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Decision Making Performance of Big Data Analytics Capabilities:The Mediating Effect of Co-Collaboration

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Abstract.This research study investigates the mediating influence of co-collaboration (Co-Collab) on the relationship between big data analytics capabilities (BDAC) and decision-making performance (DMP). Using a quantitative approach, 189 managers with experience and competence in using data in Indonesian public service sector organizations were empirically evaluated. Structural Equation Modeling analysis was applied to examine the impact of BDAC on DMP and mediating effects of Co-Collab on this relationship. The results demonstrate that BDAC and Co-Collab significantly influence DMP, and BDAC significantly affects Co-Collab. Notably, Co-Collab was identified as a complementary mediator in the relationship between BDAC and DMP, explaining the majority of their effects. These findings suggest the significance for organizational leaders and managers to develop plans that nurture BDAC and implement Co-Collab processes to maximize the business's utilization of big data. Therefore, deriving value from big data to improve organizational DMP requires collaboration between data science experts and business users. Thus, organizations can establish policies and strategies to extract value from data and leverage business community and DMP through BDAC. This approach not only transcends the conventional views of big data analytics as a resource for attaining competitive advantage but also acknowledges its role as a business community that can drive performance within organizations, thereby enriching the existing social capital theory literature. Moreover, the study highlights opportunities for future studies, including comparative analysis across different organizations, experimental research on Co-Collab and DMP, and the application of concurrent or sequential mixed methods to explore context and process relationships among variables.

Keywords: decision-making performance, big data analytics, co-collaboration, public sector institutions.

1. Introduction

In recent years, the rapid development of information technology has brought significant changes worldwide. It has resulted in the increasing utilization of data and analytical capabilities to transform multifarious industries by guiding and producing data revolution driven by the volume, speed and diversity of complex data. As a result, business processes and services become faster and are almost not limited by space and time. The growth of the Internet has further contributed to this data revolution. Public institutions are experiencing an extraordinary explosion in data volume. Internal data in the form of business process input and output, electronic mail, as well as documents and reports from work units become abundant. Similarly, data originating outside the organization, such as public information from other regulators, grows exponentially. Thus, it highlights the importance of data and analytical skills for guiding and generating potential data, leading to improved decision-making performance (DMP) within the organization (Carillo et al., 2019; Chen et al., 2012; Upadhyay & Kumar, 2020; Urbinati et al., 2019; Vidgen et al., 2017).

Organizations need to leverage data analytics capabilities, which refers to the ability to deploy data analytics-based resources effectively and combine data with other related resources and capabilities. This enables enterprises to make better, more informed, and faster decisions, making it an essential capability to achieve organizational success (Fernández et al., 2014; Loebbecke & Picot, 2015; Olszak, 2016). By leveraging data, managers can make decisions based on evidence rather than intuition (McAfee & Brynjolfsson, 2012). Data can empower managers to understand their business better, transform the resulting knowledge into efficient decisions, and improve overall performance throughout the decision-making process (Gupta & George, 2016). In addition, data has the potential to transform traditional business, especially when the technology needed to collect large amounts of data is available and cheaper than before.

In this context, the increasing use and reliance on big data and data analytics involve a combination of processes and tools. These include predictive analytics, statistics, data mining, artificial intelligence, and natural language processing (Chae, 2015; George et al., 2014; Russom, 2011). These methods are commonly applied to harness scattered data sets and gain valuable insights to enhance informed decision-making (Ertemel, 2015).

Ghasemaghaeiet et al. (2018) found that improving big data analytics capabilities (BDAC) can help organizations improve internal decision-making through the use of data. Data analytics allows managers to gain insights that previously could not be obtained by understanding large amounts of data and uncovering patterns and relationships. McAfee and Brynjolfsson (2012) also discovered that more data-driven companies perform better on objective financial and operational outcomes measures. Specifically, companies in the top third of their industry that use data-driven decision-making achieve, on average, 5 per cent higher productivity and 6 per cent higher profitability than their competitors.

Organizations adopt data analytics to support their decision-making processes and improve both internal processes and external offerings (Grover et al., 2018; Sharma et al., 2014). Leveraging data analytics effectively has the potential to distinguish between high and low-performing organizations (Côrte-Real et al., 2019). However, the application of data analytics encounters various challenges, including issues regarding data quality, processes, and data analytics management itself. Furthermore, many organizations require a lot of substantial effort for large-scale transformation (Dremel et al., 2017; Sivarajah et al., 2017).

In all innovation activities within an organization, overcoming data analytics challenges requires effective analytical activity management through data analysis governance. Data analysis governance refers to "establishing and following structures, rules, policies and controls for data analysis activities" (Gröger, 2018, p.8). Therefore, organizations with more experience managing different types of knowledge tend to be more innovative (Andersson et al., 2015; Nuruzzaman et al., 2018) and effectively leverage internal capabilities such as data analytics. In fact, organizational tendencies and orientations for managing, integrating, and promoting co-collaboration (Co-Collab) between business users and data scientists fall within the relational spectrum. It includes knowledge-sharing communication and alignment, which enhance the impact of data analytics on organizational DMP (De Haes & Van Grembergen, 2004; Khan & Vorley, 2017; Michalczyk et al., 2021; Peterson, 2004; Tian, 2017).

Data-driven analytical capabilities favor collecting, storing, processing information, advanced analysis, and visualization of large and varied amounts of data. These capabilities are essential in extracting and recognizing consumer perceptions (Chen et al., 2012; Côrte-Real et al., 2019). This terminology covers the concepts of big data analytics (BDA) and artificial intelligence (AI), which are virtually indistinguishable, as machine learning and deep learning are increasingly used to handle Big Data (BD). Business analytics (BA), BDA, and AI are extensions of the data science continuum (Davenport & Bean, 2018). In management, data science is applied through the concepts of BD and BA, which are operationalized using information technology. Despite their association with technological artifacts, BD and BA are organizational capabilities beyond data. These capabilities include diverse elements such as technology, processes, methods and techniques used to interpret BD for extracting valuable information, which is essential for data-driven decision-making (Huppertz et al., 2021; Vidgen et al., 2017).

