers, platforms, and applications. It also increases government budget efficiency by over 75 % and provides international standard facilities and operational systems (high Service Level Agreement), including Infrastructure as a service (IaaS), Platform as a Service (PaaS), Software as a Service (SaaS), and Security as a Service (SecaaS).

PDN enables the government to implement One Data Indonesia (SDI), forming the basis for policy-making across various sectors. Indonesian government data governance is guided by the SDI policy. Presidential Regulation No. 39 of 2019, concerning SDI, outlines the government's initiative to data-driven policy effectiveness. The SDI regulation governs central and regional government data governance, providing implementation guidelines and references. It aims to ensure accurate, integrated, up-to-date, and accessible data, promote data transparency, and support the national statistical system. Improving government data governance is increasingly urgent for digital transformation, including SPBE, especially in the disruption era. Ongoing efforts to enhance data governance focus on ensuring government data meets standards related to data asset management, data quality monitoring, metadata (structured information for data search and management), data interoperability (data exchange between agencies), and the use of reference codes and master data (data representing government business processes).

2.3. Theoretical background

Dynamic capabilities view (DCV) refers to an organization's capabilities to develop, integrate, and reconfigure internal and external resources to respond rapidly to environmental changes within organizations (Teece et al., 1997; Teece & Pisano, 1994). This perspective aligns with resource-based theory (RBT), which identifies key organizational assets that drive firm performance (Barney, 1991). RBT is widely applied in information systems (IS) and other business disciplines to explain the relationship between organizational resources and firm performance. In the context of BD, firms must develop organizational capabilities by integrating tangible resources (e.g., data, technology), human resources (e.g., managerial and technical skills), and intangible resources (e.g., data-driven culture, organizational learning intensity (Gupta & George, 2016). RBT argues that firms gain a competitive advantage when their resources are valuable, rare, inimitable, and non-substitutable (Eisenhardt & Martin, 2000).

The literature highlights how firms use these assets to develop their ability to survive and compete in their respective sectors (Winter, 2003). Additionally, firms utilize their organizational capabilities to build dynamic capabilities (DC), which allows them to adapt and reconfigure their assets in response to external factors (Helfat et al., 2023; Teece, 2018). In the current context of analytics and digital transformation, BD is relevant to DCV due to its knowledge-related nature (Shaqrh & Alzighaibi, 2023; Thakral et al., 2024). When combined with machine learning techniques (Ghasemaghaei & Kordzadeh, 2024; Spreitzenbarth et al., 2024; Wamba et al., 2024), analytical skills (Abuzaid, 2024; Banasiewicz, 2023; Fattah, 2024b) and a supportive culture (Barbala et al., 2024; Chaudhuri et al., 2024; Wamba et al., 2024), BD becomes a powerful tool that delivers significant value to companies (Chatterjee et al., 2023; Horani, Khatibi, Al-Soud, et al., 2023; Makhoulfi et al., 2023; Medeiros & Maçada, 2022; Ram & Desgourdes, 2024; Shi et al., 2024; Talib et al., 2024).

The effectiveness of analytical capabilities and dissemination mechanisms determines how BD can be translated into valuable knowledge, which significantly influences the type and quality of decisions. When managed through appropriate routines, this knowledge can be applied across various situations (Pedota, 2023). BD holds the potential to enhance multiple functional areas by integrating disciplines such as machine learning, information systems, statistics, operations research, and management science, making it an interdisciplinary field (Fattah, 2024b; Schmitt, 2023). Furthermore, the industrial transformation driven by BD is reshaping work practices in academia, business, and the public and private sectors. BD provides positive insights and impacts across these sectors, offering legal, economic, political, social, and ethical contributions. It drives innovation, increases efficiency, enhances decision-making, and ensures better returns on investment (Omoyiola, 2023; Shi et al., 2024).

Recent research has increasingly applied the DC perspective to explore the relationship between BD analytics capabilities and firm performance. Empirical evidence has demonstrated that process-oriented DC plays a mediating or moderating role in this relationship (Gao & Sarwar, 2024; Gupta et al., 2024; Li et al., 2024). Furthermore, several studies underline the importance of BD in driving innovation, both directly and indirectly. Data-driven improvements across functional areas enable companies to develop digitally enabled routines to sense, utilize, and reconfigure resources. Digitally enabled routines such as support scenario planning practices, agile cross-functional teams, and integration of IT processes and knowledge drive process innovation (Pedota, 2023). When companies master these routines and leverage them to improve the efficiency of their processes, they may be driven to increase productivity, performance, and innovation in service delivery and policy-making processes (Fattah, 2024b).

In addition, an effective way to obtain knowledge resources and various sources is to examine the trust, support, resources, skills, and knowledge of individuals within an organization through social capital

theory (SCT). The capacity to develop and utilize DC is often shaped by the organization's social capital (SC), which supports learning and reconfiguration processes (Teece et al., 1997). SCT, first defined by Bourdieu (1985), refers to the aggregate of actual or potential resources associated with the possession of a durable network of relationships that are more or less institutionalized based on mutual acquaintance or recognition. The basic premise is that social interactions and networks provide value to their members by granting them access to the social resources embedded within the network. These social networks need to be developed through investment strategies focused on institutionalizing group relations, which become reliable sources of benefits (Portes, 1998). SC generally consists of two elements: (a) the social relationship itself, which allows individuals to claim access to resources possessed by their associates, and (b) the amount and quality of those resources (Bourdieu, 1985; Portes, 1998). The use of SCT provides a valuable theoretical lens for this study. Our focus on SCT is motivated by the fact that SC is embedded in relationships at various levels. The application of SCT aims to understand social ties, social interactions, trust, and reciprocity among individuals who collect, process, analyze data, and make decisions and how these factors affect DMP. In this case, the DCV and SCT perspectives provide an appropriate theoretical basis for the study.

The existing literature identifies BAC as a form of DC (Abdellatif et al., 2024; Fattah, 2024b; Tetteh et al., 2024). Both DDC and DLS facilitate the availability of data and information, while KM supports the analysis of information, leading to knowledge creation. These are essential for the development of DC, specifically BAC and DMP in this study's context. Given these insights, we propose that DDC, DLS, and KM contribute to the improvement of DC through BAC and further enhance the critical role of SC in driving better DMP.

2.4. Data-driven culture

The concept of Data-Driven Culture (DDC) extends the idea of organizational culture, which refers to the shared values, beliefs, norms, and behaviors that define how an organization operates (Griffin & Holcomb, 2023a). Organizational culture shapes employee attitudes, interdepartmental relationships, and the overall work environment. DDC, on the other hand, specifically focuses on the shared values, beliefs, attitudes, and practices that emphasize the use of data in decision-making. It suggests that organizational decisions should be driven by data insights, promoting continuous knowledge acquisition and skill development within the organization (Fattah, 2024a; Medeiros & Maçada, 2022). This underscores the dynamic relationship between organizational culture, DDC, and strategic success, which requires continuous alignment and adaptation as the organization evolves (Fattah, 2024a; Griffin & Holcomb, 2023a). As a result, DDC is a complex concept, as it must align with the broader principles of analytical decision-making, which itself can be challenging to articulate and maintain effectively (Barbala et al., 2024; Fattah, 2024a). The effectiveness of DDC relies on the organization's ability to adapt and align its culture to continuously support data-driven decision-making practices.

The complexity of DDC stems from the need to consistently align data-driven decision-making principles with broader cultural values (Griffin & Holcomb, 2023a; Staudt & Hoffmann, 2024). This includes the adoption of technologies that enable effective analysis of multiple types of data (Chaudhuri et al., 2024; Oliver et al., 2024; Tamm et al., 2022), creating an environment that supports and empowers individuals to leverage data in a rapidly evolving business landscape (Griffin & Holcomb, 2023a; Wamba et al., 2024) and fostering organizational structures that influence data accessibility, collaboration, decision-making, and data-driven mindsets (Barbala et al., 2024). DDC addresses collective behavioral patterns and shared practices based on the belief that having, understanding, and using certain types of data and information is critical to organizational success (Medeiros & Maçada, 2022). This concept captures the importance of data to companies and the extent to which they base their decisions on perception rather than

instinct (Fattah, 2024a; Tamm et al., 2022). A strong DDC not only enables effective data development and utilization, but also helps organizations gain greater value from previously underutilized data. In the context of this study, the elements of DDC consist of owning, understanding, and encouraging the use of data in various facets of business operations. This process includes developing new ideas, conducting experiments and projects based on data-driven business strategies, leveraging data for evidence-based decision-making, leveraging data insights to develop offerings, and recognizing the strategic urgency for organizational success.

2.5. Data literacy skills

Data literacy skills (DLS) are the ability to understand, evaluate, and work with data effectively (Banasiewicz, 2023; Griffin & Holcomb, 2023b). These skills encompass a range of skills, including the capacity to interpret data, ask relevant questions, analyze information, and derive actionable insights. DLS is not confined to technical proficiency with data tools and technologies but also includes a broader understanding of the data context, including limitations and ethical considerations (Fattah, 2024b; Griffin & Holcomb, 2023b; Oliver et al., 2024). DLS is a foundational skill set that empowers individuals at all levels of an organization to interact with data. It enables employees to become critical consumers and producers of data, fostering a data-driven mindset that permeates decision-making processes and drives innovation (Griffin & Holcomb, 2023b).

Furthermore, DLS is directly related to individual behavior in accessing, interpreting, critically assessing, managing, handling, and using data ethically (Fattah, 2024b; Ongena, 2023). This highlights that DLS is more than the ability to understand and use data effectively; it involves transforming information into actionable knowledge. DLS enhances the ability to collect, analyze, and interpret all types of data (Jirakitpaibool et al., 2023; Ongena, 2023). It is an emerging and evolving approach that enhances knowledge of data handling skills tailored to specific purposes. This includes understanding data sources and constructs, the analytical methods and techniques applied, and the ability to describe use cases, applications, and the value generated (Gartner, 2022; Pörtner et al., 2024). Therefore, DLS reflects skills necessary for using and interpreting data to obtain actionable insights, highlighting the importance of analytical and strategic behavior.

2.6. Knowledge management

Knowledge management (KM) is an interdisciplinary field that encompasses a variety of methods and practices for developing, sharing, utilizing, and managing knowledge and information within organizations (Rehman et al., 2024). Its goal is to capture and utilize the knowledge base of its employees to improve efficiency, productivity, and competitiveness.

Knowledge itself is defined as a set of justified beliefs that can be arranged and managed to enhance an organization's performance through effective actions (Goswami et al., 2024; Rehman et al., 2024). KM refers to the process of converting developed knowledge into practical business applications. One key part of KM is knowledge application, where acquired knowledge is put into action to drive business processes (Makhloufi et al., 2023). BD plays a crucial role in KM by comprehending and extracting essential knowledge, helping organizations in improving operations. Analytical approaches used for knowledge discovery are essential to KM, with BD serving as the main source of explicit information (Goswami et al., 2024; Schaefer & Makatsaria, 2021). Given the importance of knowledge in designing, implementing, and using BD analytics, it is emphasized that KM should play a central role in managing and using data analytics within organizational settings (Goswami et al., 2024). With effective handling of KM through BD and analytics, hidden knowledge can be revealed and new knowledge as a strategic resource can be generated (Dahiya et al., 2022; Goswami et al., 2024;

Shaqrah & Alzighaibi, 2023). This contributes to strengthening various KM processes such as knowledge application, knowledge conversion, and knowledge acquisition (Rehman et al., 2024; Schaefer & Makatsaria, 2021). The literature defines KM as the ability to enhance data analysis processes through the creation, discovery, and application of knowledge to enhance decision-making and problem-solving processes, a definition adopted in this study.

