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Conceptual Model Development of Big Data Analytics Implementation Assessment Effect on Decision-Making

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Abstract

The significance of big data advancement has benefited various organizations to leverage the potential insights and capabilities of big data in organizational performance and decision-making. However, the analytics outcome and quality of big data analytics (BDA) implementation has yet to be addressed. Therefore the aims of this paper are to identify and analyze the affecting factors and elements of BDA implementation and to propose a conceptual model for effective decision-making through BDA implementation assessment. The model is developed based on three dimensions such as performing data strategy (organization), collaborative knowledge worker (people) and executing data analytics (technology). The findings of this ongoing study proceeds with designing a proposed conceptual model with the research hypothesis and may provide a better assessment model for effective decision-making in the long run.

Keywords

Big Data, Data Analysis, Decision-Level, DSS, E-assessment.

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I. Introduction

Many organizations have shifted to data-driven decision-making as a result of the advancements of big data benefits. The use of analytics in real-time decision-making has significant impacts on business activities and performance enhancement [1]. Most of them have benefited from big data analytics (BDA) implementation in many ways, such as information technology (IT) infrastructure, operational, managerial, strategic and organization benefits [2] [3]. The IT infrastructure benefits including using sharable and reusable IT resources that reduce operation cost for IT management and increased IT infrastructure capability. Indirectly, it helps to improve the operational activities by reducing information process cycle time, productivity and quality improvement [2]. Likewise, the analytics results used by business leaders have improved decision-making and facilitate better planning in business management activities. BDA implementation will also benefit in strategic long-term planning to support business growth and business value creation that leads to organizational performance enhancement [3][4].

Big data analytics implementation includes processes of managing the big data analytics capabilities and resources (such as technologies, people and analytics processes) [5], and transforming big data into valuable and understandable information [3] by using the analytics applications to gain insights for effective decision-making and enhance the organizational performance [6] [7]. Therefore, business leaders play an important role in achieving the goals of BDA implementation. The understanding of analytics deliverables and effective decision-making totally depends on the influencing factors. Several factors such as organizational capability, technology capability, analytics capability, talent or human capability, and the information quality are effecting the success of its implementation [8].

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Valuing the information systems (IS) investments for BDA implementation and assessing its application will be worthwhile in the organization's effort to develop new big data business model in the future, sustaining competitive advantages and to address new issues and challenges [9]. In the course of assessment during BDA implementation stage, the aim is to determine the relevance and fulfilment of objectives, sustainability of the current business model [10] and business survival for the long term. At this point in time, the assessment of BDA is only at the stage of readiness [11], which focusing only on the big data capabilities and resources. Nonetheless, the assessment of BDA implementation impact is still an understudied research topic. Therefore, the aims of this paper are: 1) to identify and analyze the affecting factors and elements of BDA implementation; and 2) to propose a conceptual model of BDA implementation assessment for effective decision-making.

The organization of this paper will be as follows: the second section focuses on the theoretical background and is followed by the third section that discusses on research methodology. The fourth section presents the discussion and findings of the affecting factors and proposes a conceptual model for BDA implementation assessment while the last section concludes the study by pinpointing the research contribution and suggesting further research work.

II. Theoretical Background

There have been a number of studies that dwelled on developing BDA capabilities models by adopting resource-based view theory (RBV) [12], and the updated version of DeLone and McLean's Information Systems Success Model (ISSM) [13]. Capabilities and resources are the key components of RBV in achieving the organizational performance and sustained competitive advantage [14].

In adopting a resource-based perspective, big data researchers have identified various BDA related capabilities and resources that serve as potential grounds of organizational performance. For example, Akter et al., 2016 [7] and Wamba et al., 2017 [15] pointed out that BDA capabilities covers management, talent and technology dimensions that positively influenced the organizational performance. Likewise, empirical findings by Gupta and colleague, 2016 [16] provided evidence on tangible, human skills and intangible resources supported by the BDA capabilities that led to market and operational performance.

