Sufficiency and necessity of big data capabilities for decision performance in the public sector

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Received 7 May 2023
Revised 15 August 2023
Accepted 30 August 2023

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Declaration of interest: none.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors.

Abstract

Purpose – *This study aims to examine the necessity effects of big data analytics capabilities (BDAC) on decision-making performance (DMP), particularly in the public sector.*

Design/methodology/approach – *The authors used the combined methods of partial least square structural equation modeling (PLS-SEM) and necessary condition analysis (NCA) to test the hypothesized relationships.*

Findings – *The findings show that the presence of all three BDAC (infrastructure, management and personnel) is significant and necessary to achieve higher levels of DMP. Specifically, the results revealed big data management capabilities to be of higher necessity to achieve the highest possible DMP. The findings provide public-sector practitioners with insights to support the development of their BDAC.*

Originality/value – *Time-sensitive domains such as the public sector require insight and quality decision-making to create public value and achieve competitive advantage. This study examined BDAC in light of the combined methods of (PLS-SEM) and NCA to test the hypothesized relationships in the public sector context.*

Keywords *United Arab Emirates, Public sector organizations, Decision performance, Necessary condition analysis, Big data capabilities, Analytic capabilities*

Paper type *Research paper*

1. Introduction

Dating back to the first industrial revolution, significant technological innovations and development have successfully transformed various decades-old tasks and processes, reaching the limits of the human capacity for improvement (Dwivedi *et al.*, 2021). The emergence of data-centric strategies resulting from the widespread technologies of the fourth industrial revolution has brought paradigm shifts in traditional business models and is paramount in designing and planning smart cities (Schwab, 2016; Bokolo, 2023). The world is continuously populated by the Internet of Things sensors that generate and communicate data. The emergence of these technologies necessitates managing large amounts of data to drive decisions in this digital environment (Alahakoon *et al.*, 2020). Society generates big data with each click, share, like and swipe, contributing to a world of potentially valuable data. However, many people lack the skills and tools to make sense of the data being made available (Ruppert, 2015). The use of analytics improves the quality of decisions, and these effects are more robust when decisions are based on insights generated from data (Awan *et al.*, 2021). Driving innovation in the public sector was found to be driven by data and the result of the "datafication of society" (Janssen *et al.*, 2017a, p. 189).

The public and private sectors, society and individuals generate data at high volumes, velocities and varieties. Initially, big data capabilities were developed for the private sector

(Aydiner *et al.*, 2019). Nowadays, data can originate from diverse sources, including policing, justice, agriculture, health, transportation, social welfare and many more. This wide array of data formats and sources forms the basis of modern-day economies (Albergaria and Chiappetta Jabbour, 2019; Duan *et al.*, 2019; Shet *et al.*, 2021; Koskinen *et al.*, 2023). The premise that value can be generated by translating insights into actionable decisions has recently become as relevant to the public sector as it is commonly perceived for the private sector (Brandt *et al.*, 2021).

Although public administrators are eager to leverage the possibilities of big data, they remain uncertain about what can and cannot be done (Guenduez *et al.*, 2020). What some regard as big data today might be considered small tomorrow, and what is not currently being captured by sensors today might be so tomorrow (Mergel *et al.*, 2016). The uses of data in public administration are varied. For example, relevant government entities can more effectively assign health and building inspectors based on predictions to improve operations or probabilities of violations (Glaeser *et al.*, 2016; Athey, 2017). Cities can use predictive policing systems to allocate resources based on anticipated crimes (Shapiro, 2019), and improve waste management, allowing them to collect and dispose of waste more efficiently (Perera *et al.*, 2014; Mingaleva *et al.*, 2020). The design of data-driven services allows for new types of value streams (Kaiser *et al.*, 2021). The current exponential spike in data availability underscores the necessity for policymakers, practitioners and scholars to seek a deeper understanding of big data to better respond to and anticipate unforeseeable risks and black swan events (Dai *et al.*, 2020; Sheng *et al.*, 2021). The proliferation and the potential of these technologies to generate vast amounts of data made available to governments aid in sound and timely decision-making capabilities (Wedel and Kannan, 2016; Wu *et al.*, 2020). However, much of that data remains untapped (Dai *et al.*, 2020) and data maturity in the public sector remains an underexamined area (Grander *et al.*, 2021). While analytics capabilities have much promise, their influence on the performance of adopters remains inadequately examined and understood (Rialti *et al.*, 2019).

Despite the growing interest of practitioners, theory-based research on data-driven decision systems in the public sector remains insufficient (Di Vaio *et al.*, 2022). The lack of empirical studies in this area hinders work on the utility of big data in governments and puts practitioners, policymakers and decision-makers in uncharted territories when pursuing such initiatives. There is a lack of evidence on how data can contribute to improving government services (Hong *et al.*, 2019). Therefore, to identify valuable practical and theoretical implications and potential avenues of research, it is essential to understand the necessity and sufficiency of different data-related capabilities and how they influence decision-making performance (DMP) in the public sector. This is addressed by drawing on the dynamic capabilities theory to examine the causal links between three big data analytics capabilities (BDAC) (management, infrastructure and personnel) and DMP along with the necessity logic of these three capabilities.

