Available online at
https://journal.uitm.edu.my/ojs/index.php/JIKM

e-ISSN: 2289-5337

Journal of Information and Knowledge Management
Vol 15 Special Issue 2 (2025)

Journal of Information and Knowledge Management

Big Data Analytics Capabilities and Strategic Decision-Making in Malaysian Public Organizations: A Proposed Framework

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ARTICLE INFO

Article history:
Received: 11 Jan 2025
Revised: 20 Mei 2025
Accepted: 26 Jun 2025
Online first:
Published 1 August 2025

Keywords:
Big Data Analytics
Strategic Decision Making
Continuous Improvement
Public Organizations

https://doi.10.24191/jikm.v15iSI2.7346

ABSTRACT

This study investigates the role of Big Data Analytics Capabilities (BDAC) in enhancing strategic decision-making within Malaysian public organizations. Using an extensive literature review, the research identifies key dimensions—management, governance, and cultural capabilities—as critical factors influencing the adoption of BDAC. Additionally, it proposes a conceptual framework integrating Continuous Improvement (CI) as a mediator, addressing existing governance and operational efficiency gaps. The findings aim to provide actionable insights for public organizations to harness BDAC effectively, improving service quality, resource allocation, and accountability. This study offers a foundation for empirical validation through surveys and case studies.

INTRODUCTION

Organizations in practically every industry, including the public sector with vast amount of data, are paying attention to leveraging data to obtain a competitive edge. Manual analysis has a hard time keeping up with the volume and diversity of data; in some circumstances, it's even outpaced the capabilities of traditional databases (Fayyad, U. and Stolorz, P., 1997). In parallel, techniques for integrating datasets have been developed and computers have become substantially more powerful, enabling deeper and more comprehensive analysis than was before possible. The confluence of these occurrences has led to an increase in the usage of data science within organizations.

Analytics and decision aids work to improve the quality of decisions by utilizing communication technologies, gathering and processing data, assisting in the analysis of data and documents, using quantitative models to identify and solve problems, completing tasks related to the decision-making process, and offering guidance (Maryam, G.,2019). As the unstructured and semi-structured decision-making exercises are complex and uncertain by nature, traditionally, technologically oriented decision aids have supported only a portion of an organizational or individual decision process. In order to supply input or data, choose how to process it, interpret the results, or make a decision, the user is expected to interact with the system in some way. In other words, the system should support the decision-ability makers to reason. These tools are generally supported by studies of human-computer interaction and statistical, mathematical, and computer science research on problem identification and solution (Shim et al., 2002). Business intelligence, analytics, and big data are relatively new fields that have emerged as a result of technological advancements in areas like artificial intelligence, data capture and storage, cloud computing, virtualization, and network speed.

The Sustainable Development Goals (SDGs), which serve as the basis for the new development agenda, were adopted by the globe in 2015. An emphasis on inclusive, participatory development that leaves no one behind is necessary to achieve these goals, which call for combined action on social, environmental, and economic concerns. There is still a lack of essential data for national, regional, and global development policies. Many governments still lack access to sufficient information about their whole population. This is especially true for the poorest and most marginalized individuals, the same people on whom policymakers must concentrate if they are to eliminate extreme poverty and all emissions by 2030 while also leaving no one behind. Big data can reveal social inequalities that were previously concealed. Women and girls, for instance, who frequently labor in the unorganized economy or at home, face societal restrictions on their mobility and are underrepresented in both private and governmental decision-making.

'Public Service Malaysia is the largest employer employing about 1.7 million of Malaysia's total workforce' (Malaysian Public Service Department, 2021). To unleash this population's full potential for the benefit of the populace and the stakeholders they serve, it must be efficiently and effectively activated and governed. Each day every new decision is being made in order to operate. The Public Sector Big Data Analytics Pilot Project was introduced by the Malaysian government in 2014, concurrent with the Big Data phenomenon and the government's goal to advance ICT services (MAMPU, 2016). The Ministry of Communications and Multimedia in collaboration with the Modernization Unit Administration and Management of Malaysia (MAMPU) and Malaysia Digital Economy Corporation (MDeC) lead the implementation of Malaysia's Big Data Analytics (BDA). It is also established that the Ministry of Communications and Multimedia will develop Malaysia's Big Data Framework in collaboration with MAMPU and MDeC. MAMPU and MDeC to collaborate in the implementation of the Public Sector Big Data Analytics Pilot Project, and MDeC to lead in the inception of Private Sector BDA (MAMPU 2016). However, the adoption of BDA remains uneven, with limited empirical evidence on how BDAC influences strategic decision-making. Despite its potential, many public organizations struggle to implement BDA effectively due to gaps in management expertise, governance structures, and cultural alignment. This study addresses the critical question: How can Malaysian public organizations develop and leverage BDAC to improve strategic decision-making? It seeks to fill the gap in understanding the interplay between BDAC dimensions and decision-making processes, emphasizing the moderating role of CI. By proposing a robust conceptual framework, this research contributes to both academic discourse and practical applications in public administration.