2.7. Business analytics

Business analytics (BA) is a statistical and technological approach that integrates methods from data science, operational research, machine learning, and information systems to extract value from data through analysis. By applying well-structured plans and strategies, BA aims to provide business insights (Fattah, 2024b; Janiesch et al., 2022; Shi et al., 2024). As a key investment for organizations, BA allows companies to uncover hidden information within their data, improve decision-making processes, and support strategic planning (Fattah, 2024b; Shi et al., 2024). This makes BA a backbone of strategic planning, where data is transformed into strategic assets that provide information for making decisions.

BA summarizes all the techniques, methods, processes, practices, technologies, applications, and skills needed to analyze critical business data. This strategy is used to achieve business goals by identifying new opportunities, finding more features, changing and developing certain systems, understanding customer behavior in business, and anticipating problems before they occur (Chatterjee et al., 2024; Fattah, 2024b; Janiesch et al., 2022; Shi et al., 2024). This analysis helps businesses understand their operations, make informed decisions, gain a better understanding of their business performance levels, and drive improvements (Chatterjee et al., 2023; Janiesch et al., 2022). Fig. 1 outlines the four key components of BA that guide business in analyzing BD,

improving the understanding of performance patterns, preparing for research and evaluation, driving innovation and creative solutions, and formulating strategies and trend analysis. The primary goal is to project forecasts, streamline operations, enhance service provision, analyze potential risks and future results, identify solutions and challenges, and adopt the best strategies to optimize objectives. This involves maximizing productivity, responding to change and opportunities, and minimizing risks, threats, and weaknesses (Fattah, 2024b; Hirvonen et al., 2024; Medeiros & Maçada, 2022; Notz & Pibernik, 2024; Shafique et al., 2024).

BA activities generate valuable insights that support better business decision-making and act as a driver of dynamic capabilities. These capabilities enable organizations to identify opportunities and challenges, mobilize resources, adapt to change, and drive innovation through analytical solutions, which eventually enhances the organization's overall ability to create greater business value (Gupta et al., 2024; Mikalef et al., 2020; Wamba et al., 2017; Yoshikuni et al., 2023). Internalizing BA activities into organizational capabilities involves integrating data analysis functions across all processes and activities within the organization (Mikalef et al., 2020; Shamim et al., 2020). This includes embedding BA into core business functions such as strategic planning, decision-making, and performance monitoring, thereby making data analytics an integral part of business operations. Doing so helps organizations manage and leverage data more effectively and sustainably in pursuit of their strategic goals (Mikalef et al., 2020).

In this study, BA is regarded as an integrated concept encompassing a range of technical systems and methodologies involved in BAC development. This development reflects an organization's capability to enhance its proficiency in process knowledge, practical skills, and technological understanding required for effective data analysis. It includes interpreting analytical results and translating them into actionable business decisions. BA goes beyond merely collecting and



Fig. 1. The four elements of business analytics.

presenting data; it involves deep analysis to understand the business context, forecast future trends, and support more informed strategic decision-making.

2.8. Social capital

Social capital (SC) refers to the collective value of actual and potential resources derived from social interactions and networks. These networks and relationships are valuable resources that can be leveraged for individual and collective benefit (Abane et al., 2024). SC is an integral part of intellectual capital and adds value to social interactions. As a result, individuals in an organization become more valuable and harder to replace when they have built SC through communities and groups (Heubeck et al., 2024; Ozgun et al., 2022). SC includes resources such as relationships, values, norms, trust, and social networks, which shape structure and quality of social relationships (Abane et al., 2024; Van Tran et al., 2024).

SC acts as a non-generic source of complementarity, helping to organize appropriate resources and knowledge and facilitating collaboration between various organizational stakeholders to develop BD analytics capabilities (Malik et al., 2024). Specifically, BD analytics capabilities have been conceptualized as socio-technical artifacts that include technologies and technical tasks necessary to generate BD (Oesterreich et al., 2022), as well as organizational factors and individual skills and knowledge (Malik et al., 2024; Oesterreich et al., 2022; Shao et al., 2023).

In this study, SC is defined as the network of interpersonal relationships that provide resources such as information, trust, and support for value creation, affecting various forms of performance (Hagen & Hess, 2021; Ince et al., 2023). It facilitates individual interactions and social networks in BD-related activities, enhancing decision-making quality. Additionally, in big data analytics capabilities, SC enables the exchange of BD-related knowledge between teams responsible for data processing, analysis, and decision-making, including knowledge about data sources and challenges related to data (Gao & Sarwar, 2024; Shamim et al., 2020).

2.9. Decision-making performance of business analytics capabilities

Decision-making performance (DMP) in organizations refers to the capacity to acquire, store, process, and analyze large amounts of BD in various forms to extract actionable insights that enhance business value for the organization by strengthening its performance (Chatterjee et al., 2024; Fattah, 2024b; Yalcin et al., 2022). Scholars have adopted a more nuanced perspective by conceptualizing DMP in terms of effectiveness and efficiency, particularly within the context of BD-driven decision-making (Fattah, 2024b). This broader conceptualization is especially significant in BD environments, where improved organization decision-making is often regarded as the ultimate goal for data analytics (Abdellatif et al., 2024; Ahmed et al., 2022). In this research, DMP specifically refers to decision effectiveness and efficiency in BD-driven contexts. Decision effectiveness focuses on achieving high-quality outcomes characterized by accuracy, precision, and reliability, while decision efficiency emphasizes the importance of timely decision-making (Fanelli et al., 2023; Fattah, 2024b; Talib et al., 2024).

Moreover, a recent literature review underscores the effectiveness of BAC in enhancing organizational business value (Chatterjee et al., 2024). BAC utilizes various data analysis methods to assist organizations in efficiently and accurately executing business processes, making timely decisions, identifying optimal solutions to practical problems, and delivering value that significantly enhances performance (Chatterjee et al., 2023; Orjatsalo et al., 2024). The impact of BD on BAC is substantial, as it shapes an organization's analytical vision within an effective data strategy. This integration not only improves operations and enhances customer experience but also drives innovation and growth, all of which are key to achieving better data transformation

success (Fattah, 2024b). By leveraging BA, organizations gain deeper insights into their decision-making processes, optimize organizational performance, and make faster, more reliable decisions (Chatterjee et al., 2023; Ram & Desgourdes, 2024; Talib et al., 2024). Therefore, BA plays a crucial role in managing the complexity of BD by directing focus toward critical decisions across various processes, operations, and business models. Through this approach, BA synthesizes completely new insights that enhance business value and improve decision-making.

Previous studies have shown that BAC enable organizations to identify areas in their business that can benefit from data-driven insights, strategically plan and execute data analytics projects, and integrate resources to transform data into actionable insights (Abdellatif et al., 2024; Chatterjee et al., 2023; Fattah, 2024a; Li et al., 2022; Mikalef et al., 2020; Orjatsalo et al., 2024; Ram & Desgourdes, 2024; Shamim et al., 2020). Therefore, BAC is the backbone of data collection, storage, access, and analytics to generate valuable business information, resulting in better decision-making (Fattah, 2024b; Hayajneh et al., 2022). This concept encompasses the fields of big data analytics (BDA) and artificial intelligence (AI), which are closely related, as machine learning and deep learning are increasingly used to process BD (Fattah, 2024b; Ghasemaghaei & Kordzadeh, 2024; Medeiros & Maçada, 2022; Spreitzenbarth et al., 2024; Wamba et al., 2024). Business intelligence/analytics, BDA, and AI extend the data science continuum through information technology and technological solutions (Fattah, 2024b; Spreitzenbarth et al., 2024; Wamba et al., 2024). These elements, processes, methods, and analysis techniques interpret BD and extract information for generating decision-making insights, thereby enhancing DMP (Abdellatif et al., 2024; Chatterjee et al., 2023; Fattah, 2024b). In this research, BAC is a crucial component and enabler of the decision-making process.

2.10. Development of the research model

The potential of data behavior and practices can create effective data use through DDC (Lega et al., 2024; Medeiros & Maçada, 2022; Oliver et al., 2024). In a dynamic framework for understanding and adapting an organization's data strategy, driving positive DDC change can improve data utilization, decision-making, and competitiveness (Fattah, 2024a). This culture enables individuals to develop the DLS necessary for effective data use, harnessing its potential, sustainable growth, targeted data initiatives, and fostering a better understanding of data as a series of interrelated and inseparable processes (Fattah, 2024a; Griffin & Holcomb, 2023a; Oliver et al., 2024). It empowers employees across roles and departments to explore and analyze data, use data ethically to solve problems, drive innovation, and enable diverse perspectives in decision-making. DDC needs to complement data analytics practices within the organization. This includes the processes, methods, interpretations, and analytical techniques used to analyze data and extract critical information that allows organizations to gain insights, promote strategies, and capitalize on opportunities for innovation with data (Barbala et al., 2024; Oliver et al., 2024). This diversity of these processes must be considered alongside DLS (Abuzaid, 2024; Banasiewicz, 2023; Griffin & Holcomb, 2023b), as they form an integral foundation of DDC (Griffin & Holcomb, 2023a). This foundation enables BD interpretation by extracting relevant data and estimating potential insights to optimize outcomes (Chaudhuri et al., 2024). Such frameworks are essential to embed analytical thinking into their work and support the use of data to provide recommendations and insights to managers (Banasiewicz, 2023; Griffin & Holcomb, 2023b). The DDC initiative highlights the positive significance and implications of DLS for organizations looking to harness the power of data and understand its value, which will make them more likely to embrace DDC.

Studies have shown that DDC has a positive impact on BA (Medeiros & Maçada, 2022; Upadhyay & Kumar, 2020). However, Almazmomi et al. (2022) and Karaboga et al. (2023) consider in their studies that DDC is a consequence of the use of BA. Given this discrepancy present in

the literature, we support the hypothesis that culture is an antecedent of other analytical capabilities since, by being an analytical aspect of organizational culture, it represents the internal context of the organization and the dominant cognitive model of its managers, which determines how data is valued in decision making. Developing a mature DDC requires a mindset shift that enhances relevant skills and knowledge across the organization. Such a shift has significant potential to gain insights, drive value, and improve decision-making processes, ultimately contributing to business success (Fattah, 2024a; Medeiros & Maçada, 2022). This maturation of DDC directly impacts and positively affects the development of BA. By optimizing DDC, organizations can recognize the importance of utilizing all available data and harness its power to make informed decisions, which leads to better outcomes (Griffin & Holcomb, 2023a). DDC is essential for effectively using resources and fostering analytical behavior in data interaction and interpretation, as well as for the successful application of BA within organizations.

Studies have revealed that organizational culture has a positive impact on KM (Azeem et al., 2021; Lam et al., 2021; Upadhyay & Kumar, 2020). Culture is a crucial factor in a company's ability to manage knowledge effectively (Lam et al., 2021) and plays a significant role in creating value through the utilization of knowledge assets as culture influences individual motivation to engage in knowledge application practices (Goswami et al., 2024; Upadhyay & Kumar, 2020). Furthermore, culture is fundamental in the development of KM practices (Lam et al., 2021). A positive culture can encourage collaboration, innovation, trust, collaboration, knowledge sharing, and shared learning, which is significantly promoted in relation to effective KM (Lam et al., 2021). Furthermore, DDC can encourage cross-functional learning and knowledge exchange. This can have a positive impact by eliminating silos and providing opportunities for employees from different departments to collaborate on data projects, organizations foster a culture of continuous learning and data-driven decision-making (Griffin & Holcomb, 2023a; Oliver et al., 2024). Therefore, culture has a positive impact as the foundation of knowledge initiatives by encouraging members to learn and share new information (Griffin & Holcomb, 2023a; Lam et al., 2021). In the context of this research, a culture that promotes knowledge sharing enables individuals to exchange best practices and insights across any DDC (Griffin & Holcomb, 2023a). Therefore, this study hypothesizes that DDC positively influences DLS, KM, and BA.