However, there is still a limited understanding of the pathways through which BDAC impact DMP. Several studies address this role for Co-Collab. A study by Wegener and Sinha (2013) indicates that managerial issues hold a more significant challenge than technological issues, underscoring the human factor of data analytics. As one example of this managerial challenge, data science experts and business users have been introduced as one of the reasons under-researched in data analytics projects (Hagen & Hess, 2021; White, 2019). Thus, organizations can empower the use of data by presenting infrastructure technology, data science experts, and business users as key collaborators in data analytics to enhance organizational decision-making (Michalczyk et al., 2021). Leveraging the insights derived from data analytics in business operations has been identified as a key driver for unlocking value from data. This highlights the importance of engaging functional business managers in analytics projects and drawing attention to their collaboration with data analytics experts, such as data and integration scientists. The optimal combination of these areas with organizational insights can be achieved through a structured and integrated network bonding approach.

In addition, Co-Collab can generate value that cannot be achieved by an individual's efforts alone as it necessitates various skills and expertise (Briggs et al., 2009). Successful collaboration is "a process through which a specific result, such as a desired product or performance, is achieved through a group effort" (Kotlarsky & Oshri, 2005, p. 40). BDA, defined as "the application of statistical, processing and analytical techniques to big data to advance business, also requires collaboration and a great deal of skill" (Grover et al., 2018, p. 390). For example, it needs a combination of business, analytical and technical skills involving business users, data science experts and software experts working together (Michalczyk et al., 2021). In this particular context of data analysis, the challenges regarding how relevant collaborative mechanisms derive from data analytics are particularly significant. The challenges include the complexity of data integration, lack of skilled personnel, data security and privacy concerns, and inadequate IT infrastructure and detailed governance mechanisms, especially relational mechanisms (Fadler et al., 2021; Gandomi & Haider, 2015).

Therefore, this study aims to answer the following research question: "Do big data analytical capabilities (i.e., data analytical capabilities from a technological, managerial, and business analytics perspective) impact decision-making performance, directly and indirectly, through Co-collaboration?" The study analyzes how BDAC affect DMP, considering the mediating role of Co-Collab. The findings suggest that the following complementary mediation is found: Co-Collab in the relationship between BDAC and DMP. It was also discovered that Co-Collab explains the transmission of most of the effect of BDAC to DMP.

With this, the study bridges an important research gap and provide empirical evidence on how BDAC and Co-Collab affect DMP, taking into account the mediating effect of Co-Collab. This is specifically relevant in practice as organizations acknowledge the significance of big data analytics in driving business value. Furthermore, Hagen and Hess (2021) explained that organizations need the collaboration of data science experts and business users to effectively leverage big data for enhancing decision making. In addition, evaluating the results of data analysis to support business or project goals requires an active participation not only from IT departments, but also from every member of a functional organization (Pagador et al., 2020). Finally, this research follows a structured approach, commencing with theoretical background, definitions, and research model development. It then proceeds with the presentation of the methods, analysis and discussion of the results, and finally, conclusions and implications.

2. Literature Review

2.1. Theoretical Background

The social capital theory has been applied to various topics where humans and groups interact, such as education, public health, and governance (Jackman & Miller, 1998; Portes & Sensenbrenner, 1993; Woolcock, 1998). In the information systems (IS) field, the theory has been used to examine the relationship between business and IT departments (Van Den Hooff & De Winter, 2011; Wagner et al., 2014). The authors apply social capital theory to guide our process design and evaluate the process's potential to nurture the relationship between data science and business professionals. Previous research has discovered that the higher the social capital within a group, characterized by stronger relationships between the group members, the better its performance (Aquino & Serva, 2005). This is because the presence of social capital can reduce transaction costs, enhance mutual commitment, and facilitate collaboration (Van Den Hooff & De Winter, 2011). As the presence of social capital positively impacts collaboration, this theory is well-suited to evaluate the quality of our process in facilitating collaboration for BDA. Specifically, the authors aim to measure how social capital develops throughout the process and identify which collaboration activities can impact the relationship in various ways. Social capital refers to "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships" (Nahapiet & Ghoshal, 1998, p. 243). It stimulates the activities of actors within a social structure (Coleman, 1990).

The theory has supported the development of new conceptualizations of capabilities such as big data analytics, which emphasizes the need for cross-department collaboration and a good working relationship between business users and data science experts (Gupta & George, 2016). In BDA projects, functional managers must utilize data insights in operations. In this case, the business community refers to managers and employees involved in the organization's main processes (Van Den Hooff & De Winter, 2011). In particular, the business community can leverage big data insights for business process improvement, product and service innovation, customer experience enhancement, organizational performance enhancement, or symbolic value creation (Grover et al., 2018). When engaged in BDA initiatives, this business community primarily represents requesters and end users of BDA solutions.

In our study, three different ways of Co-Collab are required for BDA. First, collaboration among data experts within their communities is crucial in developing advanced data science solutions (Grossman & Siegel, 2014). Second, business managers must collaborate within their communities to leverage cross-functional data insights (Trolio et al., 2017). Third, data and business communities must work together to enhance their technical and managerial skills and achieve business value based on BDA (Gupta & George, 2016). This research particularly focuses on the third form of collaboration. Therefore, we adopt social capital theory as it allows us to examine community relationships (Bharadwaj, 2000; Van Den Hooff & De Winter, 2011), which aligns with this study's objectives.

2.2. Big Data Analytics

BDA has gained considerable attention among scholars and managers because it has the capacity of firms to manage, process, and analyze big data (Wamba et al., 2017). Hagel (2015) displayed how BDA is increasingly becoming a key component of decision-making processes in different types of businesses, promoting a new proactive and forward-looking approach. However, the value extracted from data relies not only on the quality of the data themselves but also on the quality of the different processes in which data are collected and analyzed. This often requires multiple actors from different disciplines and diverse processes and practices (Ferraris et al., 2016; Janssen et al., 2017).