According to Malaysia Digital Economy Corporation (MDEC), Malaysia's big data analytics (BDA) industry is anticipated to increase from US$1.1 billion in 2021 to US$1.9 billion (about RM7.85 billion) in 2025. With the help of government policies and other MDEC-led capacity-building initiatives with regional and international partners, MDEC has worked to better prepare the local labor force for jobs that are rapidly growing in the digital sector, such as programming, data science and analytics, and online content creation.

LITERATURE REVIEW

Big Data Analytics (BDA)

Big data analytics has attracted a lot of interest recently for its potential to guide organizational decision-making (Mikalef et al., 2020). In order to learn vital information that will offer them a competitive advantage, more and more businesses are speeding up the deployment of their big data analytics programs (Constantiou et al., 2015). Big data has been considered the new frontier for innovation, competition, and productivity by several practitioners and experts (Manyika, J. et al., 2011), while others have even asserted that it is a revolution that will change the way we think, live, and work (Walker, 2014).

Significant advancements in methods and technology for data storage, processing, and visualization have been reported in response to the fast growth of data volume, velocity, and diversity. Nevertheless, empirical studies on the competitive advantages that big data analytics may provide are still developing, and there is a widespread dearth of knowledge on the processes through which such investments lead to competitive performance (Gupta and George, 2016). This result is rather unexpected given the influx of businesses entering the big data analytics market (SAS, 2013). Additionally, there is little study on how firms should continue integrating big data analytics into the organizational structure, and there is also limited understanding of which organizational competencies should be strengthened in order to maximize investment returns (Mc Afee, 2012).

Up until this point, the majority of reporting on the business usefulness of big data has come from consulting companies, the media, and individual case studies that lack theoretical understanding (Gupta and George, 2016). As a result, there is no consensus on how businesses should handle big data efforts, and there is insufficient empirical evidence to back up the assumption that these expenditures provide any discernible commercial benefit (Mikalef, P. et al 2018). While big data analytics has generally been seen as a groundbreaking technical accomplishment in both academic and commercial circles (Davenport et al, 2012), the question of whether and under what circumstances such technologies may result in improved competitive performance is still up for dispute (Abbasi, A. et al 2016). Arnott and Pervan (2016) warn against big data programs that are too optimistic, although more research is being done on the conflicts that businesses have when trying to use big data to improve their decision making and competitive performance (Günther, 2017).

Big Data Analytics Capability (BDAC)

In general, the big data phenomenon has given rise to two significant analysis and development areas. One of them is concentrated on aspects of the computational and technological infrastructure, specifically technical and data analysis challenges, and has been termed “Big Data Analytics” (BDA) (Dong and Yang, 2018). The second field of research is known as BDA capability and it deals with the challenges presented by managing and incorporating big data into organizational operations (Gupta and George, 2016).

BDA is referring to a comprehensive method of analyzing and using big data to produce value (Wamba et al., 2017). It is increasingly seen as a crucial element to increase effectiveness and efficiency, with both operational and strategic potential. According to Wamba et al. (2017), the flexibility of the BDA infrastructure, the management capabilities, and the personal expertise capabilities of the BDA are the three main factors that determine BDA capability. BDA connectivity, compatibility, and modularity are all aspects of the flexible BDA infrastructure. Technical knowledge, technology management competence, business knowledge, and relationship knowledge are all included in the BDA personal expertise competency (Akhtar et al., 2018; Wamba et al., 2017). One of the best-constructed models is the BDA capacity construct created by Wamba et al. (2017).

Literature, however, also cites culture, talent management, and leadership as key contributors to BDA management competency, particularly for decision-making (Shamim et al., 2019). Big data experimentation, contextualization, democratization, and execution were introduced to the big data management capacity architectured by Shamim et al. (2019b) and Zeng and Glaister (2018). All of these elements allow firms to make data-driven decisions, or decisions based on data. BDA is now a recognized factor in organizational performance (Germann et al., 2014). BDA enables businesses to assess their plans using data (Amankwah-Amoah, 2016). BDA is becoming a very important part of the decision-making process and enabling businesses for data-driven decision-making. (Hagel, 2015; Janssen et al., 2017).

