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Decision Making Performance of Business Data Analytical Capabilities: The Mediating Effect of Analytics Competency

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Abstract: This research study investigates the mediating influence of analytics competency (AC) on the relationship between business data analytical capabilities (BDAC) and decision-making performance (DMP). Using a quantitative approach, 167 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 AC on this relationship. The results demonstrate that BDAC and AC significantly influence DMP, and BDAC significantly affects AC. Notably, AC 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 the use of AC to maximize the business's utilization of big data. Thus, organizational leaders and managers can determine the policies and strategies needed to extract value from data, determine the direction of the organization in data-driven decision-making, thereby building better and faster decision quality through AC and BDAC. Moreover, the study highlights opportunities for future studies, including comparative analysis across different organizations, experimental research on AC and DMP, and the application of concurrent or sequential mixed methods to explore context and process relationships among variables.

Keywords: decision-making performance, Business data analytical capabilities, Analytics competency, Public sector institutions.

1. INTRODUCTION

In recent years, data analytics has become a very popular topic in various industries in the world, even being the main topic of discussion for researchers and practitioners for almost a decade now [52,76]. 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. When determining the wiggle room for data utilization, organizations need to interpret some of this data to turn it into business value [28,58,68].

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 [8,11,69,70,71].

Organizations need to leverage data analytics capabilities, which refers to the ability to deploy data analytics-based resources effectively. This enables enterprises to make better, more informed, and faster decisions, making it an essential capability to achieve organizational success [21,48,56]. By leveraging data, managers can make decisions based on evidence rather than intuition [49]. 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 [31].

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 [1,9,14,25,60]. These methods are commonly applied to harness scattered data sets and gain valuable insights to enhance informed decision-making [20].

Ghasemaghaeiet et al. [27] found that improving big data analytics capabilities 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 [49] 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 [29,64]. Leveraging data analytics effectively has the potential to distinguish between high and low-performing organizations [13]. 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 [18,66].

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 [11,13]. 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)

However, there is still a limited understanding of the pathways through which BDAC impact DMP. A few studies address this role to analytics competency (AC), considering AC is one of the main effects on decision making [10,27,31,39], where, improving data analytics capabilities can help organizations improve internal decision making based on data and in data analytics, the use of data is used for organizational purposes thereby enabling managers to gain insights that previously could not be obtained by understanding large amounts of data and uncovering patterns and relationship

Therefore, this study aims to answer the following research question: "Do business data analytical capabilities impact decision-making performance, directly and indirectly, through Data Analytics Competency ?" The study analyzes how BDAC affect DMP, considering the mediating role of AC. The findings suggest that the following complementary mediation is found: AC in the relationship between BDAC and DMP. It was also discovered that AC 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 AC affect DMP, taking into account the mediating effect of AC. This is specifically relevant in practice as organizations acknowledge the significance of big data analytics in driving business value. Furthermore, organizations developing data analytics capabilities (i.e., the ability to effectively deploy data analytics-based resources in combination with other related resources and capabilities) to make better, more informed, and faster decisions, resulting in the ability to utilize all available information, so that become a very important capability for organizational success [56]. 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.

2. LITERATURE REVIEW

2.1 Theoretical Background

Competence-based theory [61] is based upon the underpinnings of theories such as the resource-based view [5], the knowledge-based view [16,44], strategic assets [2], and competitive heterogeneity [38] that emphasize the importance of organizational resources and capabilities in creating value and competitive advantage for firms. The theory has supported the development of new conceptualizations of capabilities in the domain of, for instance, big data analytics [31].

RBV posits that organizations compete based on unique firm resources that are rare, difficult to imitate, and valuable. This suggests that an organization is more successful when it controls more effective and/or efficient resources than its competitors [5]. An organization can only be more successful than its peers if it can make use of the available resources more effectively and/or efficiently [24]. This requires action-related competences that utilize these rather static resources in value-added activities for the organization.

Within a competence-based approach, competence models are used to unify individual capabilities with organizational core competences [71]. Sanchez [62], for instance, refers to skills and defines them as ‘special forms of capability, usually embedded in individuals or teams. A competency is generally defined as a set of observable performance dimensions, including individual knowledge, skills, attitudes, and behavior [7].