H1. *Data-driven culture has a significant positive influence on data literacy skills.*

H2. *Data-driven culture has a significant positive influence on business analytics capabilities.*

H3. *Data-driven culture has a significant positive influence on knowledge management.*

DLS is essential for transforming data into value by identifying internal or external data sources (Ongena, 2023). Proficiency in creating and understanding visual data representations (e.g., graphs and pie charts) is crucial for effectively interpreting visually rich data sets (Banasiewicz, 2023; Duan et al., 2020; Medeiros & Maçada, 2022; Ongena, 2023). Developing DLS enhances data analysis capabilities, which leads to higher expectations for data quality and a deeper understanding of data sets presented to stakeholders (Fattah, 2024b; Griffin & Holcomb, 2023b). Therefore, DLS allows users to better understand BD as a validation effort derived from analytical models or statistical analysis required to extract insights and provide a positive impact in making better decisions.

DLS includes an understanding of basic data analysis methods and statistical and logical techniques used to evaluate and interpret data. These techniques play an important role in identifying and extrapolating trends, patterns, or correlations in data, refining business processes to maximize business outcomes, and developing strategic plans for various possibilities (Fattah, 2024b; Medeiros & Maçada, 2022; Pörtner et al.,

2024). Thus, understanding these methods and techniques can have a positive impact and become a strong basis for making decisions that are right, informed, clearer, more reliable, and effective.

Furthermore, DLS and BA are considered a combination of skills and insights that together enhance analytical capabilities. The skills associated with DLS mediate the relationship between DDC and BA, generating meaningful insights that inform strategic planning, set appropriate goals, and monitor organizational progress. In this context, DLS is fundamental for empowering individuals to navigate, interpret, and communicate data effectively to drive informed decision-making within the organization (Griffin & Holcomb, 2023b; Pörtner et al., 2024). Thus, besides influencing BA with strong DDC as an antecedent, DLS stimulates individual capabilities, promoting analytical behavior, data critique, exploration, and interaction with data. This leads to rapid insights and appropriate actions, leading to improved business outcomes. Therefore, this study proposes the following hypothesis:

H4. *Data literacy skills have a significant positive influence on business analytics capabilities.*

H5. *Data literacy skills mediate the relationship between data-driven culture and its impact on business analytics capabilities.*

KM is a fundamental element for the success of data analytics as it generates a knowledge base that can be applied to data sets (Schaefer & Makatsaria, 2021). KM involves a systematic process of finding, selecting, organizing, and presenting information in a way that emphasizes the importance of knowledge in guiding the use of BA within organizations (Shaqrah & Alzighaibi, 2023; Subrahmanyam et al., 2024). This places KM as a primary consideration for managing BD transparently and dynamically. KM capabilities have a positive impact on the spectrum of BD capabilities for enterprise system value-addition processes (Cheng et al., 2023; Shaqrah & Alzighaibi, 2023; Thakral et al., 2024). This understanding highlights the broad awareness of KM processes and their analytic capabilities in the industrial enterprise system environment. The analytical process applied in KM facilitates the creation of new knowledge and the discovery of hidden knowledge (Goswami et al., 2024). These processes and knowledge form the basis for addressing previously defined problems and informing or initiating subsequent organizational actions and strategies.

Research conducted by Dahiya et al. (2022) revealed that KM has a positive impact on BD capabilities. This reveals that relevant absorptive capacity and KM strategy are essential for developing BA. KM practices play a vital role in driving BA (Shabbir & Gardezi, 2020). This is because individual skills in understanding and effectively using data are contingent upon the foundational knowledge acquired. As a result, organizations tend to focus on managing and integrating knowledge and experience to extract relevant information, which is often presented in explicit forms, thereby enhancing BA outcomes (Schaefer & Makatsaria, 2021).

In implementing BA processes and techniques, organizations strive to structure tacit knowledge to enhance knowledge sharing (Rehman et al., 2024). KM also documents explicit knowledge artifacts, such as operating procedures and knowledge, which are then leveraged to develop predictive models for specific business applications (Goswami et al., 2024; Thakral et al., 2024). KM fosters easy accessibility of information by promoting a culture of knowledge sharing among individuals, thereby generating and enhancing business innovation (Shamim et al., 2020; Thakral et al., 2024). Key constructs, such as tacit knowledge of data analysis techniques, relational management, and business knowledge, are important to this process. Therefore, KM is closely related to employee management skills, and the synergy between business knowledge and relational knowledge enhances employees' ability to work effectively in teams. This knowledge can only be used effectively when the intellectual and professional gaps among employees are bridged with cultural support (Lam et al., 2021; Passos et al., 2022; Upadhyay & Kumar, 2020). Thus, it is argued that KM influences

BAC and explains the transmission of DDC effects to it. Therefore, this study proposes the following hypothesis:

H6. *Knowledge management has a significant positive influence on business analytics capabilities.*

H7. *Knowledge management mediates the relationship between data-driven culture and its impact on business analytics capabilities.*

Empirical studies demonstrated that this BAC could improve analysis and insight, leading to better business decisions that positively impact organizational performance (Chatterjee et al., 2024; Cheng et al., 2023; Fattah, 2024b; Janiesch et al., 2022; Li et al., 2022). BAC refers to an approach that considers various aspects of the business holistically, including market trends, customer behavior, and operational efficiency (Fattah, 2024b). This approach aims to understand the broader business context and provide key insights for changes in business operations for value creation. This is a key factor in increasing effectiveness and efficiency that has operational and strategic potential. Business activities enabled by BAC can help corporate organizations evaluate strategies that are critical to improving organizational business processes and facilitating business decisions, which in turn impact better organizational performance (Chatterjee et al., 2024; Gupta et al., 2024; Horani et al., 2023; Ram & Desgourdes, 2024).

Thus, BAC is evidence that shows the critical point to gain value from data by generating valuable business insights and helping to improve DMP by exploring BD analysis, improving understanding of performance patterns, preparing research and investigations for environmental evaluation and formulating strategy analysis, and finding patterns or trends in operations, consumer behavior, and services in business decision making (Fattah, 2024b; Medeiros & Maçada, 2022). In this context, data-driven decision-making is seen as a powerful way to add value to the business; thus, justifying the main role of BAC will have a positive impact on DMP in this study. Therefore, this study proposes the following hypothesis:

H8. *Business analytics capabilities have a significant positive influence on decision-making performance.*

SC has a significant influence on the development of BAC, with far-reaching implications. Malik et al. (2024) support this notion, highlighting that SC is a key complement in the sustainable and effective application of BD analytics to generate actionable insights. This insight provides a more comprehensive understanding of the relationship between BAC and DMP. However, SC can hinder this understanding when complexities arise, such as limited access to and ownership of data, inadequate business alignment, a lack of shared understanding between the business and data communities, insufficient understanding of technology, and poor collaboration. Empirical studies suggest that high SC fosters cooperation, motivation, engagement, and trust, which, in turn, build strong social networks. These networks encompass both social elements (such as individual and organizational knowledge of digital technology and the ability to generate actionable insights from data) and technical elements (such as technology infrastructure required to process BD). Developing BD analytics capabilities requires a robust ecosystem or organizational network (Davidson et al., 2023; Malik et al., 2024; Shipilov & Gawer, 2020).

SC plays a critical role in enhancing information-sharing practices through statistical analytics, which can ultimately improve performance (Heubeck et al., 2024). Frequent social interactions build SC by aligning shared goals, values, and practices among network members. Through these interactions, members exchange cultures, codes, values, and practices, which collectively contribute to the formation of an analytical vision for the organization. This shared understanding benefits the organization's data strategy and decision-making processes (Fattah, 2024b). Previous research also shows that higher SC within groups—characterized by strong relationships and trust—leads to better performance (Chen et al., 2023; Singh et al., 2021). This is due to SC's

ability to reduce transaction costs, foster cooperation, and increase mutual commitment (Chummangoon et al., 2023; Lim et al., 2024). Thus, it is reasonable to assume that SC moderates the relationship between BAC and DMP. Organizations with strong SC are better positioned to leverage BA for enhanced decision-making. Based on the insights from prior research, this study proposes the following hypothesis:

H9. *Social capital moderates the relationship between business analytics capabilities and decision-making performance*

Fig. 2 presents the conceptual model of this research. The proposed research model highlights the role of DLS and KM as consequences and mediators of DDC, thus facilitating the development of BAC to acquire DMP and the subsequent interaction between BAC and DMP, which SC moderates. This study advances knowledge by clarifying culture, skills, knowledge, and social networks in relation to BA.

3. Research methodology

3.1. Research design and measurement

The current study adopts a quantitative approach, using a structured questionnaire based on existing literature to evaluate the research model empirically. Following Elangovan and Sundaravel's (2021) recommendations, survey items were derived from previous studies to represent the construct accurately. Measurements were adopted, adapted, and adjusted to fit the public sector context. To ensure content validity, five specialists (two BD/analytics professionals, a Master of Management, and two Doctors of Information Systems) assessed the instrument. Adjustments were made to demographic and domain-related questions, refining relevance, accuracy, and clarity. Revisions included eliminating ambiguity, integrating overlapping items, and refining language to avoid bias. These refinements enhanced the survey instrument's overall quality and effectiveness.

The research questionnaire consists of four parts. The first part ensures confidentiality and encourages honest responses. The second includes screening questions to verify that respondents meet the sampling criteria. The third part collects demographic data such as positions, education, professional experience, organization size, tools used in data analytics, public sector areas, and work unit functions. The survey remains anonymous to protect participants' identities. The fourth part contains construct-specific questions measured on a 6-point Likert scale (1 = Strongly Disagree to 6 = Strongly Agree). The study includes six constructs with 33 items: DDC (6 items) from Fattah (2024a), Griffin and Holcomb (2023a), and Medeiros and Maçada (2022); DLS (5 items) from Griffin and Holcomb (2023b) and Ongena (2023); KM (5 items) from Schaefer and Makatsaria (2021) and Shaqrah and Alzighaibi (2023); BAC (5 items) from Fattah (2024b) and Janiesch et al. (2022); SC (5 items) from Hagen and Hess (2021) and Van Tran et al. (2024); and DMP (7 items) from Fattah (2024b) and Shamim et al. (2020). Table A1 (see appendix) details variable operationalization.

3.2. Data analysis

For data analysis, the IBM SPSS Statistics 26 and SmartPLS 4.1.06 softwares were utilized. Initially, the constructs were checked, and subsequently, the measurement model was evaluated, and the structural equations were modeled by minimum partial frames (partial least squares-structural equation modeling (PLS-SEM)). PLS-SEM is a preferred method for working with complex models and is particularly well-suited for explaining the variance of constructs in theoretical development (Hair et al., 2022). PLS-SEM is effective in handling complex models with multiple constructs and paths, allowing for more comprehensive analysis (Sarstedt et al., 2022).