Data's source, collection, storage, handling, and analysis are central to theoretical and empirical breakthroughs in BDA. They are elements that are not unfamiliar to the organizational setting but that take on a new and complicated taking into account the enormous rise in data generation. This is due to the ease with which data is generated, as well as the variety of sources of origin, including telemetry, sensors, GPS, and the widespread use of technological devices, including smartphones connected to social networks, among others, which together constitute a continuous, very reliable source of data. Scholars have so far specified seven categories or traits to help identify the primary problems of BDA (Mikalef et al., 2018; Sivarajah et al., 2017; Chen et al., 2013; Barnaghi et al., 2013). Volume is the initial feature of BDA. This characteristic relates to data size, which is relevant to big data since it is growing exponentially and presents difficulties for data storage, acquisition, and processing, and necessitates significant expenditures on technical infrastructure (George et al., 2016). The difficulty of data heterogeneity, which includes audio, video, text, and pictures, is connected to the second characteristic of BDA, variety (Constantiou and Kallinikos, 2015). The speed with which data may become out-of-date, which makes it difficult to design new tools for data analysis, is the third feature. In certain circumstances, this velocity even necessitates real-time analysis (Sivarajah et al.,2017; George et al., 2016). Veracity, which is associated with data quality and refers to the veracity and dependability of the data and its sources as a guarantee for its possible use, is in the fourth position. Visualization, which is the capacity to convey facts in meaningful ways, is the fifth quality (Seddon and Currie, 2017). The value of the big data gathered for an end user and its contribution to enhancing performance in the case of businesses make up the sixth attribute (Sivarajah et al., 2017; Gandomi and Haider, 2015). The continual and quick change in data meaning and interpretation is the seventh and last aspect of BDA (Seddon and Currie, 2017; Sivarajah et al., 2017).

In contrast, a company's management skills are referred to as having a BDA capacity, which is the ability to continuously use and deploy big data resources with the strategic aim of creating value and forging a competitive edge for the organization. (Wamba et al., 2017; Garmaki et al., 2016; Gupta and George, 2016; Kiron et al., 2014). The literature identifies three resource types that take the BDA capabilities into account. In the first resource category, tangible resources and infrastructure, the emphasis is on the value of data as a resource, taking into consideration its origin, collection, and environment, as well as components related to the physical and technical infrastructure needs that permit effective data utilization. This efficiency is made possible by improved database technology, and efficient data handling is ensured by a more durable infrastructure that is tailored to the enormous volumes of big data. In order to make the necessary investments in big data initiatives, which take enough time to accomplish and produce the desired yield, the organization must conduct the necessary analysis (Wamba et al., 2017; Gupta and George, 2016).

The second category, which is divided into two groups, is intangible resources whereby programming, machine learning, artificial intelligence, statistical analysis, data cleansing, and extraction, as well as the capacity to pick up and comprehend new technology trends, make up the first group of individuals with the technical skills needed for big data. The second category consists of persons with expertise in big data management, and who is in charge of organizing implementing, and managing big data-related processes and resources, as well as, perhaps more crucially, who are aware of the various ways that the organization can use the knowledge collected from big data (Wamba et al., 2017; Gupta and George,2016).

Intangible resources, which represent the significance of two specific features, make up the third group: the first is a data-driven culture, which enables managers at all levels of the organization to make their decisions on the facts that the data suggests rather than acting intuitively based on prior experiences; The second intangible resource is organizational learning, which suggests that businesses with developed capabilities explore, accumulate, share, and transform knowledge possess a key inventory of valuable knowledge, very useful when contextualizing and validating the results from big data. In other words, high levels of organizational learning allow for the synthesis and confirmation of information drawn from massive data, facilitating the ability to make well-informed decisions (Gupta and George,2016).

PROPOSED FRAMEWORK DEVELOPMENT

After careful consideration of previous literature, a research framework has been proposed in this study. The purpose of the conceptual framework is to facilitate a logical understanding between variables and problems situations and studies that cover independent variables, moderating variables and dependent variables as discussed in the sub-section.

Management Capability

Even though data today dominates corporate reality, senior executives and managers still rely on their gut feelings to make decisions in the majority of organizations (Kiron, et al., 2014) and especially in public organization. In many organizations, making ground-breaking choices still prioritizes the highest-paid employee's judgment about data (McAfee and Brynjolfsson 2012). However, research suggests that leaders and managers should begin integrating data-based insights into their personal experiences and work to put their faith in data-based recommendations. Therefore, executives must gain a general understanding of analytical techniques in order to understand why recommendations based on analytics may differ from their own experience. (Ransbotham et al. 2015).