In line with Wamba et al. (2017) and the literature on IT capabilities by Gupta and George (2016), the authors perceive BDA as a crucial organizational capability that leads to sustainable competitive advantage in the big data environment. Business analytics provides the models, formulas and algorithms to configure a set of rules or instructions designed to solve business problems (Delen & Zolbanin, 2018; Duan et al., 2020). Therefore, business analytics contributes to the analysis of big data, improving the understanding of performance patterns, preparing research and investigations to evaluate the environment, and formulating strategy and trend analysis. The goal is to enable forecasting, analyze potential risks and future results, and identify and adopt best strategies to optimize objectives, maximize opportunities and potentialities or minimize risks and weaknesses (Appelbaum et al., 2017; Ashrafi et al., 2019; Delen & Zolbanin, 2018; Duan et al., 2020; Hashem, 2023; Sivarajah et al., 2017).

2.3. Co-Colaboration

As our study focuses on the procedural perspective of BDA to increase business value and the necessary collaboration activities, the authors adopt the definition of in understanding BDA as "tools and processes often applied to large and dispersed datasets for obtaining meaningful insights" (Ghasemaghaei et al., 2018, p. 104) In essence, BDA comprises the application of analytical skills to analyze the data and functional skills to deduce business-relevant insights (Russom, 2011). This requires a good working relationship between data science experts and business users and collaboration among them (Gupta & George, 2016). In general, the authors understand collaboration as "the process through which a specific outcome, such as a product or desired performance, is achieved through group effort" (Kotlarsky & Oshri, 2005, p. 40). In the context of BDA, collaboration is the process through which business value based on BDA is achieved through a joint effort between data science experts (e.g., data scientists and data engineers) and business users (e.g., functional business professionals from the marketing or supply chain department).

Existing BDA processes field offer initial understandings of the major activities and the stakeholders involved. First, Jagadish et al. (2014) and Jagadish (2015) pointed out that the big data lifecycle is more than an analysis of big data and comprises the following steps: data acquisition, information extracting and cleaning, data integration/aggregation/representation, modelling and analysis, and interpretation. Human collaboration is a BDA characteristic that makes these steps challenging to provide concrete recommendations on how to shape this collaboration. Moreover, the focus is on analytical activities associated with BDA, and business activities are only considered in the final step. Second, Philipps-Wren et al. (2015) suggest in their BDA framework that the activities needed to proceed with data sources are: data preparation, storage, analysis, and data access and usage. Data science experts are primarily involved in the first three phases (preparation, storage, analysis) while business users participate mainly in the final stage (usage). Third, according to Abbasi et al. (2016), the big data information value chain comprises data, information, knowledge, decisions, and actions. Likewise, data experts are primarily responsible to the first part of the value chain (data and information), while managers play a role in the second part (decisions and actions). In the knowledge phase, the authors suggest the involvement of both parties.

2.4. Decision-Making Performance

DMP is commonly assessed based on the accuracy of decisions and the time taken to make them (Speier et al., 2003). However, some scholars take a broader perspective to examine DMP and discuss its effectiveness and efficiency, encompassing accuracy and resource use (Shamim et al., 2019; Visinescu et al., 2017). It also followed the conceptualization of and explained DMP in terms of effectiveness and efficiency in the context of big data-driven decision-making. Big data-driven decision-making involves the creation of informational value through the use of big data. It highlights making decisions purely based on data rather than depending on hunches (Elia et al., 2020; Provost & Fawcett, 2013). Big data enables the firm to take data-driven decisions and enhances DMP (Janssen et al., 2017). Data-driven decision-making requires the support of data sciences. In fact, many decisions are now being supported by artificial intelligence and other related technologies. Several industrial sectors are adapting the automatic data-driven decision-making, and companies such as the financial and telecommunication sectors are the early adapters (Provost & Fawcett, 2013). This highlights the critical role of a firm's capability to manage and analyze the data effectively.

3. Research Model and Hypothesis Development

Implementing BDA necessitates various capabilities and resources, such as technological, managerial, and analytical processes (Adrian et al., 2017; Koronios et al., 2014). The goal is to transform big data into valuable and understandable information (Wang et al., 2018) using analytical applications to gain insights that drive effective decision-making and improve organizational performance (Akter et al., 2016). To achieve a competitive advantage, organizations need to combine and use multiple BDA resources and organizational-level capabilities. In this case, having big data alone is insufficient to create effective BDAC (Gupta & George, 2016; Wamba et al., 2017).

BDAC with technological expertise enable organizations to handle the bulk of the data. Research has revealed that integrating and using data analytics can enhance the decision-making capabilities of an organization (Ghasemaghaeiet al., 2018; Thomas & Chopra, 2020), resulting in better, faster, and more informed decisions (Fernández et al., 2014). Technological expertise, therefore, plays an important role in implementing big data decisions, while technology management uncovers capabilities for alliance-influenced big data decision-making capabilities, fosters knowledge sharing, and facilitates analytics related to big data.

Considering the growing influence of BDA, Hagel (2015) and Wamba et al. (2017) stated that data analytics is an important tool in the company's decision-making process. This argument is further supported by researchers including Brown et al. (2011), Ghasemahaei et al. (2018), Ma & Guo (2023), and McAfee & Brynjolfsson (2012), who claimed that the increasing popularity of BDA stems from its potential to make corporate decisions better in quality and fast in speed. In the big data revolution, today's organizations have vast amounts of both external and internal data, and their primary interest lies in exploiting this data to gain competitive advantages through effective decision-making and improve the performance of decision-making through BDA (Ertemel, 2015; Brynjolfsson et al., 2011). This view is also supported by Thirathon (2016) in his research, highlighting that it is not solely the presence of big data that leads to increased company performance but rather the organizations' ability to derive practical insights through BDA, improving decision-making performance and thereby resulting in better company performance. Based on the earlier arguments, the following hypotheses are proposed:

H1: BDA capabilities have a significant impact on co-collaboration.

H2: BDA capabilities have a significant impact on decision-making performance.