The statistical hypothesis testing in PLS-SEM relies on the bootstrapping technique, making it unaffected by the normal distribution assumptions. Unlike covariance-based structural equality modeling (CB-

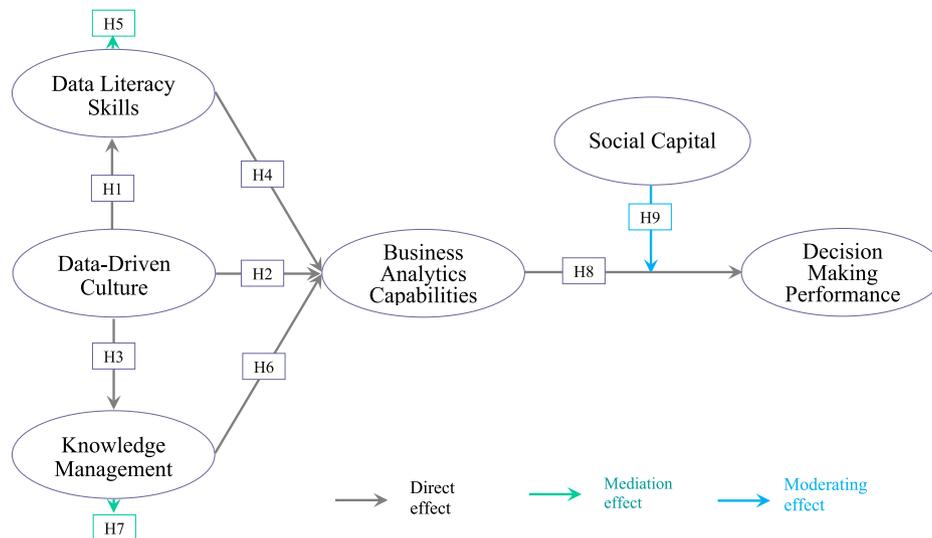


Fig. 2. Research model.

SEM), PLS-SEM is preferred for business researchers who experience challenges with data normality (Hair et al., 2019). In addition, PLS-SEM is valued for its predictive capabilities, making it ideal for models focused on understanding and forecasting relationships (Hair et al., 2022). Since this study emphasizes theory development and prediction, PLS-SEM is the appropriate method. Its main objective is to maximize the variance explained in the dependent construct while assessing the quality of the data based on the characteristics of the measurement model (Dash & Paul, 2021). PLS is widely applied in management, technology, and various fields of social science research (Dash & Paul, 2021; Kante & Michel, 2023) and is particularly prevalent in information systems research (Kante & Michel, 2023). Given this, PLS-SEM is well-suited for exploring the interactions of DDC, DLS, and KM on BAC, as well as BAC's impact on DMP, with SC moderating this relationship.

In PLS-SEM, highly abnormal data can lead to unsatisfactory statistical significance of parameters (Guenther et al., 2023; Hair et al., 2022). Therefore, researchers must assess the normality of the data (Sarstedt et al., 2022) to ensure meaningful residual variance in the model's indicators (Guenther et al., 2023) and align with the predictive nature of the research objectives (Hair et al., 2022; Ringle et al., 2023). In this study, data normality was evaluated using the Skewness and Kurtosis test, with acceptable limits ranging from -2 to +2. All question items within each latent construct fell within this range, indicating that the data were normally distributed. This confirms the absence of severe abnormalities, ensuring valid univariate distribution, as presented in Table 2.

3.3. Collection of data and samples

Data for this study were collected via online questionnaires from executives and managers (administrative and supervisory roles) in Indonesian public institutions (government) between July and August 2024. A purposive sampling technique, within the framework of non-probability sampling, was employed to ensure respondents met predefined eligibility criteria. These criteria, adapted from Fattah (2024a, 2024b), required participants to be involved in data administration, BD activities, data analytics utilization, and data-driven decision-making. Additionally, new criteria were added: participants must be implementing strategic initiatives in BD and BA for business process improvement, digital transformation, organizational efficiency, and policy formulation. These additions align with the evolving public sector context of BA in Indonesia.

Initially, 371 questionnaires were collected. After excluding

Table 2
Data normality.

Construct	Item	Kurtosis	Skewness
Data-driven culture	DDC1	0.937	-0.594
	DDC2	0.058	-0.494
	DDC3	-0.662	-0.413
	DDC4	0.939	-0.615
	DDC5	0.249	-0.605
	DDC6	0.937	-0.594
Data literacy skills	DLS1	-0.073	-0.550
	DLS2	0.422	-0.648
	DLS3	-0.103	-0.282
	DLS4	0.844	-0.705
	DLS5	0.630	-0.646
Knowledge management	KM1	-0.103	-0.282
	KM2	1.152	-0.756
	KM3	-0.288	-0.506
	KM4	0.050	-0.534
	KM5	0.119	-0.706
Business analytics capabilities	BAC1	0.931	-0.654
	BAC2	0.663	-0.723
	BAC3	0.723	-0.768
	BAC4	1.119	-0.817
	BAC5	1.407	-0.734
Social capital	SC1	-0.655	-0.245
	SC2	-0.713	-0.317
	SC3	-0.711	-0.476
	SC4	0.637	-0.853
	SC5	0.448	-0.671
Decision-making performance	DMP1	0.469	-0.771
	DMP2	-0.481	-0.700
	DMP3	-0.763	-0.540
	DMP4	0.406	-0.905
	DMP5	-0.637	-0.850
	DMP6	0.396	-0.523
	DMP7	-0.928	-0.284

incomplete or unusable responses, 348 questionnaires were deemed suitable for analysis. Subsequently, 18 responses were removed for failing filtering criteria, specifically from institutions confirming non-use of BA in decision-making processes, based on provided definitions and examples. The final sample comprised 330 valid responses, yielding an 89 % response rate, which is statistically acceptable and ideal for survey research (Sataloff & Vontela, 2021). Table 3 presents the respondents' profiles and institutional backgrounds.

Table 3
Respondents' profile.

Characteristics	Category	N	Percentage (%)
Respondent position	Senior/Executive manager (administrative)	119	36.1
	Middle/First line manager (supervisory)	211	63.9
Education	College diploma	6	1.8
	Bachelor's degree	40	12.1
	Master's degree	254	77.0
	Ph.D. degree	30	9.1
Professional experience x = years	x ≤ 3	99	30.0
	3 < x ≤ 5	158	47.9
	5 < x ≤ 10	40	12.1
Number of employees	x > 10	33	10.0
	< 500	33	10.0
	501–1000	46	13.9
Tools used in data analytics	> 1000	251	76.1
	Tableau	99	30.0
	Python	73	22.1
	Power BI	66	20.0
	Orange	33	10.0
	Stata	26	7.9
	R. Studio	20	6.1
	Etc	13	3.9
Public sector area	Public services	33	10.0
	Fiscal policy	73	22.1
	State treasury & assets	46	13.9
	State revenue and expenditures	59	17.9
	Financing risk and management	99	30.0
Work unit function ^a	Education and training	20	6.1
	Technical/Business Process	165	50.0
	Data/Information Systems	66	20.0
	Transformation/Technology	33	10.0
	Services/Public Relations	26	7.9
	General/Operational	17	5.2
	Education/Training	13	3.9
Supervision	10	3.0	
Total informants/organizations (n) = 330			

^a Work unit function where informants/organizations operate.

3.4. Common method bias

The authors ensured participants' confidentiality and anonymity. To minimize response bias, the questionnaire's question order was randomized to prevent recognition of dependent and independent constructs. Common method bias (CMB) was assessed to support the study's validity (Kock et al., 2021). Following Kock (2017), this study used variance inflation factors (VIFs) from a full collinearity test to detect potential CMB contamination. A VIF value above 3.3 suggests possible bias, whereas values below 3.3 indicate the model is free from CMB. The results showed that all VIF values were below this threshold, confirming that CMB was not a concern. Thus, the study's reliability and validity were strengthened. Table 4 presents the detailed findings.

4. Analysis and results

4.1. Measurement model

This study assessed the model's reflective constructs using SmartPLS software to ensure reliability and validity. Internal consistency,

Table 4
Common method bias.

Latent Variables Score	DDC	DLS	KM	BAC	SC	DMP
VIF	2.048	2.117	2.164	2.458	1.616	1.435

Note(s): Data-driven culture (DDC); data literacy skills (DLS); knowledge management (KM); business analytics capabilities (BAC); social capital (SC); decision-making performance (DMP).

composite reliability, convergent validity, and discriminant validity were examined. Cronbach's alpha and composite reliability (CR) values exceeded 0.70 for all constructs, indicating strong internal consistency and reliability (Hair et al., 2022). Convergent validity, calculated using average variance extracted (AVE), confirmed that all constructs met the recommended threshold of 0.50 (Hair et al., 2022). Factor loadings and AVE values further supported the construct's convergent validity. Discriminant validity was evaluated using two methods: (1) Fornell and Larcker's (1981) criterion and (2) the heterotrait-monotrait ratio (HTMT) criteria by Henseler et al. (2016). The AVE criterion confirmed that correlations did not exceed the squared AVE values, while the HTMT results showed that all constructs remained below the 0.85 threshold. As shown in Table 5, the constructs demonstrated normality, internal reliability, convergent validity, and discriminant validity.

4.2. Structural model

The structural model was evaluated based on the magnitude and sign of path coefficients, significance levels, effect size (f^2), R-square (R^2), predictive validity (Q^2), and model fit indices, including chi-square (χ^2), normed fit index (NFI), standardized root mean residual (SRMR), squared Euclidean distance (d_{ULS}), and geodesic distance (d_G). A bootstrapping procedure with 5000 samples was conducted to assess the significance of the hypothesized paths and the variance explained in the dependent variables by the explanatory variables (Hair et al., 2022). This approach enhances the robustness and reliability of the results. The hypothesis testing was carried out, with the results of direct effects and effect size (f^2) presented in Table 6. The effect size (f^2) was assessed to determine the contribution of each exogenous in explaining the endogenous variables in the model. According to Cohen (2013), $f^2 > 0.02$ represents a small size effect, $f^2 > 0.15$ indicates a medium-size effect, and $f^2 > 0.35$ suggests a large size effect. Cohen's f^2 is calculated by analyzing the change in R^2 when a specific antecedent is removed from the model.

Based on Table 6, the direct effect and effect size analysis demonstrates that DDC ($\beta = 0.365$, t -value 4.839, and p -value 0.000), DLS ($\beta = 0.538$, t -value 7.776, and p -value 0.000), and KM ($\beta = 0.446$, t -value 6.207, and p -value 0.000) have a positive and significant effect on BAC. Among these, DLS and KM exhibit medium effects, while DDC shows a small effect. Additionally, DDC has a strong positive and significant effect on DLS ($\beta = 0.758$, t -value 10.921, and p -value 0.000) with a large effect size. Similarly, DDC also significantly impacts KM ($\beta = 0.801$, t -value 13.196, and p -value 0.000) with a very large effect size. Furthermore, BAC positively and significantly affects DMP ($\beta = 0.409$, t -value 6.743, and p -value 0.000), though with a small effect. Consequently, hypothesis H1, H2, H3, H4, H6 and H8 are supported.