Furthermore, the use of business analytics tools has enabled decision making effectiveness in health care through absorptive capability [17]. Several studies have adopted RBV theory to deepen their understanding of BDA capabilities in achieving organizational performance such as, in manufacturing [4] [18], health care [17] [19], retail [15], and non-specific domains [7] [16] [20] [21]. On the other hand, the adoption of ISSM theory focuses only on data, information and system quality factors towards organizational impact and benefits. Thus, system quality and information quality are significant to enhance business value and firm performance in big data surroundings [21].

A. Big Data Analytics Capabilities

Various concepts have been utilized in the big data literature to describe BDA capabilities. A systematic literature found that the following three concepts were the most commonly used to describe BDA capabilities. The first concept described BDA capability as the most competence to provide business insights using data management, talent (personnel context) and infrastructure (technology context) capability to transform information business into a competitive force [7] [15]. The second concept mainly used the context in health care, where BDA capabilities is regarded as having the ability to acquire, store, process and analyze a large amount of health data in various forms, and deliver meaningful information to users that allow them to discover business values and insights in a timely fashion [2]. The third concept used BDA capability to assemble, integrate, and deploy its big data-based resources in big firms [16]. This study points out the BDA capabilities factors as shown in Table I that includes management capability, organizational capability, technology capability, talent capability (data analytics personnel expertise), information processing capability and other related capabilities.

TABLE I. BIG DATA ANALYTICS CAPABILITIES FACTORS AND VARIABLES

Factors	Variables		Sources
Management capability	• Big data analytics planning • Investment decision-making	• Coordination and control	[7] [15]
Organizational capability	• Collaboration, BDA strategy • Information strategy • Top management support	• Strategic groundwork • Organizational readiness	[22] [4] [5] [23] [24]
Technology capability	• Infrastructure flexibility • Process integration and standardization • Integration of IT systems	• Effective use of data aggregation tools • Effective use of data analysis tools • Effective use of data interpretation tools	[7] [15] [22] [23] [4] [5] [17]
Talent capability	• Technical knowledge • Technology management capability • Relational knowledge • Managerial skills	• Business knowledge • Analytics capabilities • People skills • Training people • Engaging people	[7] [15] [16] [23] [4] [5]
Information processing capability	• Analytical capability • Patterns of care • Unstructured data analytical capability • Decision support capability • Traceability capability	• Speed of decisions • Predictive analytics • Interoperability • Data analytics (data collection, data analysis and modelling, data visualization, insight generation)	[18] [19] [23] [2]
Other capability	• Process-oriented dynamic capabilities	• Absorptive capability	[15] [17]

TABLE II. INTANGIBLE AND TANGIBLE RESOURCES FACTORS AND VARIABLES

Factors	Variables		Sources
	Tangible Resources		
Data	• Data standardization • Data openness • Data quality • Data privacy & security	• Data provisioning (include data sourcing, access, integration and delivery)	[16] [25] [4]
Technology	• Data aggregation & processing • Data storage	• Analytics platform • Application	[16] [25] [24]
Basic resources	• Basic resources • Investment	• Support (include laws & regulations, government policies)	[16] [25] [4]
	Intangible Resources		
Data-driven culture	• Data-driven culture	• Decision-making culture	[16] [18] [22] [17] [23]
Intensity of organizational learning	• Intensity of organizational learning		[16]
Perceived benefits	• Perceived benefit of external data usage	• Perceived benefit of internal data usage	[20]

B. Big Data Analytics Resources

Based on RBV theory, some studies have categorized BDA resources into tangible and intangible resources. Table II listed factors and variables for tangible and intangible resources discussed in BDA studies. The big data analytic capability model developed by Gupta and George (2016) [16] equally relies on tangibles resources such as data, technology, basic resources, and intangibles resources such as data-driven culture and intensity of organizational learning. Furthermore, intangible resources also include perceived benefits of external and internal data usage [20].