2. Theoretical background

More organizational activities are being designed and delivered using various digital platforms. These technologies are reshaping work arrangements in the public sector (Palumbo, 2021). The dynamic capabilities perspective describes how organizations redesign their approach to generating value through technology, adding to the IT-business value discourse (Schryen, 2013). The surge in data availability creates ground-breaking opportunities in the development and management of urban cities (Allam and Dhunny, 2019). By attaining valuable insights from different sources both in and out of the organization, big data analytics technologies allow users to collect, store and analyze data of unprecedented breadth, depth and scale (Miah *et al.*, 2017; Wang *et al.*, 2017). However, a significant hurdle to its wider adoption is the shortage of big data skills required to fully realize its potential (Choi *et al.*, 2018). To improve the quality of their decisions, decision-makers require a different set of capabilities than they currently possess (Janssen *et al.*, 2017b). Recently, the dynamic capabilities theory was used to better understand BDAC (Wamba *et al.*, 2017). According to Teece *et al.* (1997), this view helps study the competitive advantage of firms, particularly in increasingly turbulent environments. To effectively respond to the ever-evolving demands of their external environments, organizations need to be able to constantly renew their capabilities (Linden and Teece, 2018).

The primary objective of the dynamic capabilities view was to address the inherent constraints of the static nature of the resource-based view. However, contemporary researchers increasingly consider it as an extension of the resource-based view (Schilke *et al.*, 2018). The dynamic capabilities view pivots the focus toward how organizations should cultivate and reconfigure their capabilities to effectively respond to and predict the changes in their external environment (Teece *et al.*, 1997). This view is a suitable lens to investigate the utilization of data-related capabilities (Chen *et al.*, 2015). Ferraris *et al.* (2019) proposed that this lens allows researchers to overcome the limitations of the resource and knowledge-based views. While the resource-based view regards data as a valuable source of information, it is indifferent toward the process required to realize its potential. The knowledge-based view does not allow for a deeper view of the range of problem-solving possibilities provided by big data. However, the dynamic capabilities view considers big data as a value-creating asset, analyzes its multipurpose potential, and allows for the investigation of the continuous need to reconfigure these capabilities to generate insights for the various strategic and operational necessities (Ciampi *et al.*, 2021). The extant literature classified BDAC as a dynamic capability (Braganza *et al.*, 2017; Wamba *et al.*, 2017) and as a facilitator of dynamic organizational capabilities (Mikalef *et al.*, 2019). Data provides decision-makers with efficiency enhancement opportunities (Aljumah *et al.*, 2021) and overall improvement of internal operations and processes (Wang *et al.*, 2018). According to Helfat and Peteraf (2009), dynamic capabilities can provide organizations with evolutionary fitness opportunities. More specifically, big data-related capabilities can strengthen their operational and dynamic capabilities (Chae *et al.*, 2014; Erevelles *et al.*, 2016). Furthermore, BDAC was shown to be influenced by dynamic capabilities (Santoro *et al.*, 2019).

3. Hypothesis derivation

3.1 Big data analytics management capabilities and decision-making performance

Nonprofit organizations are increasingly interested in data-driven approaches to better manage their operations and develop their predictive capabilities (McCosker *et al.*, 2022). The quality of decision-making is primarily influenced by data-related decision-making capabilities (Shamim *et al.*, 2019). Decision-makers can alter how companies work, operate and create value (Raguseo *et al.*, 2020; Grander *et al.*, 2021). To facilitate this, leaders of organizations significantly impact the creation and reconfiguration of dynamic capabilities (Schoemaker *et al.*, 2018) and provide an effective means to drive the directions of their organizations (Dessler *et al.*, 2001). More specifically, the leadership of an organization plays a pivotal role in using data for decision-making (McAfee *et al.*, 2012). The dynamic environment in which companies operate necessitates that decision-makers make high-quality decisions from strategic, tactical and operational perspectives to remain competitive (Dubey *et al.*, 2020). These capabilities improved organizations' cost and operational performance by positively impacting their overall health (Dubey *et al.*, 2019a). The benefits offered by the use of data remain a key concern for the management teams (Huang *et al.*, 2020). The leadership and organizational culture it creates is the starting point to address the challenges to big data management that hinder its adoption (McAfee *et al.*, 2012). The necessity of big data analytics management capabilities (BDAMC) is evident as many organizations have gone bankrupt as a result of mismanaging information technologies (Dwivedi *et al.*, 2015). Hence, we hypothesize the following:

Sufficiency-based hypothesis – H1: BDAMC positively influences DMP.

Necessary condition hypothesis – NC_1: The presence of BDAMC is a necessary condition for the presence of DMP.