BDA is widely acknowledged as a key driver of business value. To improve organizational decision-making and extract value from big data, collaboration between data science experts and business users is necessary. According to Abbasi et al. (2016), the big information value chain consists of data, information, knowledge, decisions, and actions. Likewise, data experts are primarily responsible to the first part of the value chain (data and information), while managers play a role in the second part (decisions and actions). In the knowledge phase, the authors suggest the involvement of both parties. Co-Collab is a complex process that requires coordination, communication, meaning, relationships, and structure (Kotlarsky & Oshri, 2005).

Groups collaborate to leverage diverse skills in order to create value that cannot be achieved individually (Briggs et al., 2009). Successful collaboration, in turn, is defined as "the process through which a specific outcome, such as a product or desired performance, is achieved through group effort" (Kotlarsky & Oshri, 2005, p.40). BDA defined as the application of statistical, processing, and analytics techniques to big data for advancing business (Grover et al., 2018), also requires collaboration and a multitude of skills. Specifically, it requires business, analytical, and technical skills, which are contributed by business users, data science experts, and software experts (Michalczyk et al., 2021).

In this work team (Carton & Cummings, 2012), business users are managers from various business units, e.g., marketing, who aim to use Big Data Analytics to improve their decision-making. Data science experts (DS) are, for example, data scientists and data engineers who contribute their analytical and technical understanding to extract knowledge from data (Michalczyk et al., 2021). Lastly, IT specialists (e.g., software developers) are the technical enabler of BDA, providing the technological infrastructure and turning data science prototypes into applications (Vidgen et al., 2017). DS experts are the new organizational actor within this collaboration, as BDA is "not just a faddish rehashing of already existing technical competencies in organizations, but the emergence of a new function" (Barbour et al., 2018, p. 258).

Thus, business managers seeking to leverage BDA need to establish new relationships with these experts. It is essential to note that BDA is a functional competency, not a technical competency (Avery & Cheek, 2015). Therefore, for the purpose of our study, we particularly focus on the collaboration between DS experts and business users within BDA work team, understanding their joint effort during the process of BDA and their shared goals in enhancing organizational DMP. Given the novelty of the BDA phenomenon, we have chosen to exclude IT specialists from our analysis. While their role in BDA is indispensable, they are not considered to be at the forefront of organizational decision-making and BDA management (Pearson & Wegener, 2013). Thus, we propose the following hypotheses.

- H3: Co-collaboration has a significant impact on decision-making performance.
- H4: Co-collaboration mediates the relationship between BDA capabilities and decision-making performances.

In addition, evidence supports the notion that the critical point for extracting value from big data lies in generating fast insights, transforming the resulting knowledge, and leveraging a wide range of business, analytical and technical skills. This collaborative work involves business users, data science experts and software experts, with the objective of translating this knowledge into actionable decisions that improve decision-making processes and performance. It is in line with the significance of analytics and Co-Collab in this model (Grover et al., 2018; Gupta & George, 2016; Michalczyk et al.,2021; Seddon et al., 2017). In this sense, the research model suggests that DMP is influenced by collaborative efforts enabled by analytical skills. Figure 1 displays the model proposed in the research.

To build a more holistic view of how BDAC relate to DMP, our model introduces an innovative perspective. It highlights the role of Co-Collab as both a consequent and mediator of BDAC to gain DMP in leveraging BDAC to enhance DMP. By establishing a clear causality, our model contributes to a comprehensive understanding of the relationship between BDAC and DMP.

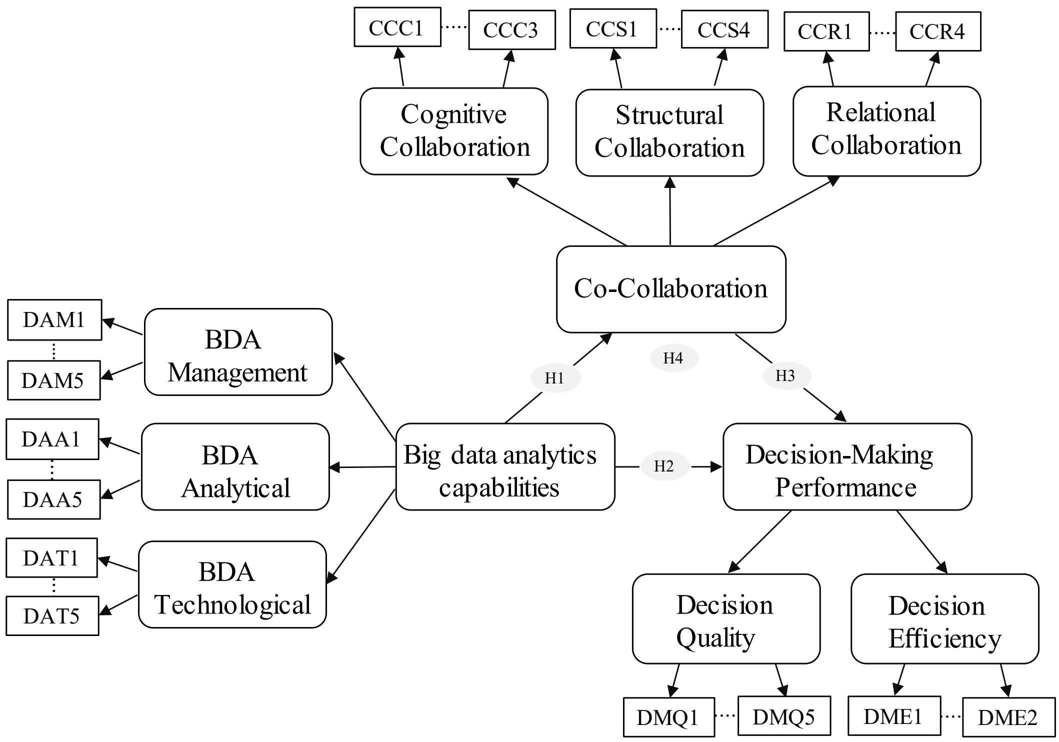


Fig. 1: Research model

4. Research Methods

4.1. Research Design and Measurement

The current study adopts a quantitative approach in order to analyze the primary data. Initially, a quantitative study was conducted to evaluate the research model empirically. Then, data was collected through a survey using a structured questionnaire. All indicators in the questionnaire were derived from the previous research literature. Variables in this study were measured through the Likert scale to measure variables, with respondents indicating their level of agreement on a 5-point scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