This study contributes to the discussion on competence-based theory to help explain how data analytics adds value to the organization. Competences refer to the capacity of an organization to deploy resources and data analytics is operational competency. This approach extends prior works in this space by not simply viewing big data analytics as a competitive advantage yielding resources, but rather viewing big data analytics as a competency that can evoke performance in governmental bodies.

2.2. Business Data Analytical Capabilities

Business Data Analytical (BDA) capability is a company's capacity to manage, process, and analyze big data [77]. For example, Hagel [32] shows how BDA is increasingly becoming a key component of the decision-making process in various types of businesses due to its novel, proactive and forward-looking approach. However, the value derived from data depends not only on the quality of the data itself, but also on the quality of the various data collection and analysis processes. This often requires multiple actors from multiple disciplines and multiple processes and practices [43].

Business analytics provides models, formulas and algorithms for configuring a set of rules or instructions designed to solve business problems [16,17). Therefore, BDA capabilities contribute to BD analysis, enhancing understanding of performance patterns, preparation of research and investigations for environmental evaluation and formulation of analysis of strategies and trends. The goal is to enable the projection of forecasts and analysis of potential risks and future results and the identification and adoption of the best strategies to optimize objectives, maximizing opportunities and potentialities or minimizing risks and weaknesses [3,16,17].

2.3. Analytics competency

Data analytics competency refers to a firm’s capability in utilizing data analytics-based resources [27]. The data analytics competency of each firm influences its outcomes [31]. Firm competencies include the processes and skills that transform inputs into outputs of better value [55,74]. Lee [46] argues that firm competency depends on the existence of valuable resources that are unsubstitutable, and inimitable by the competitors.

According to Popovic et al. [57], the value that data analytics toolsgenerate is considerably influenced by its data quality. Employee analytics capability is identified as another critical data analytics competency resource which refers to the skills of employees in integrating and analyzing data while using data analytics tools. Having employees with the right skills and talent is an important resource for firms to generate value from data analytics tools [27].

Tools sophistication is the maturity of the analytics tools in providing in-depth analyses and it is considered another vital resource that forms data analytics competency in firms [15]. Tools that have high levels of sophistication can provide analyses regarding current and past events, projections of future happenings, and the possible best courses of actions and the outcome of each [27].

2.4. Decision-Making Performance

Decision-making performance (DMP) for organization has been defined in the literature and described in terms of decision accuracy and time required for decision-making [67].

Some scholars use a broader lens to look at decision-making performance and discuss it in terms of decision effectiveness and efficiency so as to include accuracy and resource use. Shamim et al. [65], Visinescu et al. [73] also follows the conceptualization and explanation of decision-making performance in terms of effectiveness and efficiency, in the context of big data-driven decision-making.

Hence, as improved orgaanization decision making has been suggested as the eventual goal for data analytics [20], in this study, decision making performance refers to the users’ evaluations of decision quality and efficiency in their decision making process. Decision quality focuses on decision outcomes that are high in terms of accuracy, precision, and reliability, while decision efficiency concerns arriving at decisions quickly [44].

Big data-driven decision-making is categorized as informational value creation through big data. Data-based decision-making means decisions based purely on data, not relying on hunches [60]. Big data enables organization to make decisions based on data and improve decision-making performance [43].

2.5 Research Model and Hypotheis Development

Effectiveness is achieved in the decision-making process if the BD ability functions optimally to make complex decisions, while efficiency refers to timely decisions within the available resources.

Organizations handle and manage BD to use data effectively for decision making [72]. The quality of decision making, if supported by data capabilities, can provide better results and efficiency in decision making [65].When data and analytics drive the organization through a collective pattern of principles, values, shared behaviors and practices, is a greater probability of the analytic data's use helps the organization get a clearer perception of the market and business opportunities based on the data, encouraging propitious changes to leverage organizational performance [16,30,37,51].