3.2 Big data analytics infrastructure capability and decision-making performance

Big data technologies help companies produce value, better decisions and gain insights (Raguseo *et al.*, 2020). Pressures from external sources force companies to adopt technologies that allow them to reconfigure their capabilities and resources (Dubey *et al.*, 2019c). Technology plays a crucial role in making sense of data. The complexity of data sources and formats has driven software developers to design tools with an increased focus on user interfaces to make it easier for decision-makers to detect patterns and interact with the data (Ruppert, 2015). BDAC is a form of IT capability that advances the overall business value as well as creates new value propositions (Müller *et al.*, 2018; Huang *et al.*, 2020). There is evidence of a clear relationship between BDAC and superior aspects of performance (Batistič and Van Der Laken, 2019; Gawankar *et al.*, 2020). Data is a crucial driver for businesses operating in the fourth industrial revolution (Dubey *et al.*, 2019b), and it can improve sustainability and urbanization (Allam and Dhunny, 2019). The need for the effective use of ICT increases when companies operate in dynamic environments (Melville *et al.*, 2007), and big data analytics tools provide organizations with enhanced performance opportunities in dynamic situations (Dubey *et al.*, 2020). Therefore, we hypothesize the following:

H2: BDAIC positively influences DMP.

NC_2: The presence of big data analytics infrastructure capability (BDAIC) is a necessary condition for the presence of DMP.

3.3 Big data analytics personnel capabilities and decision-making performance

To marshal different organizational capabilities in seizing opportunities to build competitive advantages, organizations aim to redefine and enhance their internal capabilities (Sambamurthy *et al.*, 2003). Contemporary organizations with information technology capabilities realized a positive, significant and sustainable impact on their performance (Sambamurthy *et al.*, 2003; Patnayakuni *et al.*, 2006). Flexible technology infrastructures allow organizations to be more agile in response to threats and opportunities (Pinsonneault, 2011). An increasing number of organizations invest considerable resources in developing their analytics capabilities, given the promises associated with improved business performance and agility (Ashrafi *et al.*, 2019). The adoption of business analytics is overhauling how organizations generate and use data. A study has shown a positive relationship between the use of analytics and performance (Ramanathan *et al.*, 2017). The critical elements in successfully implementing business analytics systems are the capabilities that support the collection, transformation, analysis and interpretation of data to support the decision-making process (Santiago Rivera and Shanks, 2015). To reap the benefits of data, companies have to build coordination networks between the various departments involved in the data value chain (Zeng and Khan, 2019). Thus, we hypothesize the following:

H3: *BDAPC* positively influences DMP.

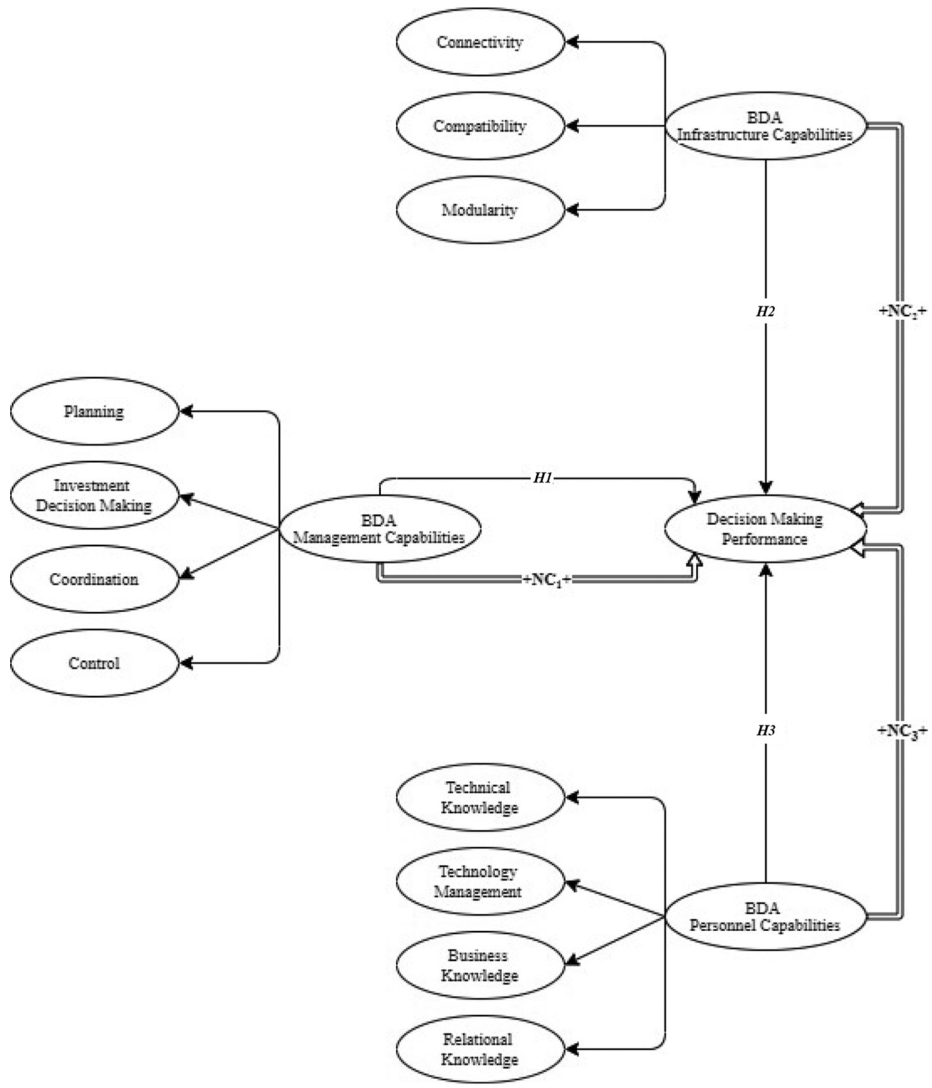
NC_3: The presence of big data analytics personnel capabilities(BDAPC) is a necessary condition for the presence of DMP.