C. Big Data Analytics Quality

BDA is associated with transforming and analyzing raw data into valuable information as well as knowledge in creating business values. In relation to this, quality of data and information are critical for organizational impact which will facilitate top management in decision-making. Earlier studies have shown that BDA quality factors are consisting of data quality, information quality and system quality as shown in Table III. An empirical study in BDA environment by Ji-fan Ren et al. (2016) [21] identified system quality and information quality is very crucial in enhancing business value and firms' performance.

Table III. Big Data Analytics Quality Factors and Variables

Factors	Variables		Sources
Data Quality	• Data consistency	• Data completeness	[20]
Information Quality	• Completeness • Currency • Format	• Accuracy • Security and integrity	[5] [21]
System Quality	• Reliability • Adaptability • Integration	• Accessibility • System response time • System privacy	[21]

III. Methodology

The development of the conceptual model in assessing the BDA implementation was carried out based on multiple steps as illustrated in Fig. 1. The review processes was based on the systematic literature review (SLR) approach [26][27], and continued with content analysis before the relevant theories were identified. The review exercise has investigated 15 articles on the implementation of BDA in various domains, and categorized them into two types of research analysis namely empirical and case study.

The initial investigation begins by formulating a research question such as 'What are the factors and elements to be considered in developing BDA implementation assessment (BDAIA) model?' Then, the process continues by searching information from electronic journal databases such as scopus, science direct, google scholar and snowballing technique, and then 15 relevant articles were selected. The relevant articles were then analyzed using matrix table (Table IV). This study has listed 4 factors and 15 elements to be considered in developing the assessment model, and the findings are discussed in the following section (Section 4). Finally, the design of the conceptual model for BDAIA with related factors and elements is presented in the conclusion.

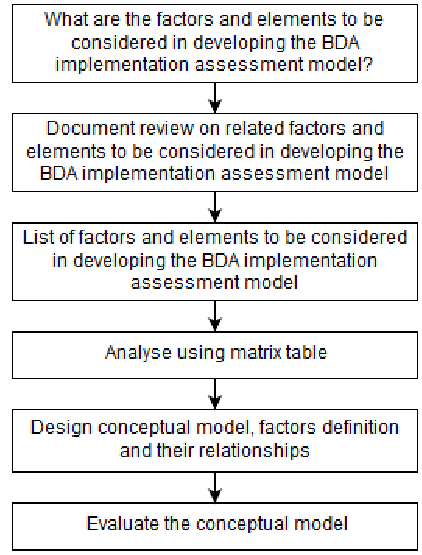

Fig. 1. The process of developing BDAIA conceptual model.

IV. Findings and Discussion

Table IV presents the related BDA factors discussed in other studies which includes BDA capabilities, tangible resources, intangible resources and BDA quality, together with their elements that affects BDA implementation. The frequency of each element were shown in Fig. 2. Technology element in both BDA capability and tangible resources, and talent or human element were shown to be the two most frequent elements highlighted in BDA implementation. This is followed by organizational capability, data-driven culture, and information processing capability elements. Subsequently, elements such as data and basic resources were the least discussed in other studies. BDA elements such as management capability, other capability, BDA quality and perceived benefits were the least discussed elements in the empirical studies as they were considered still in their infancy stage in the big data environment.

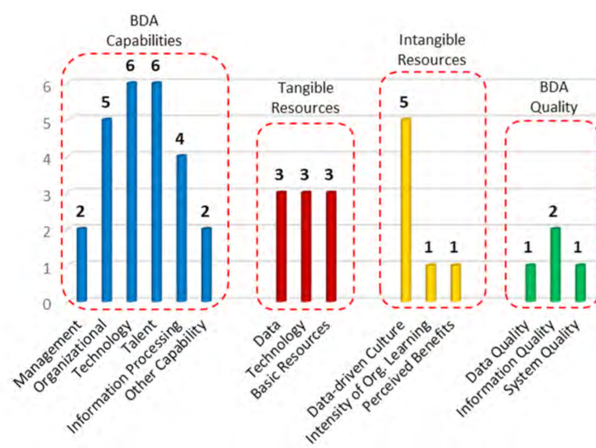

Fig. 2. The frequency of BDA elements.