BDAC is also considered as an important factor in shaping data analytics competence in companies [27]. For this reason, BDAC is a critical capability that aims to increase the trend of insight and knowledge towards the use and utilization of big data. BDAC is the basis for making decisions in organizations and the accuracy of data can play an important role in an efficient decision-making process. BDAC includes processes used by organizations. BDAC under the BD chain is the basis for efficient decision making [47]. Based on the earlier arguments, the following hypotheses are proposed:

H1. Business data analytical capabilities have a significant impact on analytics competency.

H2. Business data analytical capabilities have a significant impact on decision-making performance.

Ghasemaghaei et al.[27] developed a framework in which they found that enterprise data analytics competence is shaped by big data utilization, data quality, analytical capabilities, and tool sophistication. Leveraging big data helps companies develop sharper insights into their markers by spotting unexpected patterns [21]. This rich information can facilitate improving quality decisions through knowledge sharing among employees. Another important factor that shapes data analytics competence is the sophistication of equipment [27].

Companies that use sophisticated analytical tools can gain in-depth insights into past, current, and future events [15]. Thus, using sophisticated tools can help companies to share more in-depth knowledge with decision makers which can improve the quality of their decisions. To create knowledge and improve the quality of decisions in the corporate environment by leveraging data analytics tools, employees need to share the knowledge necessary to make high quality decisions. One of the key sources of successful knowledge sharing is competence in creating, integrating, and utilizing knowledge [46]. Organizations need the ability to interpret data and to understand the processes and procedures involved in the industry/company to identify knowledge that needs to be shared with decision makers [77]. If organizations do not have adequate BDAC, they may not be able to derive useful insights from analytical tools and they may not properly share the knowledge they gain from using data analytics with decision makers. Thus, we propose the following hypotheses.

H3. Analytics competency has a significant impact on decision-making performance.

H4. Analytics competency mediates the relationship between business data analytical capabilities and decision-making performance.

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. In this sense, the research model proposes that a BDAC-activated AC impacts DMP. 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 AC 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.

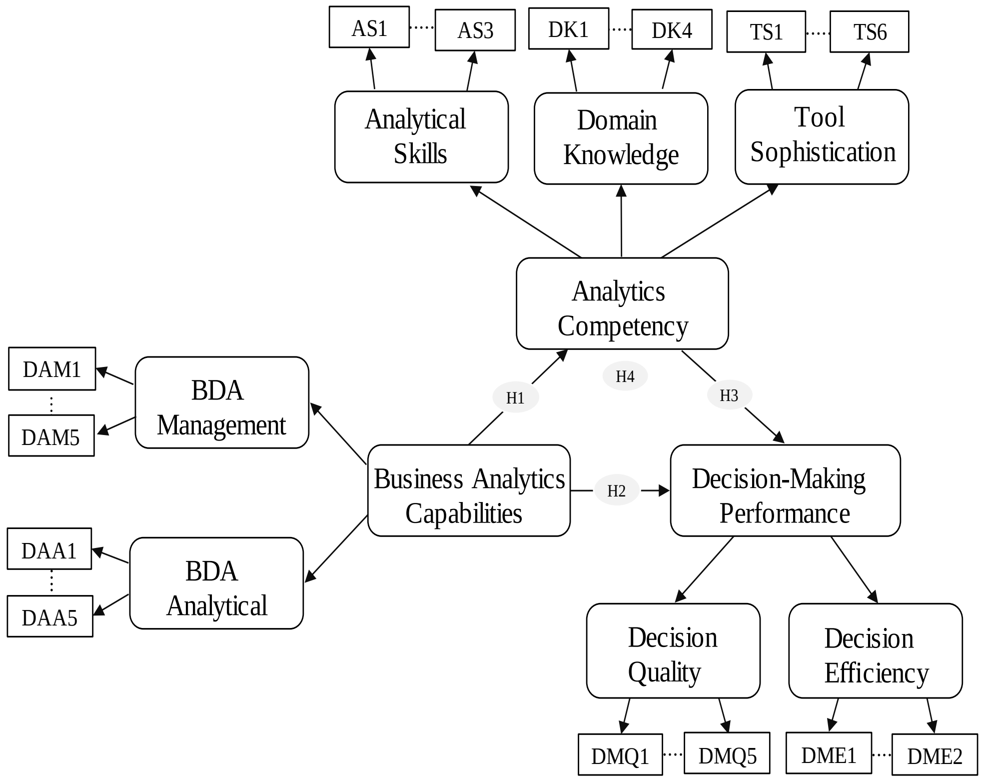

Figure 1: Research model

3. RESEARCH METHOD

3.1. 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).