4. Methods

4.1 Instrument development

We used established scales (see Online Supplementary Table S.I) to examine the sufficient and necessary conditions of the hypothesized research model (see Figure 1). Apart from

Figure 1 Proposed research model



Notes: H: Sufficiency-based hypothesis; NC: Necessary condition hypothesis
Source: Developed by authors

the demographic questions and control variables, all items were measured using a seven-point Likert scale. A qualitative pretest was adapted to ensure the target audience understood the measurement survey (Groves *et al.*, 2011). As such, individuals with backgrounds in research (two people), academia (two people), public administration (one person), information technology (one person) and big data (two people) reviewed the online survey's items, wording, structure and user experience for clarity and appropriateness in assessing the subject area (DeVellis, 2016).

4.2 Conceptualization approach

Various researchers have advocated for multidimensional constructs due to their holistic representation of complex phenomena. In their view, this allows for assessing the impact of broad predictors on overall outcomes (Hulin, 1991; Hanisch *et al.*, 1998). Although multidimensionality offers researchers a more comprehensive view, assessing the individual subconstructs (second-order constructs) can provide greater clarity and precision (Edwards, 2001). We tested the effect of the second-order constructs in an unrelated conceptualization model on performance (Kim *et al.*, 2012). The article's quantitative method relies on data gathered through an online survey. The survey was based on scales previously validated in different contexts. Perceptions about the interplay between the different BDAC were measured using 46 items ("1 = strongly disagree" to "7-strongly agree") (Kim *et al.*, 2012). DMP was measured using four items ("1 = strongly disagree" to "7 = strongly agree") (Shamim *et al.*, 2020).

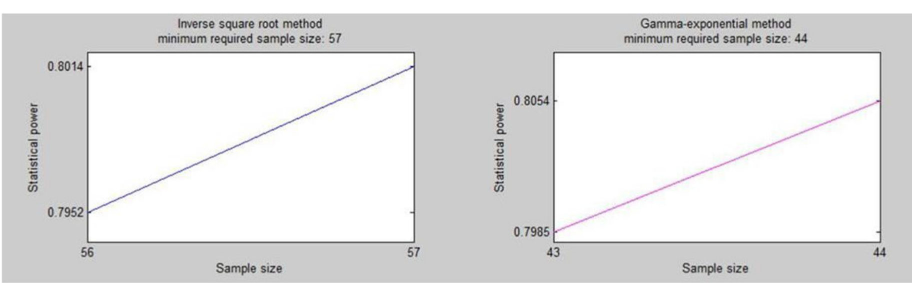
4.3 Study area and sampling

Data was collected from individuals who held managerial positions in key departments that make decisions influencing their organizations, with at least seven years of experience, and who were working in a government entity in Dubai at the time of the study. Identifying the sample size is fundamental in partial least square structural equation modeling (PLS-SEM); however, the "10-times rule" approach to sample sizes (Hair *et al.*, 2011) was shown not to yield precise estimates (Kock and Hadaya, 2018). Thus, we followed the recent recommendations that suggest using the inverse square root method, the Monte Carlo simulation and gamma exponential to estimate the minimum sample size (Robert and Casella, 2013; Kock and Hadaya, 2018; Kock, 2020). The results revealed that a minimum sample size of 100 is sufficient to obtain a statistical power above the cut-off point value of 0.80 for testing the factor covariances (Cohen, 1988; Wang and Wang, 2020) (see Online Supplementary Table S.II, Column 4). Similarly, Figure 2 shows the sufficiency of a minimum sample size of 57 and 44, respectively, for both methods, using a statistical power of 80% (Kock, 2020).

4.4 Data collection

Representatives of 48 government entities in Dubai were identified based on their experience and knowledge of their entity's use of big data. The study followed a multistage random cluster sampling approach. First, we developed a contact list of these individuals. Then, the initial communication was sent to capture their interest in participating in the voluntary and anonymous survey. They were then e-mailed a link to the survey. The link was sent to 350 individuals, and 218 responses were returned, of which 145 were usable, with a response rate of 62.28%. For studies that investigate organizational representatives' points of view, an acceptable response rate is around 36.1%, with a standard deviation of 18.2%

Figure 2 Minimum sample size requirement outputs



Source: Developed by authors

(Baruch, 1999). Thus, our response rate is well-above the recommended response rate. Online Supplementary Table S.III outlines the profiles of the respondents.