4.2. Development of the Survey Instrument

During the development of the instrument, guidelines by MacKenzie et al. (2011) were followed. After conceptualizing the constructs, the existing literature was used to develop items that represented the definition of the constructs. In addition, the face and content validation of the instrument was carried out with the support of five specialists in the field (including two professionals, a master's in Management, and two PhDs in Information Systems). During the validation process, adjustments were made to the questionnaire structure, such as removing items with ambiguous definitions, integrating items with similar meanings, and enhancing the description of certain items. The final version of the instruments consisted of three variables, eight dimensions, and thirty-three indicators, illustrated in Table 1.

Table 1: Variable Measurement

Variable / Dimension	Item	Indicator	Reference
BDA capabilities			
BDA management	DAM1	BDA planning processes are systematic and formalized	Akter et al., 2016; Byrd & Turner, 2000; Duan et al.,
	DAM2	The responsibility for BDA development is clear	
	DAM3	There is innovative opportunities for the strategic use of BDA	

	DAM4	When making BDA decisions, consider employee productivity as a key factor.	2020; Kim et al., 2012; Medeiros & Macada., 2021
	DAM5	Information is widely shared between business analysts and line peoples	
BDA analytical	DAA1	Understand what happens in the business	
	DAA2	Find out the causes of a particular problem	
	DAA3	Identify behaviors and predict trends	
	DAA4	Predict future results	
	DAA5	Identify the best alternatives and optimize business objectives	
BDA technological	DAT1	All remote, branch, and mobile office are connected to the central office for analytics	
	DAT2	Organizations utilize open system network mechanisms to boost analytics connectivity	
	DAT3	User interfaces provide transparent access to all platforms and applications	
	DAT4	Organizations utilize object-oriented tools to create their own analytics applications	
	DAT5	Applications can be adapted to meet a variety of needs during analytics tasks	
Co-collaboration			
Cognitive Collaboration	CCC1	Provide an understanding of participation, in capabilities information processing and retrieval to achieve successful goals	Baijens et al. 2020; Grover et al., 2018; Hagen & Hess., 2021
	CCC2	Develop resolution processes to solve problems a range of data	
	CCC3	Support information transfer and understanding data sources, and most relevant ones can be chosen from a selection of data	
Structural Collaboration	CCS1	Interaction between unit (processes and management), to interpreting and understanding data, that needs in decision makers	
	CCS2	Develop contributions between unit, in understanding data that is relevant and representing quality data	
	CCS3	Increase interaction and facilitation in the benefits of data, to obtain quality data for effective decisions	
	CCS4	Responsibilities between unit, to big data utilization with sharing knowledge to make high-quality decisions	
Relational Collaboration	CCR1	Commitment to achieving common goals and produce better services	
	CCR2	Engagement and motivation to mutually support the provision and processing of data	
	CCR2	Partnerships increase assertiveness in the decision-making proces	
	CCR4	Visibility can interpret data outputs and results confidently and critically	
Decision-making performance			
		Data and analytics usage has improved decision outcomes ...	Jarupathirun, 2007; Shamim et al., 2019; Visinescu et al., 2017
Decision quality	DMQ1	... the reliability of our organization	
	DMQ2	... our organization's correct	
	DMQ3	... our organization's error-free	
	DMQ4	... our organization's flawless	

	DMQ5	... the error-free of our organization
Decision efficiency	DME1	Our organization has gained strategic advantages with the time to arrive at decisions is fast
	DME2	Overall, our organization have the speed of arriving at decisions is high

4.3. Collection of Data and Samples

The population of the study consisted of operational managers working in public service sector organizations in Indonesia. The data collection process took approximately three months, from October to December 2022. A total of 212 respondents participated in the study by filling out a survey in electronic form. To ensure the sample quality, participants were screened regarding their "Yes" or "No" answers to observe whether public institutions use data analytics based on definitions and examples of these tools. After the screening, the authors retrieved 189 questionnaires valid for statistical processing, indicating a response rate of 89.2% as statistically accepted. The profiles of the respondents and institutions are shown in Table 1.

As this is primary data, it is necessary to ensure that no systematic bias affects the information collected. Thus, a single-factor test by Harman (1976) was performed. The nonrotated solution indicated that the single factor explained 47.66% of the variation, below the 50% limit. Furthermore, the AFC test on the SPSS software, with rotation varimax and eigenvalue equal to 1.0, shows the presence of the three expected components for a total explained variation of 74.33%. This confirms all dimensions provided in the model. In addition, Armstrong and Overton's (1977) procedure compared the mean constructs of the initial 80% of respondents to the final 20%, stating that "non-response" bias is not a problem.

4.4. Data Analysis

For data analysis, SmartPLS V4 software was adopted. Initially, the constructs were examined, the measurement model was evaluated, and the structural equations were modelled with minimum partial frames (partial least squares- structural equation modeling (PLS-SEM)). PLS-SEM was chosen as it allows for working with complex models and is fit for theoretical development and explanation of construction variants (Hair et al., 2017), management research (Henseler et al., 2014), and information systems (Mikalef & Pateli, 2017). Furthermore, the mediation analysis followed the guidelines proposed by Hair et al. (2017).