Drawing on RBV theory and ISSM, big data analytics implementation assessment is conceptualized and being determined by three dimensions: organization, people and technology. Performing data strategy factor is an important criteria in organization dimension. It refers to the organizations' assurance in performing strategic analytics alignment, managerial commitment and resources management. Meanwhile, collaborative knowledge worker factor is determined by the people dimension which refers to the analytics personnel skills,

Table IV. Factors and Elements Affecting the BDA Implementation

Factors/ Elements \ Authors	Koronios et al., 2014 [5]	Akter et al., 2016 [7]	Wamba et al., 2017 [15]	Janssen et al., 2017 [22]	Popovič et al., 2016 [4]	Dutta & Bose, 2015 [23]	Chen et al., 2015 [24]	Wang &Byrd, 2017 [17]	Gupta &George, 2016[16]	Cao & Duan, 2014 [18]	Wang & Hajli, 2017 [19]	Wang et al., 2018 [2]	Kim & Park, 2016 [25]	Kwon et al., 2014 [20]	Ji-fan et al., 2016 [21]	Frequency
BDA Capabilities																
Management		X	X													2
Organizational	X			X	X	X	X									5
Technology	X	X	X	X		X		X								6
Talent/Human	X	X	X		X	X			X							6
Information Processing						X				X	X	X				4
Others			X					X								2
Tangible Resources																
Data					X				X				X			3
Technology							X		X				X			3
Basic Resources					X				X				X			3
Intangible Resources																
Data-driven Culture				X		X		X	X	X						5
Organization Learning									X							1
Perceived Benefits														X		1
BDA Quality																
Data Quality														X		1
Information Quality	X														X	2
System Quality															X	1

Table V. Factors, Elements and Definitions

Factors	Elements	Definition	Sources
Perform Data Strategy	• Strategic Analytics Alignment	• The alignment of BDA goals to support the business and IT strategy, and their goals.	[4] [23]
	• Managerial Commitment	• The organization leaders and top management commitment to support the BDA implementation and provide sufficient resources.	[16]
	• Resources Management	• The management of BDA resources include technology, people and competency development.	[15] [16]
Collaborate Knowledge Worker	• Analytics Skills	• The capability of analytics personnel to analyze big data effectively with the specific capability, level of knowledge and skills.	[5][7][15]
	• Organizational Relationship	• The collaboration and interaction between analytics personnel and domain experts in achieving BDA goals.	[7][22]
	• Analytics Culture	• The practice of organization leaders and decision-makers using statistical data and analytics information in decision-making.	[18][22]
Execute Data Analytics	• Infrastructures	• The technology of IT equipment's and application systems used to operationalize the BDA implementation.	[6][7]
	• Information Processing	• The capability of IT platforms and analytics applications to process raw data and transform to the valuable information.	[5][25]
	• Data Governance	• The governance of big data includes formulating data policy, data integration and data management.	[4][2]
	• Data Quality Management	• The management of data and information quality in processing big data to provide complete, accurate and quality reports.	[20][21]