4.5 Control variables and endogeneity

In explaining and predicting the phenomena of interest, it is advisable to control relevant variables that could extraneously affect the hypothesized relationships under examination (Bernerth and Aguinis, 2016). This is essential to ensure the generalizability that contributes to the empirical benefits of the research for individuals and organizations (Becker, 2005). Using controls allows for eliminating variances associated with nonfocal variables (Carlson and Wu, 2012). Control variables can also be used to handle the problem of endogeneity, but their selection must be grounded in previous studies and theories (Bernerth and Aguinis, 2016; Motamarri *et al.*, 2020). In line with the preceding observation, the following control variables were used: firm size, age, gender, education and experience.

4.6 Partial least square structural equation modeling and necessary condition analysis

We combine PLS-SEM and necessary condition analysis (NCA) methods to analyze the data collected for this study (Richter *et al.*, 2020). PLS-SEM is used to quantify the relationships between the three BDAC and DMP. The higher statistical power provided by PLS-SEM makes this approach suitable for exploratory research (Hair *et al.*, 2019). Given the predictive nature of our hypothesized model, PLS-SEM becomes a particularly relevant approach to examining the theoretical model (Rasoolimanesh *et al.*, 2020). The approach is revered as suitable for examining complex and simple models with large or small sample sizes (Hair *et al.*, 2019). When compared to CB-SEM, PLS-SEM has a more predictive-oriented nature and is robust to handle nonnormal data (Hair *et al.*, 2016a). Two key deciding factors for the use of PLS-SEM over CB-SEM are the model's formative constructs and the causal-predictive hypothesized relationships in the model (Hair *et al.*, 2019). The combined use of PLS-SEM and NCA allows for the advancement of theory and generates insights for practice (Richter *et al.*, 2020).

5. Results

Data were analyzed using SPSS, SmartPLS for the PLS-SEM analysis, and R Package to run the NCA.

5.1 Measurement model assessment

Three metrics were assessed for the reflective model: "internal consistency, convergent validity, and discriminant validity" (Hair *et al.*, 2016a, p. 111). As shown in Online Supplementary Table S.IV, Cronbach's alpha, CR and rho_A (ρA) values were above the threshold of 0.7, indicative of internal consistency and reliability (Hair *et al.*, 2016a). All the AVE values were larger than the cut-off value of 0.5 (Hair *et al.*, 2019), indicating convergent validity. Two indicators were dropped due to low loading below 0.7 (DMP3 and MDL4). Twelve more items (CMP2, MDL2, BDAP2, BDACR2, BDACN3, TK3, TK4, TMK2, BK1, BK2, BK3, RK1 and RK2) were dropped from further analysis because "the deletion leads to an increase in composite reliability and AVE above the suggested threshold value" (Hair *et al.*, 2016a, p. 122). Finally, the heterotrait–monotrait (HTMT) criteria (Henseler *et al.*, 2015) and the Fornell–Larcker criterion (Fornell and Larcker, 1981) were assessed. Online Supplementary Table S.V shows adequate discriminant validity since the square roots of the AVE scores are higher than the correlation among the factors (Fornell and Larcker, 1981). The discriminant validity of all the constructs was fulfilled as the HTMT values were less than 0.85 (Henseler *et al.*, 2015; Kline, 2015; Voorhees *et al.*, 2016; Papastathopoulos *et al.*, 2020).

5.2 Structural model assessment

Different assessment criteria were used to evaluate our reflective model: path coefficients, coefficient of determination (R^2), blindfolding and predictive relevance (Q^2), effect size (f2) and PLSpredict to evaluate the out-of-sample prediction power of the proposed model (Shmueli *et al.*, 2019). Since none of the indicators in the PLS-SEM analysis had higher root mean squared error values than the naïve linear regression model benchmark, we concluded that the model has high predictive power (see Online Supplementary Table S.VI). According to the analysis, all hypothesized relationships were found to be positive and significant (see Table 1). Moreover, we used Stone Geisser's Q^2 for the model's endogenous construct to assess the model's predictive ability. In this case, we noted the value of Q^2 at 0.599, which indicates predictive relevance at $Q^2 > 0$ (Peng and Lai, 2012). Finally, the confounding effect of the control variables was examined and found to be insignificant.

5.3 Common methods bias

The validity of research findings is seriously impacted by common method biases, given that data is collected from the same source and point in time (Lindell and Whitney, 2001; Malhotra *et al.*, 2006). Therefore, *a priori* and post hoc actions were used to lessen the impact of common method variance on our findings (Wang and Papastathopoulos, 2023). First, the survey was pretested with 37 participants to detect any ambiguities and misunderstandings that might arise from the wording of the questions. Second, no personal identifying details were collected to protect the anonymity and confidentiality of the respondents. Third, once the data were collected, full collinearity was used. Online Supplementary Table S.VII denotes the value of the hypothesized paths before and after the correction, which show no significant changes. All the variance inflation factor values were below five, the acceptable cut-off point (Kock, 2015). The values ranged from 1.518 to 4.876. As a result, both tests demonstrate that common method bias does not pose a potential concern.