Table 2: Respondents' profile

Total informants/organizations (n=189)							
Professional experience	(%)	Size of the organization	(%)	Public Sector Area	(%)	Work unit function[1]	(%)
$x \leq 3$	4	Small	19	Public services	9	Business process	58
$3 < x \leq 7$	8	Medium	32	State treasury & assets	6	Data Management	24
$7 < x \leq 10$	19	Large	49	State revenue & expenditures	24	Regional office	12
$10 < x \leq 15$	27			Financial & risk	48	Operational	6
$x > 15$	42			Fiscal management	13		

Note (s) : [1] Work unit function where informants/organizations operates

5. Results and Discussion

5.1. Measurement Model

The model deals with reflective constructions; therefore, with support from SmartPLS software, internal consistency, composite reliability, convergent validity and discriminant validity were examined. All constructs demonstrated satisfactory internal consistency and reliability, with Cronbach's alpha and composite reliability (CR) values greater than 0.70 (Hair et al., 2017). The convergent validity, calculated using each factor's average variance extracted (AVE), indicated how much a given composition of the observable variables represents a single latent variable. The AVE indicators for each were higher than the recommended threshold of 0.50 (Hair et al., 2017). From the analysis of factor loads and AVE of each factor, it is concluded that the constructs have convergent validity. The outler loadings of the items are presented in Table 3.

Table 3. Outler Loadings

	Dimension	Item	Outer Loadings	Result
BDAC	BDA management	DAM1	0.877	Valid
		DAM2	0.751	Valid
		DAM3	0.812	Valid
		DAM4	0.748	Valid
		DAM5	0.760	Valid
	BDA analytical	DAA1	0.851	Valid
		DDA2	0.769	Valid
		DDA3	0.774	Valid
		DDA4	0.860	Valid
		DDA5	0.825	Valid
	BDA technological	DAT1	0.813	Valid
		DAT2	0.838	Valid
		DAT3	0.769	Valid
		DAT4	0.843	Valid
		DAT5	0.774	Valid

	Dimension	Item	Outer Loadings	Result
Co-Collab	Cognitive Collaboration	CCC1	0.901	Valid
		CCC2	0.848	Valid
		CCC3	0.868	Valid
	Structural Collaboration	CCS1	0.864	Valid
		CCS2	0.859	Valid
		CCS3	0.836	Valid
	Relational Collaboration	CCR1	0.860	Valid
		CCR2	0.844	Valid
		CCR2	0.918	Valid
		CCR4	0.818	Valid
DMP	Decision quality	DMQ1	0.852	Valid
		DMQ2	0.860	Valid
		DMQ3	0.844	Valid
		DMQ4	0.918	Valid
		DMQ5	0.781	Valid
	Decision efficiency	DME1	0.834	Valid
		DME2	0.844	Valid

Discriminant validity indicates how different a construct is from the others. Two approaches were adopted: (1) Fornell and Larcker's (1981) criterion and (2) the Heterotrait-monotrait ratio (HTMT)'s criterion by Henseler et al. (2014). According to the first criterion (AVE), it was observed that no correlation raised to the square comes close to the AVE of the factors. The second criterion (HTMT) also showed that all constructs met the predefined limit of 0.85. These analyses establish the reliability and validity of the constructs in this model. Table 4 demonstrates the constructs' normality, internal reliability, and convergent and discriminant validity. Then, the structural model and mediations were analyzed to assess the nomological validity.

Table 4. Construct analysis: Internal consistency, convergent, and discriminant validity

	Inicators[2] CR			Fornell-Larcker criterion[3]			HTMT criterion		
Construct[1]	α	CR	AVE	BDAC	Co-Collab	DMP	BDAC	Co-Collab	DMP
BDAC	0.898	0.936	0.831	0.867					
Co-Collab	0.940	0.962	0.894	0.728	0.908		0.745		
DMP	0.965	0.983	0.966	0.450	0.492	0.920	0.462	0.505	

Note(s) : [1] Decision-making performance (DMP); big data analytics capabilities (BDAC); co-collaboration (Co-Collab); [2]Cronbach's alpha(α); composite reliability (CR); average variance extracted (AVE); [3]Square root of AVE is in the diagonal and highlighted in italic

5.2. Mediation Structural Model

The evaluation of the structural model is performed using the magnitude and sign of the path coefficients, the level of significance of the relationships, the effect size (f^2), the Pearson determination coefficients (R^2), predictive validity (Q^2) and model adjustment (standardized root mean residual (SRMR)). Initially, the collinearity between the constructs was analyzed using the variance inflation factor, with values between 1.000 and 1.969, lower than the limit of 5 (Hair et al., 2017). Next, a bootstrapping procedure (5,000 samples) was used to assess the hypothesized paths' significance and the amount of variance in the dependent variables attributed to the explanatory variables (Hair et al., 2017). This analysis delivers a comprehensive assessment of the model's significance and suitability.The results of testing the hypotheses regarding direct effects and the analysis of effect size (f^2) are illustrated in Table 5.

Table 5. Significance of the direct paths and effect size

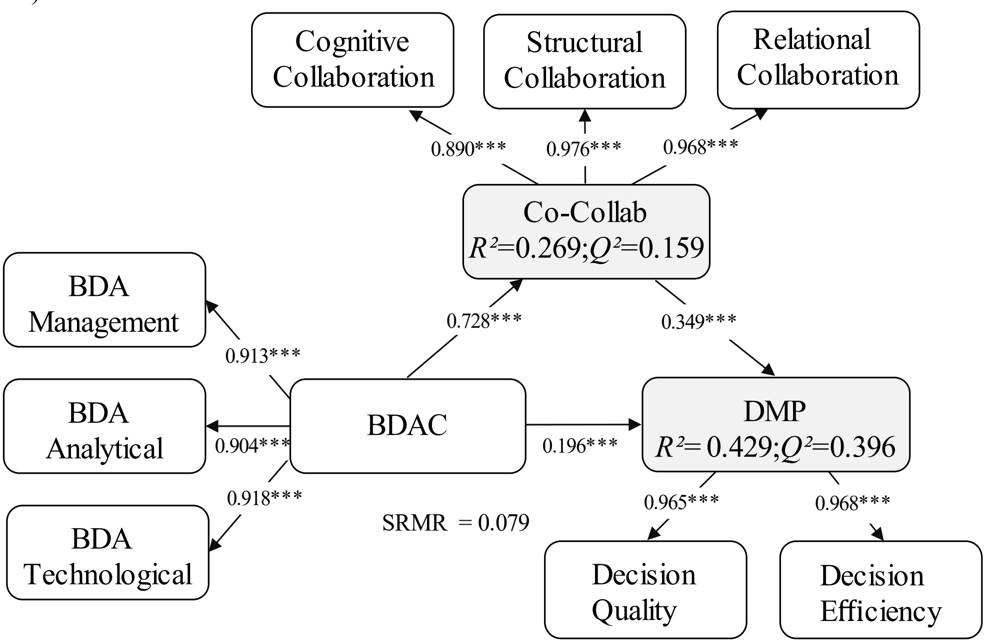
Hypothesis[1]		Path coefficient	T statistic	p -value[2]	Effect size(f^2)	Analysis of Cohen's f^2	Empirical evidence
H1 :	BDAC → Co-Collab	0.728	9.924	0.000***	0.425	Large	Supported
H2 :	BDAC → DMP	0.196	2.736	0.000***	0.024	Small	Supported
H3 :	Co-Collab → DMP	0.349	4.118	0.000***	0.078	Small	Supported