According to academics, the management team's expertise, readiness, and openness, as well as past experience making choices based on analytics, are all essential, but underrated, elements for company success in the Big Data era (Olszak 2014). It's critical to realize that businesses don't outperform rivals "just because they have more or better data," but rather because their executives know how to use it. (McAfee and Brynjolfsson 2012). According to research, it is crucial to spend money developing management skills since managing people at all levels of an organization's structure presents a higher managerial challenge than the actual technical one of employing big data (Yasmin et al. 2020, p. 2). To meet the challenge of successfully implementing BDA, an organization must improve the individual competencies of certain people or roles, such as leadership, coordination, decision-making, and control. The term "management capability" serves to condense these talents. According to Gupta et al. (2019), organizational contexts have a strong hold on leadership styles, which are a reflection of the traits among the pertinent executives (Pedro et al. 2019).

An effective leader should possess managerial abilities, business expertise, and general comprehension of analytical concepts. First and foremost, managers must help operational and business departments work together inside a company (Cragg et al. 2011), considering that most cross-functional contact in the context of BDA is unexplored and presents a number of difficulties (Arunachalam et al. 2018). The development of exceptional human big data abilities may result from forging cooperative working relationships between data managers and functional managers, which is equally important (Gupta and George, 2016). In addition, having a strong grasp of impending data-related trends, such as changes in customer behaviour, and having a keen sense of analytics are all helpful in producing ideas for how to employ analytical approaches effectively (Olszak 2014). (Elbashir et al. 2013). Executives must also possess industry knowledge of best practices and rivals in order to dedicate adequate resources to analytical projects (Ciampi et al. 2021). Last but not least, CEOs want a broad analytical understanding of BDA. Making the right decisions requires the capacity to comprehend, interpret, and properly evaluate data outputs (Shamim et al. 2019).

Coordination as well as the distribution of resources and the management of information is a particularly important ability for senior management in a BDA situation. (Hao et al. 2019). Managers of a company must coordinate BDA efforts in a highly dynamic environment in accordance with both formal and informal policies and procedures (Shokouhyar et al. 2020). (Kim et al. 2012). Determining the necessary IT infrastructure in accordance with the needs of the company is therefore crucial (Elbashir et al. 2013), as it allows for the allocation of actual resources, the formation of a team of functional and analytical experts, and the provision of unambiguous decision-making guidance (McLaughlin 2017). To reduce the workload for employees, managers must organize activities and coordinate efforts (Akter et al. 2020). Furthermore, executives are responsible for facilitating the necessary cultural transformation while implementing BDA by ensuring an open and direct information exchange among all concerned personnel (Kiron et al. 2014).

According to Rialti et al. 2019, regular cross-functional gatherings promote interpersonal dialogue and frank functional debate, which improves the use of analytics and, in turn, the quality of the executives' decision-making recommendations based on derived data insights. Consequently, set the company out from rivals (Wang and Hajli, 2017). Executives should actually comprehend and apply these decision-making patterns in their daily job. Executives frequently need to reconsider their methods and adjust to a new way of working when making decisions that are based on data recommendations rather than personal opinions (Dubey et al. 2018). Organizations should ultimately reach a point where managers are confident in the data-driven judgments they have made. Consequently, it is fundamental to strike a balance between one's own evaluation and the findings of the analysis (Kiron et al. 2014). Additionally, it's critical that CEOs exhibit a great propensity for analytical thinking coupled with the capacity to understand complex analyses (Mikalef et al. 2020a). In order to sustainably anchor data-supported decision processes in organizations (Upadhyay and Kumar 2020), processes must be appropriately structured, decision bodies must be clearly assigned, and escalation levels must be transparent (McLaughlin 2017).

BDA's expensive investment expenses are justified by the value produced by better decisions (Shokouhyar et al. 2020). Certain competencies that can be ascribed to a single person or function as part of the development of management competencies. Executives need a number of diverse talents to manage BDA projects because there are so many parties involved. Both the capacity to direct and lead others as well as the coordination and control of resources are necessary talents. Since BDA is a relatively new concept for many firms, it is especially crucial to guide employees through the transformation while keeping a clear strategic goal in mind. Management abilities are a crucial component of a BDA project's success.