5.4 Necessary condition analysis

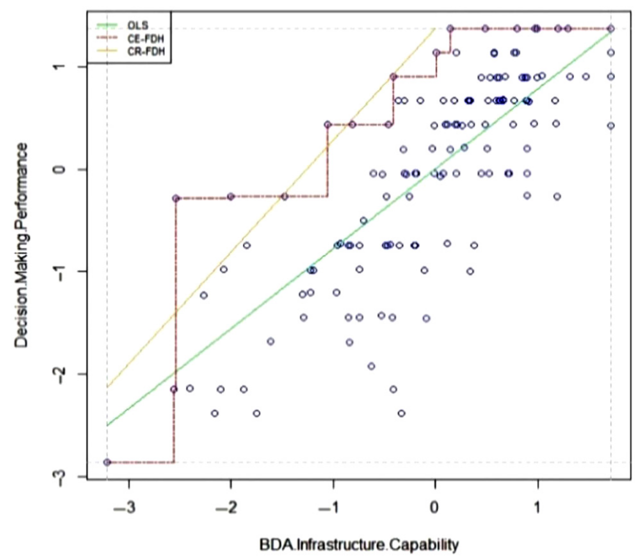
The NCA method can potentially complement parametric and nonparametric analysis methods (Dul, 2019) and provides researchers with insights regarding the necessary conditions to realize specific outcomes (Erasmus Research Institute of Management, 2021). We conducted NCA to explore whether each BDAC is necessary for DMP. The causal paradigm of testing necessity conditions allows researchers to test bivariate relationships to investigate how single determinants are necessary but not sufficient for a given outcome (Dul, 2019). Figures 3–5 show the scatterplots for the NCA output of the three capabilities and DMP, with a space above the space of the study's observations suggesting the

Table 1 Hypothesis testing results

Hypotheses and paths	β	t	p	*BCa*	R^2	Q^2	f^2	*Decision*
H1: BDAMC → DMP	0.340	3.572	0.000	[0.177; 0.570]	$R^2_{DMP} = 0.706$	$Q^2_{DMP} = 0.599$	0.102	S
H2: BDAIC → DMP	0.237	2.463	0.014	[0.047; 0.418]			0.048	S
H3: BDAPC → DMP	0.320	3.125	0.002	[0.123; 0.526]			0.099	S
CV1: Exp → DMP	−0.043	0.612	0.541	[−0.167; 0.095]				US
CV2: Gender → DMP	−0.001	0.027	0.978	[−0.110; 0.092]				US
CV3: Size → DMP	−0.040	0.967	0.334	[−0.130; 0.040]				US
CV4: Age → DMP	−0.013	0.187	0.852	[−0.147; 0.105]				US
CV5: EDU → DMP	−0.022	0.394	0.694	[−0.119; 0.089]				US

Notes: CV = control variable; β = beta coefficients; t = t-statistics; p = p-value; BCa 95% CI = bias-corrected and accelerated 95% confidence intervals; R^2 = coefficient of determination; Q^2 = predictive relevance; f^2 = effect size; S = supported; US = unsupported
Source: Developed by authors

Figure 3 Necessary condition analysis plot: BDAIC (*x*-axis) and DMP (*y*-axis)



Source: Developed by authors

potential presence of necessary conditions (Dul, 2016). The line that separates the empty spaces from the data observations space is the ceiling line (Goertz *et al.*, 2013) and indicates the degree to which the three BDAC are necessary conditions for DMP (BDAIC d = 0.292, BDAMC d = 0.324 and BDAPC d = 0.352) and showed significant necessity conditions.

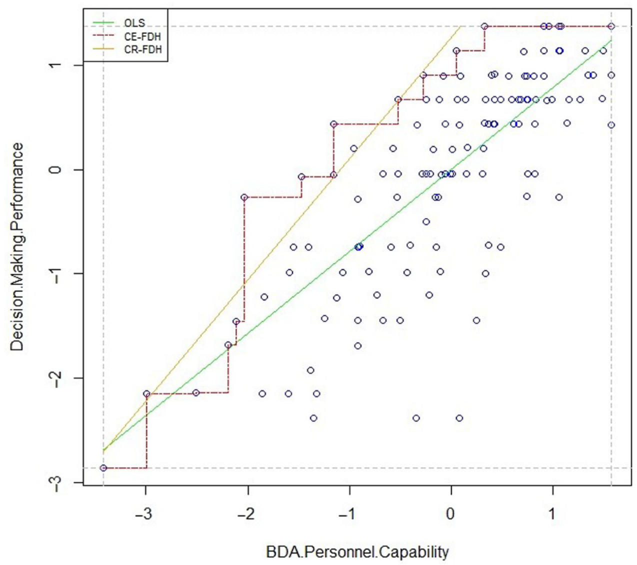
Regarding BDAIC being necessary for DMP (see Figure 3), a medium-size effect of 0.292 is found. For BDAMC and BDAPC being necessary for DMP, a large size effect of 0.324 and 0.353 (see Figures 4 and 5) is found, respectively. Table 2 summarizes the outcomes of the NCA.

Finally, we identified thresholds of the determinants to reach certain levels of the outcome using the bottleneck technique. For example, to achieve high levels of DMP (where DMP = 80), all three capabilities must be within the same level of maturity (see Table 3). However, to achieve the highest levels of DMP (where DMP = 100), the BDAMC and BDAPC must be higher than the BDAIC, and BDAMC must be higher than all other capabilities.