Notes (s) : [1]H4 represent (indirect mediating effects; [2]$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, ns – not significant

Figure 2 presents the path coefficient, the significance level of the relationship, Pearson's determination coefficient (R^2) and predictive validity (Q^2). First, as the data show linear correlations and regressions, the significance of the results must be analyzed; p value < 0.05 was obtained (Hair et al., 2017). Thus, all hypotheses were supported and showed significance at a level of less than 0.01%. Next, a portion of the variance of the endogenous variables was assessed, which is explained by the structural model using Pearson's coefficient of determination (R^2). The BDAC, Co-Collab and DMP construct variance is explained with significant effects, as they have R^2 > 26% (Cohen, 1988).

To verify each exogenous variable portion in explaining the model's endogenous variables, the effect sizes were evaluated. It was observed that in all relationships, Cohen's indicator (f^2) was higher than 0.02, which shows adequate results for latent factors (Henseler et al., 2009). According to Cohen(1988), $f^2 > 0.02$ represents a small size effect, while $f^2 > 0.15$ is a medium size effect, and $f^2 > 0.35$ is a large size effect. Therefore, as indicated in Table 4, there is a large effect observed in the relationship between BDAC → Co-Collab and small effects in the relationships between BDAC → DMP and Co-Collab → DMP. In addition, it is also essential to assess the predictive relevance of the model, which is measured by the Stone–Geisser indicator (Q^2).

The results show that the model prediction accuracy for the endogenous variables is satisfactory because they all have $Q^2 > 0$ (Hair et al., 2017). To assess the quality of model fit, the only criterion recommended for SEM by PLS is SRMR (Hu & Bentler, 1999). Notably, the SRMR index (0.058) meets the most stringent parameter in the literature, which is less than 0.08 (Hair et al., 2017; Hu & Bentler, 1999).



Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ns – not significant
Decision-making performance (DMP); Big data analytics capabilities (BDAC); Co-collaboration (Co-Collab)

Fig. 2 : Mediation Structural model

Table 6 shows the results of the effects obtained based on the mediation analysis of the procedure outlined by Baron and Kenny (1986), Hair et al. (2017), and Nitzl et al. (2016). An effective approach to assessing the strength of partial mediation is to calculate the ratio of the indirect effect to the total effect. This proportion is known as variance accounted for value (VAF) in which this index determines the extent to which the mediation process explains the variation of the dependent variable. Values below 20% indicate the absence of mediation, between 20% and 80% indicate typical partial mediation, and above 80% indicate complete mediation (Nitzl et al., 2016).

Table 6. Mediation analysis

Hypothesis		Direct effect	Indirect effect	Total effect	*T* statistic	*p* -value[1]	VAF[2]
H4:	BDAC→ Co-Collab → DMP	0.196	0.254	0.450	5.834	0.05**	56%

Notes (s) : [1]$p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, ns – not significant; [2]VAF - Variance accounted for value is the ratio of the indirect effect to the total effect, VAF[2] : 56% >> Mediation type : Complementary mediation

Therefore, the VAF assessment supports the mediation hypothesis. The findings indicate the existence of the following complementary mediations: Co-Collab in the relationship between BDAC and DMP, with high strength. Thus, an important theoretical contribution is delivered when Co-Collab explains the transmission of most (56%) of the effect of BDAC to DMP.

5.3. Findings

The findings of this study support hypotheses H1 and H2, confirming that in the big data revolution, BDAC play an important role in effective decision-making, leveraging data utilization and analysis, and fostering a shift towards a data-driven mindset. Numerous research (Duan et al., 2020; Ertemel, 2015; Holsapple et al., 2014; Tabesh et al., 2019; Upadhyay & Kumar, 2020) has revealed the significance of BDAC in generating invaluable insights and improving decision-making processes within the context of the big data revolution. Moreover, big data-based views and decisions imply interaction and joint interpretation in the process of strengthening the governance mechanisms of BDA by operationalizing Co-Collab and its mechanisms in organizational management to improve organizational decision-making (Baijens et al., 2020; Kiron et al., 2013; Tabesh et al., 2019).

Co-Collab, involving collaborative work between data science experts and business users, is crucial in succeeding BDA projects and impacts decision-making positively (Chanias et al., 2019; Michalczyk et al., 2021; Schuritz et al., 2017; Shamim et al., 2019; Sharma et al., 2014). This study sheds light on the role of Co-Collab as a critical driver of business value and its impact on organizational decision-making, highlighting its significance in BDA governance and management practices. This study confirms that BDA enablers, such as Co-Collab, are not widely recognized as being at the forefront of organizational decision-making and BDA management (Pearson & Wegener, 2013). The results explain the relationship between these constructs, underscoring the need for greater recognition and integration of Co-Collab as a key driver for effective decision-making in organizations.