Culture And Governance Capability

No matter the position, all employees behave in accordance with their own moral principles, standards, and unspoken external expectations. The cultural norms for all company actions are formed by these implicit rail guards (Shamim et al. 2020). Due to a discrepancy between the organization’s current culture and skills and the new strategies to properly use analytics, many firms struggle to implement BDA successfully (Barton and Court 2012, p. 82). The importance of regulatory systems as basic rules for the strategic direction of a firm and the values of its employees, attitudes, and standards is becoming more and more clear (Vidgen et al. 2017).

The organization's governance contains a summary of these rules and guidelines. Politics and Culture Capability encompasses an organization's capacity to create a BDA-related culture, morals, and values involving norms and rules for governance as well as for the efficient management of BDA. In the context of BDA, corporate culture refers to the culture and atmosphere of the organization, and the commitment as well as adaptability of senior management.

The business strategy, vision, and goal must be the source of values, norms, tacit behaviors, and artifacts in order for them to effectively and subtly influence employee behavior and foster a data-trusting environment (Olszak 2014). The ability of top management to truly follow data-driven decision rather than their intuition and to modify previous judgments if data analysis is successful is a critical component of a data-driven workplace (Mikalef, P., et al. 2018).

A data-driven culture is also characterized by upper management's strong commitment to data-driven decision-making (Chen et al. 2015; Gong and Janssen 2020). The acceptability and engagement of employees are strengthened when initiatives and analytical activities are supported at the highest levels of the organization (Cao et al. 2019; Chen et al. 2015). Persuasive Executives who view data as an asset and perceive the necessity of integrating BDA into the broader corporate strategy has a good impact on the success of BDA implementation. (Dubey et al., 2018) (Kiron et al. 2014). Analytical methodologies may become a political issue if senior management buy-in is lacking; as a result, BDA projects won't get off the ground (Arunachalam et al. 2018). Finally, organizational readiness to change is a significant aspect of corporate culture since an uncertain environment requires businesses to continually enhance analytical processes and methodologies as well as get rid of present organizational and psychological obstacles (Ngo et al. 2020)(Bharadwaj 2000).

For businesses or organizations to succeed, best practices across organizational units must encourage people to adopt an agile and flexible mentality (Olszak 2014). The most important thing is to realize that information and data are both extremely valuable resources (Galbraith 2014). For all of the aforementioned facets of BDA, regulatory rules must be established through contract governance, information governance, and internal policies. First, in terms of gathering and utilizing external data, effective stakeholder management and committed communication are crucial. (McLaughlin 2017). Therefore, it is crucial to have contractual governance to guarantee a constant flow of high-quality, relevant data (Shamim et al. 2020). To guarantee this high level of quality, contracts and agreements with providers of big data must include precise roles and procedures (Janssen et al. 2017). Second, information governance controls how any sort of information is handled and strengthens companies' pertinent competencies with reference to "the creation, capture, valuation, storage, usage, control, access, archival, and the deletion of information and related resources over its life cycle" (Mikalef, P. et al., 2020). Third, internal governance factors that affect the development of trust among organizational entities consist of internal procedures and frameworks (Munodawafa and Johl 2019), ethics (Ngo et al. 2020), processes, and policies (Bhatt and Grover 2005), as well as internal communication and knowledge sharing (Shabbir and Gardezi 2020). An organization must experience transformational changes in several areas in order to implement BDA. This change has a significant impact on values, norms, and corporate culture. It is necessary to change current systems of values and norms, especially in relation to data exploitation (Zubof 2015). The effective management of this cultural transformation is facilitated by the presence of defined governance and organizational norms.

Continuous Improvement (CI)

Continuous improvement (CI) is a concept that implies a sustained effort to enhance various activities and structures in an organization. This involves constantly attempting to make small steps towards increasing efficiency, quality, and production outputs. In public organizations, CI is crucial in the development of learning organization, and organizational change and to meet the changing needs of the customers. Several tools and techniques like Lean, Six Sigma and Total Quality Management (TQM) have been proven to enhance performance in different industries including healthcare, education, and public administration. This philosophy is based on the assumption that organizations can always become better regardless of their performance at a given point in time. As pointed out by Nadeau (2017), CI entails the continuous assessment and enhancement of processes and this is more so in public organizations that are under immense pressure to deliver and answer to the expectations of their customers.

The CI approach also integrates the participation of all the employees in the improvement process, to ensure commitment and ownership towards the organization's performance. Several techniques have been developed to help organizations implement CI, each with its own approach and toolkit for identifying problems and generating solutions.