Table 7 and Fig. 3 illustrates the path coefficients, significance levels, Pearson's coefficient of determination (R^2), and predictive validity (Q^2). The significance of the results was analyzed, revealing linear correlations and regressions with a p -value < 0.05 (Hair Jr., 2021). All hypotheses were supported, with significance levels below 1%. The variance of the endogenous variables was assessed using R^2 within the structural model. As shown in Table 7, BAC ($R^2 = 0.543$) and DMP ($R^2 = 0.586$) exhibited significant effects, exceeding the 26% threshold (Cohen, 2013). In social sciences, $R^2 > 0.25$ represents a small effect size, $R^2 > 0.50$ indicates a medium effect, and $R^2 > 0.75$ suggests a large effect (Hair et al., 2022). A value approaching 1 implies that the independent variable can nearly fully predict the dependent variable. Furthermore, the R^2 value for DMP increased from 0.580 to 0.586 with SC included as a moderating variable, indicating a medium predictive effect. Additionally, the predictive relevance of the model was evaluated using the Stone-Geisser indicator (Q^2). In PLS-SEM, Q^2 values compare the prediction errors of the PLS path model, helping to assess its predictive accuracy. The results obtained through the blindfolding procedure in PLS-SEM indicate that the model's predictive accuracy is satisfactory, as all endogenous variables have Q^2 values greater than

Table 5
Construct analysis: internal consistency, convergent validity, and discriminant validity.

Construct ^a	Indicators ^b			Fornell-Larcker criterion ^c						HTMT criterion					
	α	CR	AVE	BAC	DMP	DDC	SC	KM	DLS	BAC	DMP	DDC	SC	KM	DLS
BAC	0.882	0.893	0.823	<i>0.863</i>											
DMP	0.910	0.913	0.819	0.594	<i>0.850</i>					0.535					
DDC	0.835	0.874	0.746	0.573	0.592	<i>0.842</i>				0.497	0.521				
SC	0.877	0.883	0.787	0.569	0.513	<i>0.587</i>	<i>0.838</i>			0.466	0.445	0.454			
KM	0.911	0.912	0.822	0.663	0.621	0.611	0.430	<i>0.871</i>		0.534	0.519	0.434	0.492		
DLS	0.898	0.900	0.815	0.706	0.522	0.518	0.527	0.443	<i>0.847</i>	0.606	0.502	0.535	0.564	0.477	

^a Data-driven culture (DDC); data literacy skills (DLS); knowledge management (KM); business analytics capabilities (BAC); social capital (SC); decision-making performance (DMP).

^b Cronbach's alpha(α); composite reliability (CR); average variance extracted (AVE).

^c Square root of AVE is in the diagonal and highlighted in italic.

Table 6
Significance of the direct paths and effect size.

Hypothesis ^{a,b}	Path coefficient	T statistic	p -value ^c	Effect size(f ²)	Analysis of Cohen's f ²	Empirical evidence
H1: DDC → DLS	0.758	10.921	0.000***	0.429	Large	Supported
H2: DDC → BAC	0.365	4.839	0.001**	0.129	Small	Supported
H3: DDC → KM	0.801	13.196	0.000***	1.291	Very Large	Supported
H4: DLS → BAC	0.538	7.776	0.000***	0.306	Medium	Supported
H6: KM → BAC	0.446	6.207	0.000***	0.291	Medium	Supported
H8: BAC → DMP	0.409	6.743	0.000***	0.137	Small	Supported

^a Data-driven culture (DDC); data literacy skills (DLS); knowledge management (KM); business analytics capabilities (BAC); decision-making performance (DMP).

^b H5 and H7 represent (indirect) mediating effects; H9 represent (direct) moderating effect.

^c *p < 0.05, **p < 0.01, ***p < 0.001, ns – not significant.

Table 7
R-square.

Construct ^a	R-square without social capital		R-square with social capital		Effect size (R ²) ^b
	R-square	R-square adjusted	R-square	R-square adjusted	
BAC	0.543	0.540	0.543	0.540	Medium
DMP	0.580	0.577	0.586	0.583	Medium

^a Business analytics capabilities (BAC); decision-making performance (DMP).

^b R² > 0.25 represents a small size effect, while R² > 0.50 indicates a medium-size effect, and R² > 0.75 suggests a large size effect.

0 (Hair et al., 2022).

The model fit was assessed using both the saturated and estimated models. The saturated model evaluates correlations between all constructs, while the estimated model considers the total effect scheme and the structural model. Since model selection based on fit criteria can be challenging, prior research suggests using the estimated model for PLS path model assessment (Dash & Paul, 2021; Hair et al., 2017). Therefore, this study employs the estimation model to report the results of the PLS path model fit, considering the total effect scheme and incorporating the structural model.

Overall model fit was evaluated based on the chi-square (*Chi*²) test, which compares differences between sample data and the adjusted covariance matrix. A direct comparison between *Chi*² and degrees of freedom is offered to indicate adequate model fit when the CMIN/df value is 3 or lower (and in some cases, up to 5) (Dash & Paul, 2021; Hair Jr., 2021). In this study, an average *Chi*² value of 4 was obtained, aligning with the model test findings and indicating an acceptable fit.

NFI is used to evaluate a model by comparing the *Chi*² value of the model to that of the null or the equal independence model (Dash & Paul, 2021). This index calculates the *Chi*² value of the proposed model and compares it to a meaningful benchmark. Since the *Chi*² value of the proposed model itself does not provide sufficient information to assess the model fit, NFI uses the *Chi*² value of the null model as a benchmark. The NFI is then defined as 1 minus the ratio of the *Chi*² value of the null

model. As a result, the NFI values range between 0 and 1, with values closer to 1 indicating a better fit. Typically, NFI values above 0.9 suggest an acceptable model fit (Dash & Paul, 2021; Hair Jr., 2021). In this study, the NFI value is 0.891, which falls within the expected range, indicating a strong and acceptable model fit.

SRMR measures the difference between the predicted model correlation matrix and the actual correlations. It helps evaluate the average difference between the observed and anticipated correlations, which acts as an absolute indicator of model fit. In addition, SRMR addresses issues associated with Root Mean Square Residuals (RMSR). It is calculated by dividing the adjusted residuals by the standard errors of the residuals with lower value indicating a better model fit (Dash & Paul, 2021). A widely accepted threshold for SRMR is 0.05 or less (Shi & Maydeu-Olivares, 2020). However, an SRMR index value below 0.08 is considered acceptable (Hu & Bentler, 1999), with values below 0.10 still indicate adequate accuracy (Dijkstra, 2010). The test results show an SRMR value of 0.058, which is below 0.10, confirming a good model fit.

The exact model fit test in PLS is evaluated using d_ULS and d_G, which are tested with a 95 % bootstrapping confidence interval to determine whether the correlation of the data model aligns with its estimates. If the estimated value of the 95 % bootstrap interval for d_ULS and d_G is greater than the original value, it suggests a well-fitting model. In this study, the estimated values for d_ULS (0.659 > 0.05) and d_G (0.408 > 0.05) confirm that the PLS model fits the data, indicating that the correlation matrix of the model closely matches the estimated model correlation matrix. The non-significant values of d_ULS and d_G further support a better model fit (Hair et al., 2017). Overall, the structural model fit meets the threshold levels established in previous literature, as shown in Table 8.

4.3. Mediation and moderation analysis

According to Hair et al. (2022), the premise of mediation is fully satisfied in this study. The study examines complementary mediation, competitive mediation, and indirect-only mediation, where complementary mediation occurs when both the indirect and direct effects are significant and point in the same direction, while competitive mediation

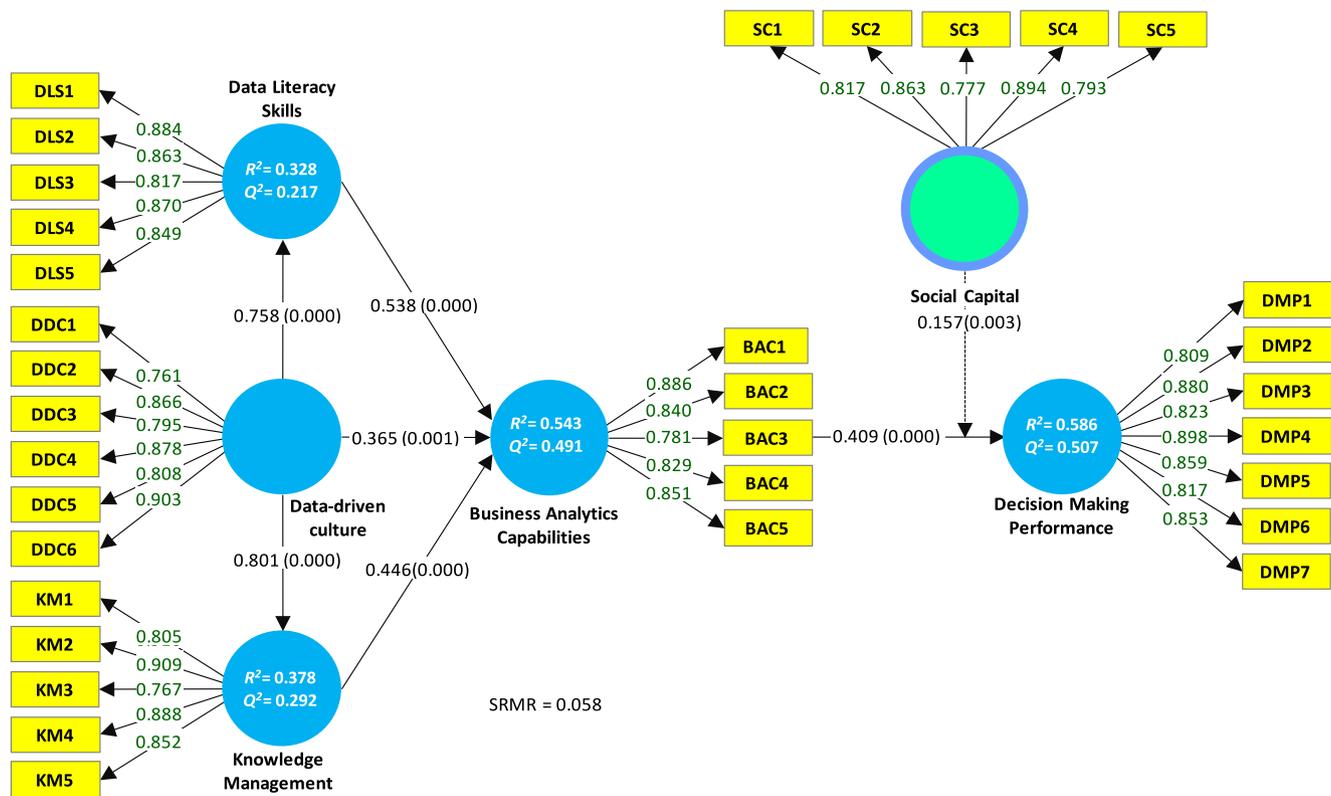


Fig. 3. Structural model.

Table 8 Model fit indices.

Measure	Estimated Model
Chi-square	4217.029**
NFI	0.891
SRMR	0.058
d_ ULS	0.659 ^{ns}
d_ G	0.408 ^{ns}

Notes (s) *p < 0.05, **p < 0.01, ***p < 0.001, ns – not significant.

arises when these effects point in opposite directions. Indirect-only mediation is marked by a significant indirect effect with no significant direct effect. In this study, all relationships show significant indirect effects, meeting the conditions for mediation. The analysis follows the procedures outlined by Baron and Kenny (1986), Hair et al. (2022), and Nitzl et al. (2016).

The mediation effect size is measured by using squared standardized upilon v^2 as described by Lachowicz et al. (2018). The formula proposed by Lachowicz et al. (2018) is a development of the effect size R^2 med is the effect size medias upilon (v^2) or upilon statistic: $v^2 = 1\beta^2MX \beta^2YM-X$, where β^2MX is the path coefficient of the influence of X on M and β^2YM-X is the path coefficient of the influence of M on Y. The

Table 9 Mediation analysis.