3.2. Development of the Survey Instrument

During the development of the instrument, guidelines by MacKenzie et al.[50] 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, seven dimensions, and twenty-seven indicators, illustrated in Table 1.

Table 1. Variable Measurement

Variable	Item	Indicator
BDAC (Reference : Akter et al., 2016; Duan et al., 2020; Kim et al., 2012; Medeiros & Macada., 2021)		
	DAM1	BDA planning processes are systematic and formalized

BDA management	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.
	DAM5	Information is widely shared between business analysts and line peoples
BDA analytical	DAA1	All remote, branch, and mobile office are connected to the central office for analytics
	DAA2	Organizations utilize open system network mechanisms to boost analytics connectivity
	DAA3	User interfaces provide transparent access to all platforms and applications
	DAA4	Organizations utilize object-oriented tools to create their own analytics applications
	DAA5	Applications can be adapted to meet a variety of needs during analytics tasks
AC (Reference : Ghasemaghaei et al.,2017;Tippins and Sohi (2003); Bassellier and Benbasat (2004)		
		Business data analysis helps our organization ...
Analytical Skills	AS1	Our data analytics users possess a high degree of data analytics expertise.
	AS2	Our data analytics users are knowledgeable when it comes to utilizing such tools.
	AS3	Our data analytics users are skilled at using data analytics tools.
Domain Knowledge		In my organization, there is a high level of knowledge of the ...
	DK1	Organizational goals and objectives
	DK2	Core capabilities of the organization
	DK3	Key factors that must go right for the organization to succeed
Tool Sophistication		In my organization, we use tools that ...
	TS1	Provide real-time insight
	TS2	Provide information processing and retrieval capabilities
	TS3	Extracting information from unstructured sources
	TS4	Identify problems & evaluate diﬀerent alternatives
DMP (Reference : Jarupathirun, 2007; Shamim et al., 2019; Visinescu et al., 2017)		
		Data and analytics usage has improved decision outcomes ...
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

3.3. 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 167 questionnaires valid for statistical processing, indicating a response rate of 91.2% as statistically accepted. The profiles of the respondents and institutions are shown in Table 2.

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 [41] was performed. The nonrotated solution indicated that the single factor explained 45.99% 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 70.17%. This confirms all dimensions provided in the model. In addition, Armstrong and Overton's (1977) procedure compared the mean constructs of the initial 73% of respondents to the final 27%, stating that "non-response" bias is not a problem.

3.4. 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 [33], management research [36], and information systems [53]. Furthermore, the mediation analysis followed the guidelines proposed by Hair et al.[33].

Table 2. Respondents' profile

Total informants/organizations (n=167)			
Professional experience	(%)	Size of the organization	(%)
x ≤ 5	10	Small	15
6 < x ≤ 10	14	Medium	30
10 < x ≤ 15	16	Large	55
x > 15	60		
Public Sector Area	(%)	Work unit function[1]	(%)
Public services	9	Business process	59
State treasury & assets	6	Data Management	35
State revenue & expenditures	24	Operational	6
Financial & risk	48		
Fiscal management	13		

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

4. RESULTS AND DISCUSSION

4.1. 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 [33].