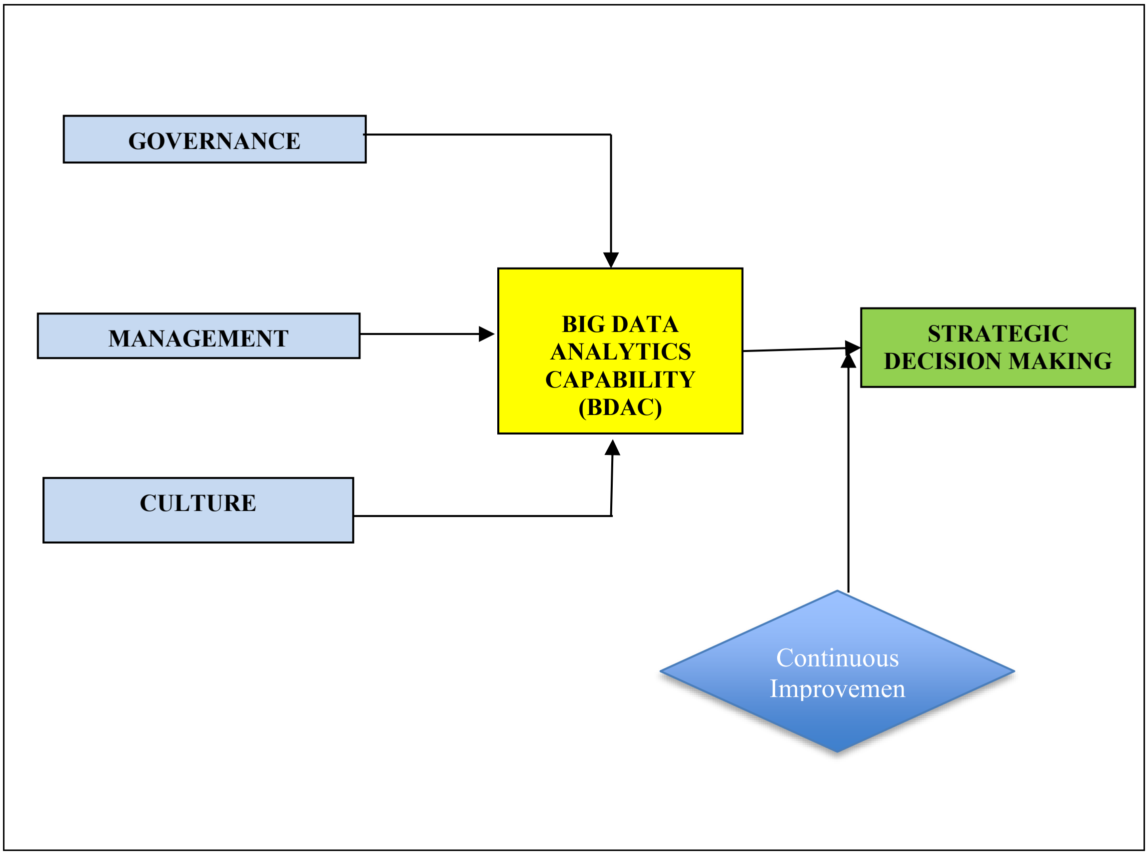

Figure 1: Conceptual Framework

Based on figure 1 above, shows that there are three (3) dimensions of Big Data Analytics Capability (BDAC) namely; Management Capability (MC), Governance Capability (GC), and Culture Capability (CC). The dependent variable is Strategic Decision Making (SDM) in Malaysian Public Organizations and Continuous Improvement (CI) as a mediator. The main aim of this proposed framework is to measure the relationship between the BDAC and Strategic Decision Making by having Continuous Improvement as a mediator variable.

CONCLUSIONS

In conclusion, the components of Big Data Analytics Capability methods have been evaluated, and a framework has been developed. The framework will serve as a guide and aid in enhancing Big Data Analytics practices methods in organizations from the point of view of public services in general. Enhancing strategic decision-making in Malaysian public organizations necessitates a transformative approach that integrates Continuous Improvement (CI) and Big Data Analytics (BDA) capabilities. The framework proposed in this paper addresses existing gaps in governance and operational efficiency while promoting agility and ensuring sustainable growth. By leveraging the power of data analytics and fostering a culture of continuous improvement, public organizations can significantly enhance their decision-making processes, leading to better resource allocation, improved service quality, and heightened accountability. The integration of CI and BDA is particularly relevant in the context of Malaysian public organizations, where the need for efficient governance and responsive service delivery is paramount. As highlighted by Ongena and Davids Ongena & Davids (2023), the development of big data analytics capabilities within the public sector can lead to improved governmental performance. This aligns with the growing recognition of the potential of big data to transform public administration, enabling organizations to make data-driven decisions informed by real-time insights. Furthermore, the ability to analyze large volumes of data allows public organizations to identify trends, forecast future needs, and allocate resources more effectively.