When considering the central role of Co-Collab, this study explores their collaborative design and investigates the relationship of collaboration mechanisms to the relationship between business users and data science experts. It also focuses on specific aspects such as shared commitment, communication, knowledge base, insights and alignment, as mentioned in the literature. This approach paves the way for developing Co-Collab incorporating various information about knowledge, skills, abilities, preferences, and other tendencies (Cannon-Bowers et al., 1993). Co-Collab represents an interaction of competencies that cannot be created individually by leveraging diverse skills and backgrounds to create value. It is based on the premise that Co-Collab is essential for BDA within their own communities to create superior data science solutions utilizing cross-disciplinary data insights. For example, it enables to get a holistic view of customers across all touchpoints, enhances both technical and managerial skills and achieves business value based on BDA (Briggs et al., 2009; Grossman & Siegel, 2014; Gupta & George, 2016; Trolio et al., 2017). Therefore, Co-Collab in utilizing BDA insights in business is the most important contributor to unlocking BDA's business value (Côrte-Real et al., 2019).

Co-Collab and critical thinking are essential to be embodied in multiple competencies not only with individual skill domains but also with the social composition of heterogeneous groups, which as a whole may have to manage, handle and use data ethically (Pedersen & Caviglia, 2019; Prado & Marzal, 2013). The business community's involvement in the BDA process requires close cooperation throughout the process. Effective collaboration between actors depends on identifiable marks of linkages, behaviour, representation and interpretation between groups. This is because the higher the social capital in a group, the better its performance (Aquino & Serva, 2005).

The empirical evidence from this study supports the proposition that Co-Collab enables DMP (H3). These findings highlight the relevance of Co-Collab factors in the decision-making process, confirming that BDA contributes to conceptualizing business, analytical and technical skills. This collaborative effort facilitates better comprehension and extraction of knowledge from data, with technical support provided through technology infrastructure and the transformation of data science prototypes into applications. These factors are dominant when the goal of using BDA is to improve DMP (Barbour et al., 2018; Carton & Cummings, 2012; Michalczyk et al., 2021; Vidgen et al., 2017).

In addition, the finding that Co-Collab mediation (supported by H4) can transmit a sizeable effect of BDAC to DMP (56%) suggests that the view of DMP, consisting of BDA and skills in relevant areas, is beneficial to leverage valuable insights between data experts and business users. This integration is a determinant of success in decision-making and policy formulation, specifically in representing and interpreting BDA applications and understanding the process of BDA in a business context. It involves identifying problems, interpreting big data, and monitoring the direction of action (Abbasi et al., 2016; Jagadish, 2015; Gupta & George, 2016; Rayna & Striukova, 2021). By properly combining business perspectives and activities collaboration into the BDA process, organizations can increase the utilization of BDA and improve DMP.

6. Conclusion and Implications

6.1. Conclusion

In this paper, the authors empirically found that to fully benefit from big data, organizations must have BDAC and a certain level of Co-Collab. This can lead to a better decision-making process in finding relevant information and decision levels in the same place (Shah et al., 2012). Therefore, in the era of big data, BDA governance refers to establishing and adhering to structures, rules, policies and controls for data analytics activities (Gröger, 2018). Thus, skilled leaders can create organizations that are flexible enough to maximize cross-functional collaboration (Shams et al., 2018).

Moreover, it is important to bring together individuals who understand the problem, not only with the right data but also with others who have problem-solving techniques to exploit the potential of big data effectively. This collaboration nurtures social bonds and increases collaboration for BDA, thereby becoming a more substantial consideration of stakeholders involved in BDA (Chanias et al., 2019; Markus, 2017; Mikalef et al., 2020). It is, therefore, necessary for organizations to have managers possessing in-depth knowledge of the current and future needs of business units, partners, and customers. Additionally, they should understand strong adherence to applying newly found values driven through data analysis to areas that can maximize the organization’s benefits (Gupta & George, 2016). Therefore, explicitly understanding collaboration as a joint effort is undisputable throughout the BDA process to improve organizational decision-making.

6.2. Practical and Theoretical Implications

This study underscores the significance of developing co-collaboration mechanisms, which have resulted in positive effects, leading to better performance. In management practice, the application of data science occurs through the concepts of big data and business analytics, emphasizing the conversion of data into business information and valuable knowledge for decision-making processes. Consequently, organizations need the collaboration of data science experts and business users to effectively leverage big data for enhancing decision-making performance.Through co-collaboration, organizations can uncover meaningful patterns in data and transform big data into valuable insights for success. This transformative process facilitates a shift in managerial mindsets towards a data-driven culture, which is essential for harnessing innovation opportunities. The findings of this research hold practical implications by assisting organizations in identifying the influential role of BDAC in leveraging data science and extracting value from big data sources such as business intelligence, analytics, and machine learning.Moreover, these findings suggest the significance for organizational leaders and managers to develop plans that nurture BDAC and implement Co-Collab processes to maximize the business's utilization of big data. Therefore, deriving value from big data to improve organizational DMP requires collaboration between data science experts and business users. Thus, organizations can establish policies and strategies to extract value from data and leverage business community and DMP through the use of BDAC.

This study contributes to the existing literature on social capital theory by explaining how Co-Collab adds value to organizations. BDA is widely recognized as an important driver of business value. Therefore, deriving value from big data to improve organizational DMP requires collaboration between data science experts and business users. This approach not only transcends the conventional views of BDA as a resource for attaining competitive advantage but also acknowledges its role as a business community that can drive performance within public institutions, thereby enriching the existing social capital theory literature.

6.3. Limitations and Future Research

Like many studies, the design of the current study is subject to several limitations. First, this research is limited to Indonesian public institutions only; thus, further research with samples from different institutions and geographical contexts is advised to reach broader and more profound implications. This current study is limited to the specific domain of data analytics within a single context and it is important to recognize that BDA is inherently context-specific due to variations within analytic institutions or industries. As this study collected data from the public sector, the finding should be carefully interpreted when extrapolating to other contexts. Finally, the conclusions of this study point to various opportunities for further research, such as (1) comparatively analyzing cases from different organizations to understand how to develop BDAC and DMP, (2) analyzing Co-Collab constructs and DMP through experimental research to identify how decision-makers leverage these capabilities to enable and generate business insights, strategy, operations, and knowledge; and (3) applying concurrent or sequential mixed methods research to explore context and/or process relationships among variables.

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