Hypothesis ^a	Upsilon coefficient ^b	T statistic	p-value ^c	Mediation type	Analysis of Ogbeibu's (v^2) ^d
H5: DDC → DLS → BAC	0.077	4.802	0.000***	Complementary mediation	Medium
H7: DDC → KM → BAC	0.085	5.939	0.000***	Complementary mediation	Medium

^a Data-driven culture (DDC); data literacy skills (DLS); knowledge management (KM); business analytics capabilities (BAC).

^b $\beta^2MX \beta^2YM-X$.

^c *p < 0.05, **p < 0.01, ***p < 0.001, ns – not significant; ratio of the indirect effect to the total effect.

^d $v^2 > 0.01$ represents a small size effect, while $v^2 > 0.075$ indicates a medium-size effect, and $f^2 > 0.175$ suggests a large size effect.

effect size v^2 has an interpretable scale with an estimated 95 % confidence interval based on the sampling distribution. This effect size is unbiased, consistent, efficient, and free from dependence on sample size. The interpretation of the upilon mediation effect size value (v) follows Ogbeibu et al. (2021), with values indicating small ($v^2 > 0.01$), medium ($v^2 > 0.075$), or large ($v^2 > 0.35$) effects.

Based on Table 9, the mediation analysis of the path interaction is as follows. The interaction DDC → DLS → BAC ($\beta_{Upsilon} = 0.077$, t -value 4.802, and p -value 0.000) reveals that DLS acts as a complementary mediator with a medium effect size. The interaction DDC → KM → BAC ($\beta_{Upsilon} = 0.085$, t -value 5.939, and p -value 0.000) also shows that KM acts as a complementary mediator with a medium effect size. Thus, both DLS and KM serve as mediators in the relationship between DDC and BAC with medium effect sizes, leading to the acceptance of hypotheses H5 and H7. This indicates that DLS and KM significantly contribute to enhancing the effect of DDC on BAC, with medium-sized effects.

Table 10 presents the results of the moderating analysis following the procedure outlined by Kenny (2018) and Hair Jr. (2021). According to Kenny (2018), the effect sizes are classified as follows: $f^2 > 0.005$ represents a small size effect, $f^2 > 0.01$ a medium-size effect, and $f^2 > 0.025$ a large size effect. However, Kenny also notes that these benchmarks may be somewhat optimistic when applied to moderation analysis. In this study, the moderating role of SC is tested through interaction model between BAC and DMP in the public sector. As shown in Table 10, the

Table 10
Moderating analysis.

Hypothesis ^a	Path coefficient	T statistic	p -value ^b	Effect size(f^2)	Analysis of Hair's f^2 ^c
H9: SC. BAC → DMP	0.157	2.790	0.003**	0.027	Large

^a Business analytics capabilities (BAC); social capital (SC); decision-making performance (DMP).

^b * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns – not significant.

^c $f^2 > 0.005$ for small size effect, $f^2 > 0.01$ for medium-size effect, and $f^2 > 0.025$ for large size-effect.

interaction between BAC and SC with DMP is positive and significant ($\beta = 0.157$, t -value 2.790, and p -value 0.003), leading to the acceptance of hypothesis H9. This result indicates that SC positively moderates the relationship between BAC and DMP in the public sector. The positive path coefficient for the moderation interaction demonstrates that SC strengthens the effect of BAC on DMP. The effect size is large, highlighting that SC has a significant and powerful moderating role in enhancing the relationship between BAC and DMP.

Furthermore, the interaction plot was illustrated using the procedure outlined by Ringle et al. (2023), which helps illustrate the interaction pattern between BAC and DMP. The plot calculates the slope of one standard deviation above (+1 SD) and below the mean SC (-1 SD), allowing for a deeper understanding of how SC moderates the relationship between BAC and DMP. In Fig. 4, the X-axis represents BAC, and the Y-axis represents DMP, with three distinct lines illustrating the moderation effect of SC on the relationship between BAC and DMP. The red line (-1 SD) represents the relationship between BAC and DMP when SC is one standard deviation below the mean. The rising line shows that BAC has a positive relationship with DMP when SC is high. The blue line (Mean SC) indicates the relationship when SC is at its mean value. The green line (+1 SD) represents the relationship when SC is one standard deviation above the mean. The upward trending lines in the plot suggest that higher levels of SC and BAC result in a stronger positive relationship between BAC and DMP. The overall trend in the plot

suggests that as SC increases, the positive relationship between BAC and DMP strengthens. Specifically, when SC is high (as shown by the green line), the effect of BAC on DMP is more pronounced compared to when SC is low (shown by the red line). These findings reinforce the significance of SC in moderating the relationship between BAC and DMP, confirming that stronger SC leads to higher DMP when interacting with BAC. In conclusion, this moderation effect highlights that SC plays a crucial role in enhancing the effectiveness of BD and BA initiatives, emphasizing its importance in the decision-making process.

5. Discussion of results

This study aims to explore how the interaction of DDC, DLS and KM enhances BAC and SC moderates the relationship between BAC and DMP within Indonesian public sector agencies that actively utilize BD for BA strategic initiatives.

The study confirms that DDC has a positive and significant effect on DLS. By leveraging data and analytical behavior, DDC potential of data and facilitate its creative use, making consolidated data more accessible to agents and decision makers (Fattah, 2024a; Medeiros & Maçada, 2022). DDC helps organizations identify opportunities for data flows that lead to advanced, understanding-oriented data use. This understanding is vital for organizations seeking to harness the potential and power of data. It encourages DLS, empowering individual to interact with and interpret data effectively by applying analytical methods and techniques to describe its use, understanding, and value (Gartner, 2022; Griffin & Holcomb, 2023a). This comprehensive understanding gained through DLS helps cultivate a data-driven mindset that permeates the decision-making process and drives innovation and enables individuals to interpret and utilize data effectively, helping to extract and estimate insights from BD. Establishing DDC within an organization requires deliberate efforts to nurture DLS across all levels (Griffin & Holcomb, 2023a; Oliver et al., 2024).

The study also confirms that DDC has a positive and significant effect on BAC. This finding highlights the critical role that DDC plays in guiding the integration of analytical practices within an organization.

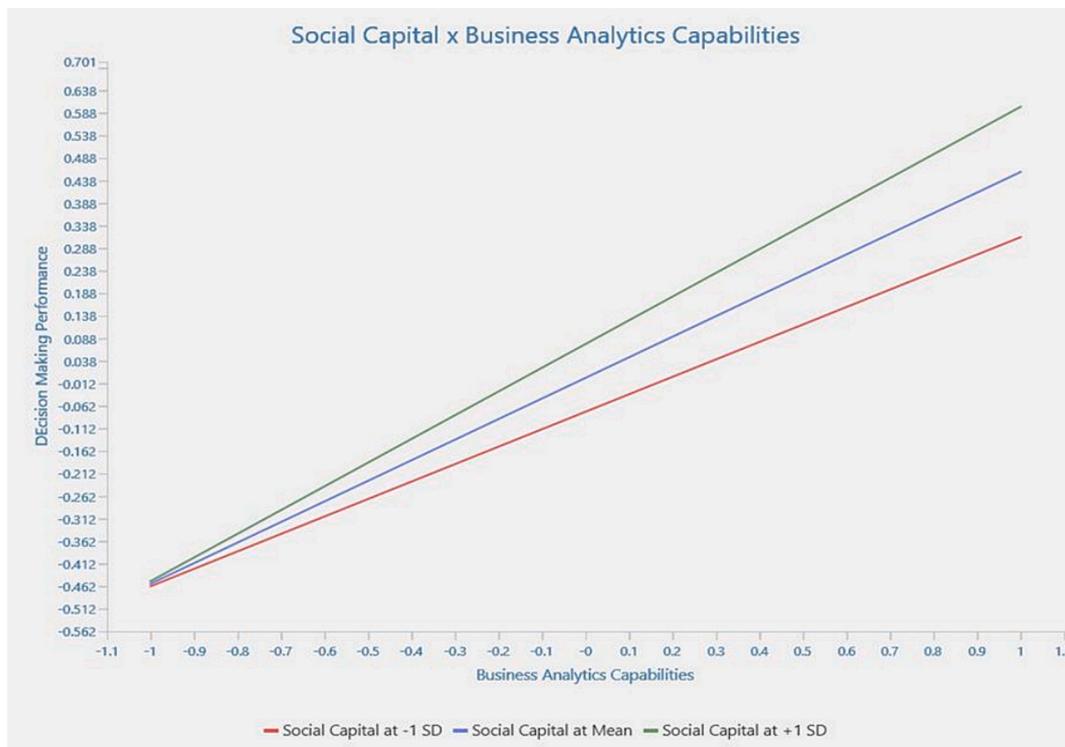


Fig. 4. Simple slope diagram of moderation test.

DDC positions BAC as essential for leveraging analytical resources and encourages behaviors that promote effective data interaction and interpretation, ultimately contributing to the success of BAC within the organization. These effective practices strengthen BAC overall, increasing the likelihood of success in data-driven projects. In this context, BAC serves as the pinnacle of data usage and flow, facilitating the understanding and differentiation practices crucial for leveraging data strategically. These findings align with previous research (Medeiros & Maçada, 2022; Upadhyay & Kumar, 2020).

Furthermore, DDC is shown to have a positive and significant effect on KM. DDC serves as the foundation for KM initiatives by fostering individual knowledge and experience and guiding the decision-making process on how information generated through data is applied in operations and management, both tactically and strategically. This plays a fundamental role in managing and implementing analytics, providing the foundation and practical experience necessary to decide what data an organization needs to operate efficiently and effectively. DDC ensures the availability of valuable information during decision-making and supports the development of knowledge-based feedback, enabling immediate adjustments in data collection and analysis in response to changes in the business environment (Goswami et al., 2024; Shabbir & Gardezi, 2020; Shaqrah & Alzighaibi, 2023). Furthermore, DDC enables organizations to respond to the automation of problems, motivates the exploration of new patterns and opportunities, and supports strategic decisions to achieve organizational goals, thus strengthening KM practices and helping organizations extract value from BD. Therefore, DDC contributes significantly to the success of KM implementation. These findings are in line with previous research (Lam et al., 2021; Passos et al., 2022; Upadhyay & Kumar, 2020), suggesting that cultural factors are crucial for the organizational prerequisites needed for an effective KM strategy.

Then, it is found that DLS has a positive and significant effect on BAC. This highlights the importance of skill-related factors in data processing and utilization. The use of DLS improves skills in creating and understanding data representations, effectively navigating data sets, and comprehending the information they contain (Banasiewicz, 2023; Griffin & Holcomb, 2023b; Ongena, 2023). This enables organizations to optimize outcomes through advanced data analysis and sharing relevant insights. Furthermore, the findings suggest that DLS acts as a complementary mediator and can transmit most of the DDC effect to BA (medium effect), suggesting that an organization's analytical perspective—comprising DDC and effective use of DLS resources—is crucial for enabling BAC. Specifically, DLS enhances data quality, stimulates analysis, and generates information through human interaction and data interpretation, which enables organizations to transform data into valuable insights through understanding data sources, construction, and analytical methods applied (Banasiewicz, 2023; Gartner, 2022; Medeiros & Maçada, 2022). These skills are key determinants of success in leveraging BA, precisely to acquire and subsidize quality data to stimulate analysis and generate insights with greater agility, reliability, speed, and timeliness (Fattah, 2024b; Jirakitpaibool et al., 2023; Medeiros & Maçada, 2022; Pörtner et al., 2024). Therefore, DLS is not limited to technical proficiency in using and interpreting data but rather includes a more effective and broader individual understanding of the data context, critical evaluation, limitations, and ethical implications of the data. Thus, these findings are important for strong organizational decision making, improving data quality, and conducting thorough analysis of data sets across all levels of the organization.