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 [33]. 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	0.841	Valid
		DAM2	0.831	Valid
		DAM3	0.912	Valid
		DAM4	0.732	Valid
		DAM5	0.748	Valid
	BDA analytical	DAA1	0.851	Valid
		DAA2	0.869	Valid
		DAA3	0.774	Valid
		DAA4	0.890	Valid
		DAA5	0.725	Valid
AC	Analytical Skills	AS1	0.813	Valid
		AS2	0.838	Valid
		AS3	0.769	Valid
	Domain Knowledge	DK1	0.843	Valid
		DK2	0.774	Valid
		DK3	0.736	Valid
	Tool Sophistication	TS1	0.890	Valid
		TS2	0.744	Valid
		TS3	0.918	Valid
		TS4	0.843	Valid
DMP	Decision quality	DMQ1	0.933	Valid
		DMQ2	0.943	Valid
		DMQ3	0.951	Valid
		DMQ4	0.860	Valid
		DMQ5	0.781	Valid
	Decision efficiency	DME1	0.834	Valid
		DME2	0.883	Valid

Discriminant validity indicates how different a construct is from the others. Two approaches were adopted: (1) Fornell and Larcker's [23] criterion and (2) the Heterotrait-monotrait ratio (HTMT)'s criterion by Henseler et al. [36]. 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.

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

		Construct[1]		
		BDAC	AC	DMP
Inicators[2]	α	0.976	0.980	0.975

	CR	0.982	0.984	0.979
	AVE	0.914	0.926	0.871
Fornell-Larcker criterion³	BDAC	0.956	0.545	0.492
	AC		0.962	0.634
	DMP			0.934
HTMT criterion	BDAC		0.557	0.504
	AC			0.647
	DMP			

Note(s) : ¹ Decision-making performance (DMP); business data analytical capabilities (BDAC); analytics competency (AC); ²Cronbach's alpha(α); composite reliability (CR); average variance extracted (AVE); ³Square root of AVE is in the diagonal and highlighted in italic

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

4.2. 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 [33]. 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 [33].

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

	Hypothesis¹		
	H1: BDAC → DAC	H2: BDAC → DMP	H3: DAC → DMP
Path coefficient	0.545	0.209	0.520
T statistic	7.429	2.918	6.136
p -value²	0.000***	0.000***	0.000***
Effect size(f^2)	0.423	0.054	0.334
Analysis of Cohen's f^2	Large	Small	Medium
Empirical evidence	Supported	Supported	Supported

Notes (s) : ¹H4 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 [33].

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, AC and DMP construct variance is explained with significant effects, as they have R^2 > 26%, Cohen [12].

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 [35].

According to Cohen [12], $f^2 > 0.02$ 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 → CA, small effects in the relationships between BDAC → DMP and medium effects in the relationships between AC → 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 $Q^2 > 0$ [33]. To assess the quality of model fit, the only criterion recommended for SEM by PLS is SRMR, Hu & Bentler,[42]. Notably, the SRMR index (0.058) meets the most stringent parameter in the literature, which is less than 0.08 [33,42].

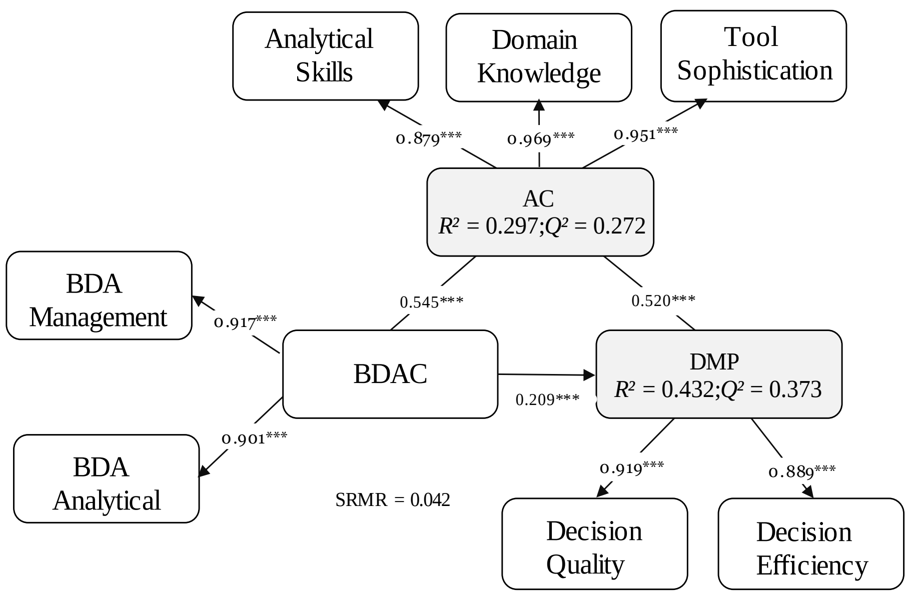

Figure 2. Mediation Structural model

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

Table 6 shows the results of the effects obtained based on the mediation analysis of the procedure outlined by Baron and Kenny [6], Hair et al. [33], and Nitzl et al. [54]. 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 [54].