ACKNOWLEDGEMENT

The authors would like to thank the Institute of Postgraduate Studies (IPSis) and Universiti Teknologi MARA, Puncak Perdana Campus, UiTM Selangor Branch, for their research support and opportunities.

REFERENCES

Abbasi, A., Sarker, S., Chiang, R.H. (2016). Big data research in information systems: toward an inclusive research agenda, J. Assoc. Inf. Syst. 17 (2).

Akhtar, P., Frynas, J. G., Mellahi, K., & Ullah, S. (2019). *Big Data-Savvy Teams' Skills, Big Data-Driven Actions and Business Performance. British Journal of Management, 30(2), 252–271.* doi:10.1111/1467-8551.12333

Arnott, D. & Pervan, G. (2016). A critical analysis of decision support systems research revisited: the rise of design science, Enacting Research Methods in Information Systems, Springer, pp. 43–103.

Arunachalam, D. et al. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice, Transportation Research Part E: Logistics and Transportation Review,Volume 114, Pages 416-436, ISSN 1366-5545, https://doi.org/10.1016/j.tre.2017.04.001.

Barnaghi, P., Sheth, A., & Henson, C. (2013). *From Data to Actionable Knowledge: Big Data Challenges in the Web of Things [Guest Editors' Introduction]. IEEE Intelligent Systems, 28(6), 6–11.* doi:10.1109/mis.2013.142

Barton, D., & Court, D. (2012). Making advanced analytics work for you. Harvard business review, 90(10), 78-83.

Bhatt, G. D., & Grover, V. (2005). Types of information technology capabilities and their role in competitive advantage: An empirical study. *Journal of management information systems*, *22*(2), 253-277.

Cao, G., Duan, Y., & Li, G. (2015). Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *IEEE Transactions on Engineering Management*, *62*(3), 384–395. https://doi.org/10.1109/TEM.2015.2441875

Ciampi, F., et al. (2021). Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *Journal of Business Research*, *123*, 1-13.

Constantiou, I.D. & Kallinikos, J. (2015). New games, new rules: big data and the changing context of strategy, J. Inf. Technol. 30 (1) 44–57.

Davenport,T.H., Barth, P., Bean, R., (2012). How big data is different, MIT Sloan Manage. Rev. 54 (1) 43.

Dong, J.Q. and Yang, C.H., (2020). Business value of big data analytics: A systems-theoretic approach and empirical test, Information & Management, Volume 57, Issue 1, 103124, ISSN 0378-7206, https://doi.org/10.1016/j.im.2018.11.001.

Dubey, R., Luo, Z., Gunasekaran, A., Akter, S., Hazen, B. T., & Douglas, M. A. (2018). Big data and predictive analytics in humanitarian supply chains: Enabling visibility and coordination in the presence of swift trust. *The International Journal of Logistics Management*, *29*(2), 485-512.

Elbashir, M. Z. (2017). Creating Value From Business Intelligence Systems Investments. In *Global Business Intelligence* (pp. 207-222). Routledge.

Fayyad, U., Stolorz, P. (1997). Data mining and KDD: Promise and challenges, Future Generation Computer Systems, Volume 13, Issues 2–3, Pages 99-115, ISSN 0167-739X, https://doi.org/10.1016/S0167-739X(97)00015-0.

Gamage, P. (2016). New development: Leveraging ‘big data’ analytics in the public sector. *Public Money and Management*, *36*(5), 385–390. https://doi.org/10.1080/09540962.2016.1194087

Garmaki, Mahda; Boughzala, Imed; and Wamba, Samuel Fosso, "THE EFFECT OF BIG DATA ANALYTICS CAPABILITY ON FIRM PERFORMANCE" (2016).PACIS 2016 Proceedings. 301. http://aisel.aisnet.org/pacis2016/301

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information and Management*, *53*(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Gupta, D., & Rani, R. (2019). A study of big data evolution and research challenges. *Journal of information science*, *45*(3), 322-340.

Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, *70*, 338–345. https://doi.org/10.1016/j.jbusres.2016.08.007

MAMPU (2016). *Analitis Data Raya Sektor Awam (DRSA).* http://www.mampu.gov.my/ms/data raya-sektor-awam-drsa

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., Byers, A.H. (2011). Big Data: The Next Frontier for Innovation, Competition, and Productivity, (2011).

McAfee, A., Brynjolfsson, E., Davenport, T.H. (2012) Big data: the management revolution, Harv. Bus. Rev. 90 (10) 60–68.

McLaughlin, M. (2017). *Decentralized decision making on human capital management in k-12 education* (Doctoral dissertation, California Lutheran University).

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information and Management*, *57*(2). https://doi.org/10.1016/j.im.2019.05.004

Mikalef, P., Pappas, I.O, Krogstie, J., Giannakos, M. (2018). Big data analytics capabilities: a systematic literature review and research agenda, Inf. Syst. E-Bus. Manag. 16 (1–32).

Olszak, C. M. (2016). Big Data–opportunities and challenges for organizations. *Risks and Opportunities–in Search of Equilibrium. Cracow University of Economics*, 113-128.

Özemre, M., & Kabadurmus, O. (2020). A big data analytics based methodology for strategic decision making. *Journal of Enterprise Information Management*, *33*(6), 1467–1490. https://doi.org/10.1108/JEIM-08-2019-0222

Pedro, J., Brown, I., & Hart, M. (2019). Capabilities and readiness for big data analytics. *Procedia Computer Science*, *164*, 3-10.

Ransbotham, S., Kiron, D., & Prentice, P. K. (2015). Minding the analytics gap. *MIT Sloan management review*, *56*(3), 63-68.

Rialti, R., et al. (2019). Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model. *Technological Forecasting and Social Change*, *149*, 119781.

SAS, Big Data Analytics: An Assessment of Demand for Labour and Skills, 2012–2017, SAS, 2013.

Shabbir, M. Q., & Gardezi, S. B. W. (2020). Application of big data analytics and organizational performance: the mediating role of knowledge management practices. *Journal of Big Data*, *7*(1), 47.

Shamim, et al. (2019). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view, Information & Management, Volume 56, Issue 6, ISSN 0378-7206, https://doi.org/10.1016/j.im.2018.12.003.

Sharma, R., Mithas, S., Kankanhalli, A.(2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations, Eur. J. Inf. Syst. 23 (4) 433–441.

Shim, J.P. et al. (2002). Past, present, and future of decision support technology, Decision Support Systems, Volume 33, Issue 2, Pages 111-126, ISSN 0167-9236, https://doi.org/10.1016/S0167-9236(01)00139-7.

Shokouhyar, S., Seddigh, M. R., & Panahifar, F. (2020). Impact of big data analytics capabilities on supply chain sustainability: A case study of Iran. *World Journal of Science, Technology and Sustainable Development*, *17*(1), 33-57.

Seddon, J. and Currie, W.(2017). A model for unpacking big data analytics in high-frequency trading, Journal of Business Research, Volume 70, Pages 300-307, ISSN 0148-2963, https://doi.org/10.1016/j.jbusres.2016.08.003.

Sivarajah, U. et al. (2017). Critical analysis of Big Data challenges and analytical methods, Journal of Business Research, Volume 70, Pages 263-286, ISSN 0148-2963, https://doi.org/10.1016/j.jbusres.2016.08.001.

Upadhyay, P., & Kumar, A. (2020). The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *International Journal of Information Management*, *52*, 102100.

Vidgen, R., Shaw, S., Grant, D.B.(2017). Management challenges in creating value from business analytics, Eur. J. Oper. Res. 261 (2) 626–639.

Walker, S.J. (2014). Big Data: A Revolution That Will Transform How We Live, Work, and Think, Taylor & Francis.

Wamba, S. F., Akter, S., & Guthrie, C. (2020). Making big data analytics perform: the mediating effect of big data analytics dependent organizational agility. *Systèmes d'information & management*, *25*(2), 7-31.

Wamba, S.F., Gunasekaran, A., Akter, S., Dubey, R., Childe, S.J. (2017). Big data analytics and firm performance: effects of dynamic capabilities, J. Bus. Res. 70 (2017) 356–365.

Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, *70*, 287-299.

Yasmin. et al. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach, Journal of Business Research, Volume 114, Pages 1-15, ISSN 0148-2963, https://doi.org/10.1016/j.jbusres.2020.03.028.

Zeng, J., & Glaister, K. W. (2017). *Value creation from big data: Looking inside the black box. Strategic Organization, 16(2), 105–140.* doi:10.1177/1476127017697510