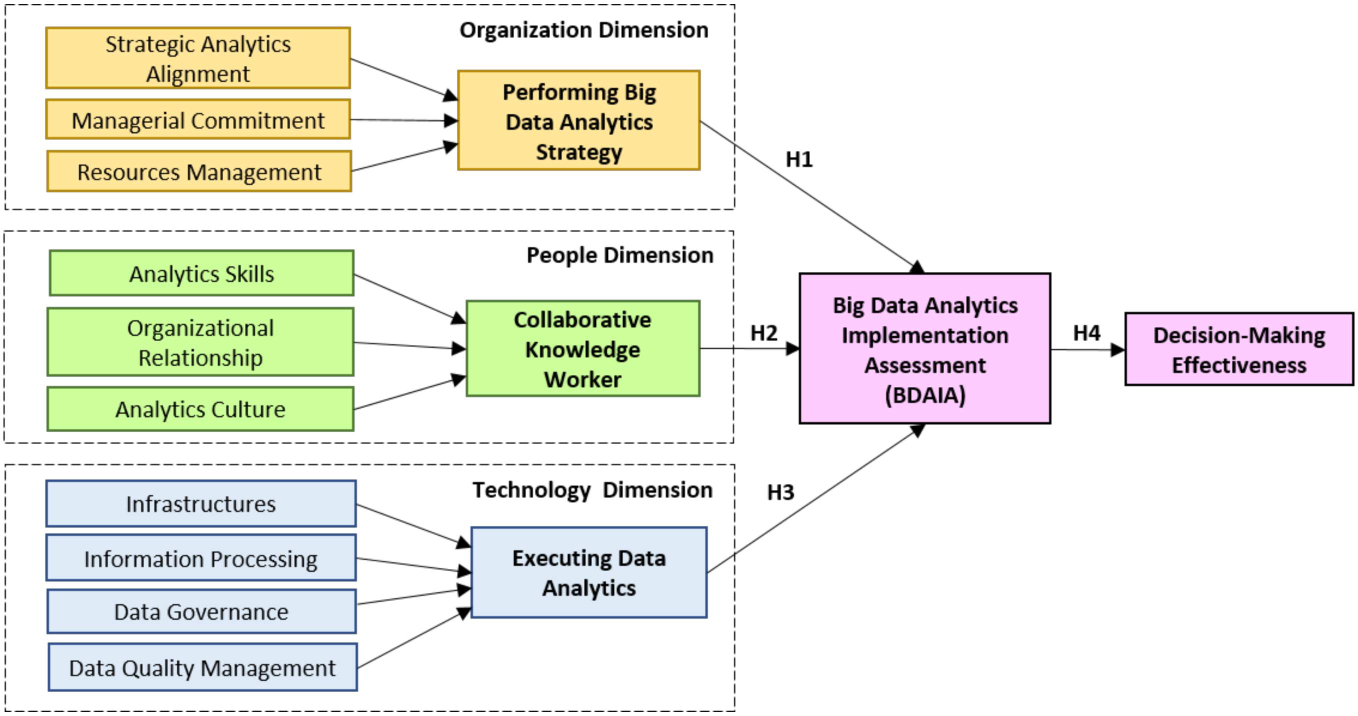

Fig. 3. Conceptual model BDA implementation assessment effect on decision-making.

organizational relationship and analytics culture. Subsequently, in technology dimension, the elements of executing data analytics factor including IT infrastructures, information processing, data governance and data quality management. Table V presents the factors with related elements and its definition that are crucial for creating the conceptual model.

Fig. 3 illustrated the conceptual model for big data analytics implementation assessment (BDAIA). The effect of BDAIA consequently influences decision-making effectiveness, as well as the indirect effect of performing BDA strategy, collaborative knowledge worker and executing data analytics factors. In this line, the study hypothesis is:

H1: Performing BDA strategy has a significant positive effect on BDAIA

H2: Collaborative knowledge worker has a significant positive effects on BDAIA.

H3: Executing data analytics has a significant positive effect on BDAIA.

H4: BDAIA has positive effects on decision-making effectiveness.

V. Conclusion

A conceptual model was found the most useful for assessing the big data analytics implementation. The model is capable of measuring the relationship of organization, people and technology dimensions that affect the assessment of BDA implementation and decision-making. The follow-up research activity will be developing a survey instrument using questionnaires. The proposed conceptual model and questionnaires will be then to be verified by experts from academics and industry. In relation to this, a pilot study will be conducted and to be followed by the actual study. The model will be validated then using statistical tools, and the results gained will provide an insight for business leaders to plan, sustain and enhance the capability of decision-making based on data-driven by assessing the relevant resources.

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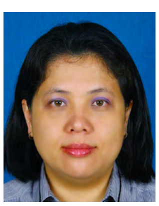

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