6. Discussion

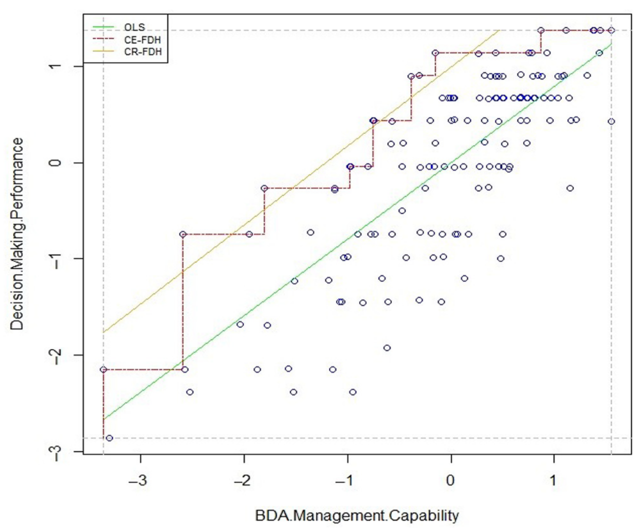
The digital transformation of cities surfaces new difficulties and uncertainties, making informed decision-making essential. Although both BDAIC and BDAPC had a statistically significant effect on DMP, the study found that the highest levels of DMP cannot be achieved without higher levels of BDAMC. This is evidence of the critical role of management in the different BDAC. This is in line with recent studies that found that decision-makers can change how their organizations operate, create value and reconfigure dynamic capabilities (Schoemaker *et al.*, 2018; Raguseo *et al.*, 2020). Their role has also been highlighted in the data-driven decision-making processes (McAfee *et al.*, 2012). Big data's promises are vast; through big data, managers can know drastically more about their organizations and can transform that insight into improved decisions and performance. Since "the computer makes no decisions," the ultimate power lies within the human decision-maker (Drucker, 1967, p. 1). Although advances in technology promise to be

Figure 4 Necessity condition analysis plot: BDAPC (*x*-axis) and DMP (*y*-axis)



Source: Developed by authors

Figure 5 Necessary conditions analytics plot: BDAMC (*x*-axis) and DMP (*y*-axis)



Source: Developed by authors

astounding, they will only transform the organizations in which their leaders enable them (Dewhurst and Willmott, 2014). It has been recently contended that these capabilities possess the potential to enhance the financial and operational efficacy of organizations, positively enhancing performance (Dwivedi *et al.*, 2015; Dubey *et al.*, 2019a; Jabbour *et al.*, 2019; Yasmin *et al.*, 2020). The necessity to possess these capabilities becomes readily

Table 2 Results of necessary condition analysis

Determinants	Outcomes	Ceiling envelopment – free disposal hul	p-value	C-accuracy (%)	Ceiling regression – free disposal hull	p-value	C-accuracy (%)
BDAIC	DMP	0.292	0.000	100	0.269	0.000	97.20
BDAMC		0.324	0.000	100	0.288	0.000	95.20
BDAPC		0.352	0.000	100	0.339	0.000	95.20

Notes: "C-accuracy," which is the number of observations on or below the ceiling line divided by the total number of observations and multiplied by 100%
Source: Developed by authors

Table 3 Bottleneck for the three big data analytics capabilities on different levels

DMP	BDAIC	BDAMC	BDAPC
0	Not necessary	Not necessary	Not necessary
10	13.3	Not necessary	8.5
20	13.5	15.6	24.5
30	13.5	15.6	26.0
40	13.5	15.6	27.7
50	13.5	15.6	27.7
60	13.5	31.7	27.7
70	43.7	53.0	45.4
80	56.7	60.6	58.0
90	65.2	65.4	69.4
100	68.2	86.1	75.1

Source: Developed by authors

apparent when decision-makers consider the number of companies that have failed because of poor management of their systems (Dwivedi *et al.*, 2015).

7. Implications and conclusion

7.1 Managerial implications

Governments are seeking to become data-driven to drive various aspects of organizational performance and are heavily investing in different technologies to support this transition. New approaches to decision-making made possible using data can enable agility and efficiency in aiding evidence-based decision-making (*Big Data for Sustainable Development* | United Nations, 2023). These insights generated by leveraging analytics capabilities can inform the identification of priorities and the determination of the most effective means for action. The United Nations has proposed a set of ideas to tackle each sustainable development goal (SDG). For example, from the use of data analytics to predict the spread of infectious diseases (SDG3) to improving public transport (SDG9) to the use of satellite sensors to track encroachments on public spaces (SDG11) (*Big Data for Sustainable Development* | United Nations, 2023). Many scholars advocate using big data to support the attainment and acceleration of the SDGs by filling critical gaps in data (Allen *et al.*, 2021; Chopra *et al.*, 2022; Teh and Rana, 2023).