Furthermore, the study reveals that KM has a positive and significant effect on BAC, with KM acting as a complementary mediator between DDC and BAC. This emphasizes KM's role in enhancing an organization's knowledge base, providing a clearer understanding of the technologies and potential capabilities of data and analytics, as well as the associated risks. KM aids in managing data across data analytics activities, ensuring alignment between data analytics and business strategy and facilitating a deeper understanding of the fundamental business processes critical to

decision-making. With the presence of mediating variables, most (medium) effects begin to be transmitted indirectly to BAC. This suggests that KM is an important capability that impacts BAC by transforming BD into extracted information and new knowledge through analytical techniques and tools (Rehman et al., 2024; Thakral et al., 2024). KM provides organizations with the opportunity to add meaning to new data and information, share alternative meanings, restructure new meanings, and decide on actions based on these new insights (Goswami et al., 2024; Schaefer & Makatsaria, 2021).

The study further confirms proved that BAC has a positive and significant effect on DMP. BAC serves as a critical bridge toward achieving DMP. It enables organizations to leverage data effectively, helping navigate the decision-making process by converting insights into business value. BAC improves decision-making quality and efficiency by generating valuable business knowledge from data. Therefore, developing BAC helps manage the complexity of BD by directing focus on critical questions across processes, operations, and business models. It synthesizes novel insights that drive business value, ultimately contributing to a better overall DMP. This interaction is critical in shaping analytical vision and empowering organizations to gain insight into the decision-making process, consider changes to optimize organizational performance, and make faster and more reliable decisions. This finding is consistent with previous studies (Abdellatif et al., 2024; Chatterjee et al., 2023; Fattah, 2024b; Horani et al., 2023; Li et al., 2022).

Finally, the study assessed the moderating role of SC and found that the interaction between BAC and DMP was positive and significant, with SC acting as a positive moderator. This finding emphasizes a stronger SC fosters shared understanding and trust in implementing BA within business operations. SC promotes data access and resource exchange, such as analytical capabilities, business knowledge, and social skills. These elements form a cognitive framework that reduces conflict, enhances strategic alignment, and strengthens DMP. SC enables shared representations, interpretation schemes, and meaning systems (e.g. shared languages, codes, practices, and narratives) between individuals. This shared understanding enhances alignment between technical aspects (e.g., algorithms, techniques, and model selection) and business realities, facilitating smoother information exchange and problem solving. The trust and collaboration fostered through SC help create a shared set of values or analytical vision, which drives the effective use of BA to generate insights, solve problems, and create business value. These results align with previous studies that highlight the importance of SC in creating business value from BD analytics (Hagen & Hess, 2021; Malik et al., 2024; Oesterreich et al., 2022; Shamim et al., 2020).

6. Conclusion and implications

6.1. Conclusion

This study analyzes empirical evidence on the impact of DDC on DMP, focusing on the mediating effects of DLS, KM, and BAC, and clarifies the causal relationships between these constructs. The finding confirms the hypothesis that DLS and KM act as mediators, where DDC influences BAC, which then enhances DMP. These results provide greater clarity in understanding this relationship. The integration of DDC reveals the transformative power of data to generate actionable insights and foster BAC success.

This study found that DDC effectively transformed the cognitive mindset of organizational members, enabling them to use data more broadly, strategically, and effectively within the organization. This shift fostered analytical, critical, and evidence-based thinking in decision-making, enhanced understanding of data's value, improved situational awareness, problem-solving abilities, and encouraged the development of new insights and creative solutions. These cognitive changes influenced members' practices, leading to shifts in policy-making, program evaluation, and strategic decision-making. The adoption of data

analytics technology facilitated the sharing of data, skills, knowledge, and insights across organizational levels. This transformation reinforced a strong DDC, creating a continuous cycle focused on data-driven and analytical decision-making. Consequently, this drove the growth of BAC, enabling more accurate, efficient, and strategic decisions, which improved DMP.

This coherence of BAC lies in the synergy between skills (DLS) and knowledge (KM). DLS equips individuals with the ability to understand, collect, and match appropriate data, recognize relationships between variables in the data, and formulate meaningful questions to apply relevant techniques and models. This fosters deeper insights from data and ensures the effective communication of results. In the era of BD, DLS involves critical thinking skills to use, interpret, and make decisions with data and then convey its significance and value to others. This proficiency enables accurate interpretation and analysis of data, requiring data-literate employees who are proficient in using data. Despite the importance of DLS, relying solely on it is insufficient for creating value through BAC. A KM perspective is needed to link the creation and use of the knowledge conversion framework throughout the analytical process. In addition, KM ensures that insights from data are embedded within organizational processes and activities, such as identifying patterns or trends in operations, consumer behavior, and services to inform business decisions. These decisions rely on knowledge across different levels to configure the rules and business parameters effectively. At the operational, tactical, or strategic level, (human) knowledge remains critical to fully capitalize on what BA offers. A comprehensive understanding of KM reveals its indispensable role in helping organizations make the most of analytics by integrating insights into processes and guiding data-driven decision-making. When an organization has DDC as a continuum at a certain level and enters a phase where DLS and KM permeate throughout its structure, including leadership and management, individuals across roles can effectively interpret and leverage data for informed insights, strategic actions, and enhanced organizational value. This integration becomes the foundation for building sustainable BAC. In this context, data-driven decision-making emerges as a powerful mechanism for adding value to businesses, reinforcing the central role of DDC on BAC, as demonstrated in this study.

Interestingly, the combination of SC and BAC provides a powerful and effective analytical solution for improving DMP. This underscores the strategic importance of SC within organizations, not only in fostering intellectual capital but also in enhancing overall business value. In the context of BA value creation, SC facilitates the alignment of trust, participation, and shared meaning systems within the decision-making process. This alignment improves the quality, inclusiveness, and adaptability of decisions by involving various relevant parties, considering diverse perspectives, and fostering a shared understanding of goals and values. Strong trust among organizational members enables more open sharing of data, information, and insights, resulting in more comprehensive and accurate analyses. Trust in accurate and reliable data, a clear and transparent analysis process, and accountable analysis results that align with business objectives enhance decision-making quality and effectiveness. When stakeholders believe in the accuracy, relevance, and validity of results, they are more likely to accept and use them to make faster and bolder decisions. Trust also encourages open communication and collaboration, allowing analysis teams, stakeholders, and other parties involved in decision-making to work more effectively with mutual confidence. Participation ensures that diverse perspectives and experiences are considered throughout the decision-making process. High participation fosters a strong commitment to maximizing benefits from data analysis and gathering varied viewpoints and ideas, which in turn increases creativity and innovation. Such involvement improves the quality and applicability of analysis results, strengthens the legitimacy of decisions, and helps ensure decisions align with business objectives and organizational values. Shared meaning systems provide an interpretive framework that ensures all parties have

a common understanding of the problem, goals, and potential consequences of different options. With a strong shared meaning system, decision-making becomes more effective and efficient, reducing conflict and uncertainty by ensuring stakeholders share a clear understanding of the situation and appropriate responses.

The findings of this study underscore the importance of DDC, DLS, KM, and SC in enhancing BAC, thereby enabling better, more informed, and faster decision-making. Therefore, this study represents a crucial step organization should consider when developing or strengthening BAC, with the potential to improve DMP in the public sector.

6.2. Theoretical implications

This research significantly contributes to operational research and existing literature by expanding knowledge and enhancing practical understanding in several key areas.

First, the findings offer valuable insights into challenges faced during data-driven organizational transformation. A key takeaway is the need for executive mindset shifts, achievable through stimulating BAC via culture change (DDC), enhancing analyst skills (DLS) and knowledge frameworks (KM), and leveraging SC to improve decision-making quality. This study supports Dynamic Capabilities (DC) Theory by positioning DDC as a dynamic driver of organizational success. It highlights the dynamic relationship between DDC and strategic success, underscoring the need for continuous alignment and adaptation as organizations grow and transform. This aligns with [Wamba et al. \(2024\)](#), who emphasized that, from a resource orchestration perspective, transformative efforts (i.e., investing in and aligning capabilities) require DDC refinement to minimize delays in Dynamic Capabilities (DC) development. Therefore, a reimagined DDC is crucial for unlocking the full potential in developing the scale of the DC view enabled by BA.

Furthermore, strategic elements such as DDC are always antecedents of elements representing the implementation of structures and resources in an organizational context, as supported by [Griffin and Holcomb \(2023a\)](#) and [Medeiros and Maçada \(2022\)](#). In addition, these findings align with and extend [Yoshikuni et al. \(2023\)](#), who demonstrated that DC's perspective on analytics effectively conceptualizes organizational analytics capability development through resource identification and data-driven transformation. This uniquely establishes the interaction between BD management challenges (DDC, DLS, KM, and SC) and BD decision-making capabilities within the public sector. While there is an underlying assumption concerning the role played by different factors in affecting BD decision-making capabilities, this study provides empirical insights into how organizational elements contribute to public sector BD value creation. This approach, similar to [Mikalef et al., 2020](#), recognizes that industry-specific BA applications, in this case, the public sector, present unique opportunities and challenges. This research thus contributes to the growing body of literature advocating for a nuanced, ecosystem-oriented approach to analytics.

Secondly, this study introduces a new perspective by emphasizing the importance of actual and potential resources (social capital) in driving innovation and intellectual capital development. Recognizing SC's strategic significance is crucial in ensuring the success of BA practices and increasing the organization's overall value. These findings highlight the strong moderating effect of SC on the relationship between BAC and DMP. This approach enriches the social capital theory (SCT) by exploring social interactions and networks' real and potential resources. These findings extend to [Malik et al. \(2024\)](#), who emphasize developing BD analytical capabilities through non-generic sources (SC) and business ecosystems. The need for radical changes in Big Data (BD) analytics utilization due to the external origin of most BD is also reinforced by [Davidson et al. \(2023\)](#) and [Shipilov and Gawer \(2020\)](#). This study addresses gaps in DC and BA research by demonstrating SC as complementary to DC development, aligning with [Gao and Sarwar \(2024\)](#), which explore SC within BDA from various perspectives. SC can describe the pathways and mechanisms used by organizations to build DC.

Therefore, SC has significant potential to enhance DC, providing a comprehensive understanding of its role in driving organizational value and performance, as supported by Shamim et al. (2020) and Van Tran et al. (2024).

Finally, the model developed in this study examines the socio-technical interactions and value creation mechanisms between BAC and DMP and contributes to the theorization of BDA affordance actualization in the public sector. Building on Dremel et al. (2020) and Farouk et al. (2025), this research emphasizes the socio-technical interactions crucial for leveraging BDA capabilities. This integrated approach facilitates a nuanced and holistic understanding of how BA generates real business value. By highlighting the dynamic affordance actualization process in building BAC, this study expands theoretical insights into BDA implementation and value realization.