Table 6. Mediation analysis

Hypothesis

	H4: BDAC→ AC → DMP
Direct effect	0.209
Indirect effect	0.283
Total effect	0.492
T statistic	6.379
p-value[1]	0.000***
VAF[2]	58%
Mediation type	Complementary mediation

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

Therefore, the VAF assessment supports the mediation hypothesis. The findings indicate the existence of the following complementary mediations: AC in the relationship between BDAC and DMP, with high strength. Thus, an important theoretical contribution is delivered when DAC explains the transmission of most (58%) of the effect of BDAC to DMP.

4.3. Findings

As BDAC directly affects AC and DMP (supported H1,H2). Such findings are consistent with research by Chae et al., [10]; Côrte-Real et al.[13]; Duan et al.[17]; Ghasemaghaei et al.[27], Gupta and George, [31]; Horita et al.[36]; Jansen et al.[43] And findings expand existing knowledge about how analytical capabilities guarantees that data may be transformed into business information and knowledge useful for improve quality and efficiency in decision-making processes [22,27].

It is also observed the confirmation of the direct impact of AC on DMP (H3 supported), with large effect size, as well as the complementary mediation of this variable mediation of this variable between BDAC and DMP (H4 supported). In the presence of the mediating variable, most (58%) of the effect starts to be transmitted indirectly to the dependent variable. This means that DAC is a capability that mediates the relationship between BDAC and obtaining DMP, corroborating propositions of [27,75].

Drawing an analogy between a successful organization and a symbiotic organism, it can be assumed that AC are the capabilities of interaction knowledge that are important and value-added capabilities for organizations. The BD phenomenon gives rise to the recognition of high operational and strategic potential in generating business value, so that the use of data and analytical capabilities to guide business decisions and operations plays a strategic role for organizations [69]. In this regard, analytical capabilities represent the development of new capability conceptualizations in domains such as big data analytics [31].

The ability of an enterprise to effectively deploy data analytics-driven resources with a combination of other related resources and capabilities to make better, more informed, and faster decisions, and enable the ability to leverage all available information, thus becoming a highly capable capability and important for organizational success [21,48,56). Consequently, AC in the analytical ability to generate DMP, by making it more effective to interpret some of this data to convert it into business value [28,58,68].

Thus, the findings show that AC are variables that are able to explain how the effect of analytical ability is transmitted to DMP.

5. CONCLUSION

This study analyzed empirical evidence how BDAC affect DMP, considering the mediating effects of DAC. The contributions, implications, limitations and proposals for future studies are described below. Theoretical contributions and managerial implications. First, this study helps to better understand how DAC relates to analytical ability to achieve DMP. In addition, the relevant finding that DAC mediation explains a large part of the transmission of BDAC effects to DMPs. In the presence of a sufficient level of DAC, the organization will be able to increase its awareness in relation to the business environment, make informed decisions by BD in real time and, thus, implement rapid pace, change execution and new business strategies [63], and AC refers to a company's ability to utilize data analytics-based resources and includes processes and skills that transform inputs into outputs with better value [27,55,74]. Secondly, however, investing in the development of analytical skills is necessary but not sufficient. To achieve DMP, organizations need to adapt and implement the necessary changes as their results are detected, evaluated and predicted. So, in short, the findings of this research are imply in the practice, as they assist organizations in identifying the analytical capabilities that impact data science use (BD, business intelligence and analytics, machine learning), and which can lead to DMPs. Based on this, managers can set policies and plans for the development of these capabilities, to manage resources, data utilization creativity, and AC to strengthen the company's analytical vision and increase business value through data-driven strategies.

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 AC 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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