Public sector organizations should understand the maturity level of their data-related capabilities to prioritize their development. Though important, BDAIC and BDAPC will not suffice to drive DMP as much as BDAMC. Data-savvy and highly capable public sector decision-makers are necessary to realize benefits in the DMP of their organizations. Integrating data-driven approaches in the public sector positively influences DMP. This is evident in organizations that pay close attention to the development of all three big data capabilities (management, infrastructure and personnel). However, the rate at which technology changes is faster than the rate at which public sector organizations are changing. The challenge lies in the inability to be proactive in the adoption of technology (Agarwal, 2018). The increase in data and the tools used to capture, store, analyze and report data creates a complex environment for leaders to navigate opportunities and threats (Sowcik *et al.*, 2015). Therefore, it will be essential for public sector decision-makers to equip themselves with the skills and expertise to make better-informed decisions. In moving forward, it will be critical for the leaders of these organizations to understand the level of maturity of their different BDACs to lead in a data-driven economy. Thus, organizations need to develop a data-oriented culture and mindset to attain the values that big data promises.

Incorporating these capabilities into public sector organizations starts with understanding the sector-specific values, investment decisions of the infrastructure and decision-maker capabilities. Capability programs are usually geared toward middle management and frontline employees, while senior leaders are typically overlooked. Since senior decision-makers can steer their organization's strategic short- and long-term directions, and front-liners deal with the daily challenges and opportunities, it is essential to optimize both the strategic and day-to-day decisions to sustain competitive advantages. Big data offers the public sector different opportunities (Mouzakitis *et al.*, 2017). However, many industries are still leveraging the rudimentary benefits. To fully unlock the "enormous but partially-tapped resource" (Dubai Future Foundation, 2021, p. 4), there is still significant room to develop to realize the value associated with using big data to drive different aspects of performance. According to the NCA results, these are heavily dependent on the ability of these organizations to develop high levels of BDAMC (planning, investment, coordination and control).

7.2 Theoretical contribution

Big data is a strategic resource for organizations, and its related analytics capabilities are considered a dynamic capability (Shamim *et al.*, 2019; Côrte-Real *et al.*, 2020). This study presents notable theoretical insights. The study examined the sufficiency and necessity conditions of BDAC for driving DMP in the public sector using dynamic capabilities theory. The study provides empirical evidence on the dynamic interplay of the different BDAC. To advance theory, we quantified the desired degrees of each level of the three capabilities to reach a specific outcome of DMP (see Tables 2 and 3). Despite rising research on the topic across industries, its public sector applicability remains under-examined. This study proposes that public-sector organizations must understand the dynamic interplay between the different BDAC to improve DMP. In doing so, we enrich the literature on data-driven decision-making in this context. Typically, BDAC is considered a higher-order construct, with little elucidation of the details of the capabilities that constitute it. Our study contributes to investigating the underlying capabilities and their influence on DMP instead of examining the effect of the overall higher-order construct. Although there is strong evidence of the disruptive capabilities of big data on strategic and tactical decisions (Merendino *et al.*, 2018), how big data can be leveraged to generate success in dynamic environments is poorly understood (Johnson *et al.*, 2017). Our findings lay the foundation for understanding these capabilities in the public sector that can drive competitive DMP. The NCA findings reveal that all three capabilities are necessary for improved DMP, thus contributing to the application of NCA in the context of data-driven decision-making. An interesting result is that BDAIC and BDAPC alone cannot improve DMP without having high levels of BDAMC, emphasizing the role of management in reaping the benefits of developing data capabilities.

7.3 Limitations and future research

Despite its practical and theoretical contributions, this work has some limitations that future studies can address. Our findings are not industry-specific (i.e. tourism, health care, policing). To increase the generalizability of the findings, we suggest testing the conceptual model in additional sectors, industries and countries. Furthermore, the views of the most senior leaders of these organizations or the beneficiaries of their services were not incorporated and could have provided the authors with some valuable insights. Finally, we did not presume big data analytics maturity when conducting the study. Thus, big data analytics maturity and data-oriented culture could be examined in future studies. We used cross-sectional data hence we encourage longitudinal studies to evaluate these capacities and activities over time. We urge that future studies use more objective performance measures to give a more realistic view of DMP. Another primary avenue for future research is the development of a scale designed specifically for data capabilities.

7.4 Conclusion

This study aimed to investigate the sufficiency and necessity of the BDAC (management, infrastructure and personnel) on DMP. The results revealed that all the sufficiency and necessity links proposed by the study were supported (*H1, H2, H3*, NC_1, NC_2 and NC_3). However, theory and practice are still short regarding the core elements related to adopting big data capabilities and empirically testing the conditions and capabilities required to assess the return on these investments. To capture the performance benefits of big data, organizations must understand the full range of capabilities essential to driving their decisions in a data-driven economy and the enablers and hindrances that get in the way. Knowing where an organization's maturity is concerning each capability allows for a more systematic approach to big data capability development. The empirical findings highlight the importance of investigating all underlying capabilities that constitute BDAC to support practice and theory. Our findings support the premise that all capabilities positively influence DMP and shed light on the dynamic necessity of all these capabilities.

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Supplementary materials

The supplementary material for this article can be found online.

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