6.3. Practical implications

First, the research model proposed in this study can be implemented to enhance BAC and achieve DMP. This finding highlights that improving DMP begins with a strong understanding and adoption of a DDC. However, the greatest challenge in building DDC lies in maintaining a continuous and sustainable transformation process. DDC must be cultivated from within the organization by actively engaging individuals at all levels to foster awareness of common goals. Studies by Barbala et al. (2024), Fattah (2024a), Griffin and Holcomb (2023a), Lega et al. (2024), and Oliver et al. (2024) emphasize that DDC development must involve all organizational levels. Leadership, managerial support, and employee commitment are key enablers of this process, facilitating cultural synthesis and organizational transformation. This structured approach helps overcome resistance to change, a common barrier to DDC implementation. Cultural change within an organization is neither a quick nor easy process. Potential challenges include organizational conflicts, lack of readiness, and resistance to change. To address these issues, organizations must implement effective change management strategies, which include establishing a clear vision and goals for DDC, ensuring strong leadership and commitment, actively engaging employees, monitoring progress, and encouraging participation in data-strategy initiatives to reinforce cultural adaptation. Successful implementation of cultural change can be seen in the emergence of a number of data-driven initiatives across various work units. Although these initiatives may not yet be mainstream, optimizing data utilization is recognized as a valuable driver of organizational growth.

In addition, accessibility and data infrastructure are important to drive DDC. Organizations need to build a robust data infrastructure, including data storage, integration, and analytics capabilities, to facilitate easy access to relevant data across the organization. This aligns with studies by Madhala et al. (2024) and Talib et al. (2024), which emphasize that data infrastructure enables business organizations to integrate data from multiple sources for analytical applications, ultimately supporting effective and data-driven decision-making.

Furthermore, Barbala et al. (2024) revealed that data accessibility is only optimized when DDC fosters collaboration across all levels of the organization through cross-functional cooperation. To achieve this, organizations must establish an appropriate organizational structure for analytics. Analytical data should not be monopolized by a single unit or limited to specific functions. Instead, the analytical data unit must be inclusive and accessible to various units at different organizational levels. Additionally, it must be interconnected with the business process owner unit to ensure alignment between analytics initiatives and business operations. This structure enhances the effectiveness and sustainability of data analysis initiatives while unifying the organization's strategy and information systems. This aligns with Mikalef et al. (2020), who stated that organizational structures that restrict efficient data and information flow are major contributors to BD and BA project failures.

In the BD era, organizations must also establish frameworks that regulate compliance, structures, policies, and controls for data analysis

activities. Effective data governance is essential, as it empowers organizations to efficiently manage valuable data assets, comply with relevant regulations, mitigate risks, and ensure sustainable data utilization. This aligns with Fattah (2024a, 2024b), who explained that data governance enables organizations to determine which data should be analyzed, unlock potential value, and overcome obstacles in developing DDC. Moreover, it instills a sense of confidence and security among stakeholders involved in data-related processes.

Secondly, the presence of DLS and KM significantly contributes to shared value creation within organizations. Organizations should align BA initiatives with DLS training to enhance the computational speed of BD collections and promote data-driven decision-making. This involves equipping individuals with essential DLS, setting training targets based on engagement and satisfaction, and measuring training effectiveness. Training programs such as mentoring, data analytics mentoring, and coaching should be encouraged. Additionally, practical training sessions (hands-on training) and hackathons should be organized to facilitate knowledge-sharing. Such alignment improves the perceived relevance of training, enhances self-efficacy in instructional settings, and strengthens knowledge in data utilization, as suggested by Li et al. (2023) and Miller-Bains et al. (2022). Importantly, DLS should not be limited to data specialists such as data scientists, analysts, or engineers. Instead, they should be cultivated across all organizational levels, including executive management and leadership, as these individuals are responsible for decision-making and determining the organization's direction. Developing DLS at all levels ensures a foundational understanding of data analytics, basic statistical interpretation, and the limitations of extrapolation, thereby strengthening decision-making capabilities (Banasiewicz, 2023; Fattah, 2024b).

A well-developed KM system enhances expertise among individuals and teams, facilitates connections between information seekers and knowledge holders, and motivates employees to share their expertise. Organizations should consider investing in BD analytics tools such as Tableau, Python, Power BI, Orange, Stata, and R Studio to strengthen KM. These tools are essential for data analysis and artificial intelligence applications, particularly in knowledge-driven organizations. This is in line with studies by Goswami et al. (2024), Rehman et al. (2024), and Shaqrah and Alzighaibi (2023), which emphasize the role of BD in strengthening KM. Effective KM allows organizations to leverage knowledge resources, fostering innovation, increasing value, and improving organizational performance (Cheng et al., 2023; Makhoulfi et al., 2023). However, implementing BD analytics in the public sector requires careful consideration of roles, processes, technologies, and strategies for KM development. These elements must align with business activities, goals, and strategies. Therefore, organizations must implement a strategic business plan for BD application in KM, which includes collaborative system/platform integration (to ensure that data and knowledge run synergistically), information security and privacy (to address cyber threats), organizational readiness, and effective use (to maximize utilization by fostering cultural and procedural changes). This aligns with a qualitative study by Goswami et al. (2024), which emphasizes the need for a KM framework that integrates KM systems with data analytics processes. Such integration ensures that BA practices are consistent with the organization's culture, values, strategy, and mission.

Third, the complexity, challenges, and issues in BD management, particularly in value creation activities, necessitate deeper involvement from a broad social network. This network should include scientists, analysts, data scientists, data engineers, business teams, and end-users (Hagen & Hess, 2021). To drive successful data-driven transformation in the public sector, organizations must consider all key stakeholders and components necessary for SC development, as they represent interrelated elements with diverse expertise. Organizations should establish an analytics business community that fosters superior data science solutions, leverages data insights, and maximizes analytics functions. Fattah (2024b) highlights the importance of developing data analytics capabilities that combine technical and managerial skills to

create business value based on BA. These findings also extend the qualitative study by Madhala et al. (2024), which emphasizes that developing analytics capabilities—such as skills, expertise, and knowledge—is essential for utilizing data and BD analytics to enhance business performance. Thus, organizations must understand the importance of data analytics expertise, domain knowledge, data analytics alignment with business, and co-collaboration in building data analytics capabilities, as suggested in the study by Fattah and Arief (2023).

6.4. Limitations and future research

This research model has several limitations, particularly in addressing cultural factors, skills, knowledge, and social networks related to the analytical perspective. While the study was conducted with scientific rigor to ensure reliability, validity, and generalizability, caution should be taken when applying the findings to different contexts, such as the public and private sectors. Variations in culture, transparency, organizational structure, diversity, teamwork, and performance management may influence how different organizations adopt and utilize BA capabilities (Rus & Rusu, 2015). Future research should explore Indonesia's unique policy environment in the public sector, particularly the role of SC and the collective value of resources. A deeper understanding of BA and the level of dependence on colleagues from other departments, such as business, IT, or geographically dispersed units, can provide insights into how a data-driven approach can empower decision-makers. This approach can help organizations leverage data more effectively to generate insights, strategies, operational improvements, change management initiatives, and policies that benefit both organizations and society. Additionally, future studies could focus on identifying and comparing regional characteristics in BA, particularly in areas with active social and economic interactions. These regions include trade and business hubs, customer engagement platforms, website traffic, financial transactions, and social media activities. Sectoral differences in BA adoption should also be examined, particularly in industries such as retail, entertainment, healthcare, tourism, education, finance, transportation, and the circular economy. Furthermore, knowledge-based industries like research and development, IT, consulting, and other intellectual services could provide valuable insights into the varying levels of BA integration and its impact on business performance. Expanding the research model by including additional constructs that influence the maturity of analytics adoption would also

be beneficial. Organizations progress through different stages of analytics maturity, from nascent and pre-adoption phases to early adoption, corporate adoption, and eventually a mature or visionary stage. Understanding the factors that drive this progression can help organizations optimize their analytics capabilities and maximize their value creation. Finally, applying mixed research methods, either simultaneously or sequentially, could offer deeper insights into the relationships between various organizational elements and analytics adoption. A combination of qualitative and quantitative approaches would allow researchers to capture the complexities of BA implementation and provide a richer understanding of the underlying factors influencing data-driven decision-making.

CRediT authorship contribution statement

Ikhsan A. Fattah: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Harjanto Prabowo:** Writing – review & editing, Writing – original draft, Validation, Project administration, Investigation, Formal analysis. **Viany Utami Tjhin:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Formal analysis. **Rano Kartono Rahim:** Writing – review & editing, Writing – original draft, Validation, Project administration, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Operationalization of construct.

Constructs and references	Item	Item description
Data-driven culture (DDC) – Fattah (2024a), Griffin and Holcomb (2023a), and Medeiros and Maçada (2022)	DDC-01	We believe that having, understanding, and using data is essential for making decisions in our business.
	DDC-02	We are open to new ideas which challenge current decision-making practices.
	DDC-03	We depend on data and evidence to support decision-making.
	DDC-04	We use data-based insights to make decisions about creating new services or products.
	DDC-05	We believe that the data generated by the organization is used in our operational decisions.
	DDC-06	We recognize the usefulness of data in achieving the organization's strategic success.
Data Literacy Skills (DLS) – Griffin & Holcomb, 2023b) and Ongena (2023)		Big data skills help our organization ...
	DLS-01	... discover data insights and understand different data sources, and the most relevant ones can be chosen from a selection of data.

(continued on next page)

Table A1 (continued)

Constructs and references	Item	Item description
	DLS-02	... represent quality data (e.g., machine processable, empty fields, duplicate detection).
	DLS-03	... identify and describe problems in practical situations using a range of data.
	DLS-04	... provide better visual interactivity with the data.
	DLS-05	... interpret data outputs and results confidently and critically.
		Knowledge management helps our organization ...
Knowledge management (KM) – Schaefer and Makatsaria (2021) and Shaqrah and Alzighaibi (2023)	KM-01	... clearly understand the technology and potential of information processing and retrieval capabilities ... leverage diverse perspectives and experiences to extract relevant information that leads to desired outcomes
	KM-02	... enhance collaborative learning practices
	KM-03	... effectively consider potential risks and solutions to solve problems
	KM-04	... align data analysis activities with business strategy and operations and organizational goals
	KM-05	Business data are analyzed by our organization ...
Business analytics capabilities (BAC) – Fattah (2024b) and Janiesch et al. (2022)	BAC-01	... to understand what happens in the business.
	BAC-02	... to find out the causes of a particular problem.
	BAC-03	... to identify behaviors and predict trends.
	BAC-04	... to predict future results.
	BAC-05	... to identify the best alternatives and optimize business objectives.
Social capital (SC) – Hagen and Hess (2021) and Van Tran et al. (2024)	SC-01	We provide analytical solutions from a technology and skills perspective so that the use of analytical capabilities is more effective.
	SC-02	We have trust, better information exchange, and confidence in the information generated (truth issues).
	SC-03	We build a vision of data analytics that is beneficial to the organization.
	SC-04	We create more awareness and appreciation of each other's capabilities.
	SC-05	We have an understanding of the problems and solutions that can help in addressing the problems of identification, representation, and proximity of analytics(computational) Data and analytics usage has improved decision outcomes regarding our organization ...
Decision-making performance (DMP) –Fattah (2024b) and Shamim et al., 2020	DMP-01	... reliability.
	DMP-02	... correct.
	DMP-03	... error-free.
	DMP-04	... flawlessness.
	DMP-05	Our organization has gained strategic advantages with the time to make decisions fast.
	DMP-06	Our organization has produced high utility in quality services.
	DMP-07	Overall, our organization's speed of arriving at decisions is high.

Data availability

The data that has been used is confidential.

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