Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Exploring the performance measures of big data analytics systems

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ARTICLE INFO

Article history:
Received 9 May 2022
Received in revised form
21 August 2022
Accepted 27 September 2022

Keywords:
Big data
Big data analytics
BDA process
Performance measures
Performance-contributing factors

ABSTRACT

Performance measurement is the process of making an evidence-based improvement. It reveals the performance gains or gaps, depending on the entity to be measured, being an organization, people, equipment, processes, or systems. After development, big data analytics (BDA) systems massively fail in organizational settings. The reasons, however, are not fully understood. This paper investigates how organizations can quantify the performance of their BDA systems. To answer this question, we investigated performance measures and performance-contributing factors in the existing literature and surveyed users' perceptions of our findings. The results show that metrics of efficiency and effectiveness can be used to measure the performance of the BDA system. The results also demonstrate that technology, competency, and working conditions are the key factors that contribute to the performance of the BDA system.

1. Introduction

Big data is referred to as high volume, high velocity, and high variety information assets that necessitate new forms of information processing that assist enhanced insights and improved decision-making. As the importance of big data has grown, more studies are focusing on it, not just from a technical point of view, but also from a socio-technical point of view which includes people, processes, and technology. The expanded area of big data research in information systems (IS) now focuses on big data in terms of analytics, infrastructure, and business transformation (Goes, 2014). Analytics or Big Data Analytics (BDA), regarded as an information systems' research focus, comprises data, data processing, analytics tools, methodologies, and most crucially, the BDA) process which ties the whole thing together. Since the BDA process generates the knowledge and insights that organizations require, attempts to enhance and optimize it are obviously justified. Such initiatives that the specific skills required to perform BDA process tasks, technology to execute the BDA process, and a conducive work environment, as well as performance measures for identifying rooms for further improvement.

The BDA process involves a number of challenges encountered through acquiring, integrating, transforming, and analyzing data, and conveying the results to users (Sivarajah et al., 2017). Issues related to structure, heterogeneity, timeliness, error-handling, privacy, and provenance exist throughout the BDA process from data acquisition to visualization (Alguliyev et al., 2017; Mittal et al., 2021), and hence affect its performance.

Big data can be seen via the lens of performance measurement. According to Veiga et al. (2018), measuring the performance of BDA systems is a form of obtaining insights from the processing time of analytics applications. The need arises in understanding how to measure and evaluate the performance of such applications and discover the factors that affect their quality (Villalpando et al., 2014).

Performance measurement is "the process of quantifying the efficiency and effectiveness of action" (Bourne et al., 2003). Performance, for BDA systems, involves the back-end and front-end performance attributes (Liu, 2014). Back-end performance attributes to examine the functionality of BDA systems. The front-end performance attributes, on the other hand, examine the satisfaction of users with the results of the big data analytics system. This elaboration strengthens the possibility of considering efficiency and effectiveness measures when scrutinizing the performance of BDA systems.

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https://doi.org/10.21833/ijaas.2023.01.013
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Efficiency is related to the information system's availability and its performance over efforts, whereas effectiveness focuses on the usefulness of information to users (Heo and Haan, 2000). Accordingly, resource utilization, capacity, time-related measures, (Villalpando et al., 2014; Brunnert et al., 2014), and throughput, response time, and latency (Onyeabor and Ta'a, 2018) are performance measures that examine the capability of the BDA System. Performance measures like usefulness, timeliness, output representation and user satisfaction could be used to assess the system's success from a user's perspective. It entails attaining both individual and organizational objectives, as well as the objectives of the BDA system.

These two aspects shed light on how the BDA system's performance might be assessed. The know-how to perform the work, and the technology required for managing the volume, variety, and velocity of data generated by organizations (Mikalef et al., 2017), are also significant factors that increase the capability of the BDA system.

2. Literature review

Big data comes with unprecedented growth in size and speed, and time and performance are two crucial factors. Examples in this regard are the performance of data transmission time and data processing time, as well as the performance, and required time the analytics results to users (Liu, 2014). Accordingly, the BDA process requires performance measures, be it internal measures such as time and resource utilization, or external measures such as the use of the results by users.

Performance measurement is a process that focuses on quantifying the efficiency and effectiveness of an action (Dissanayake and Rupasinghe, 2021). Efficiency is related to information systems' capability and availability. An effective system, on the other, that, supports the end users and adds value to their business (Gatian, 1994). Therefore, performance measures in information systems efficiency include capacity, throughput rate, response time, speed, reliability, and resource utilization metrics (Grover et al., 1996; Heo and Haan, 2000). Effectiveness measures include system usage estimation, system quality, user satisfaction, performance in decision-making, utility analysis, and information quality and information satisfaction (Thong and Yap, 1996; Scott, 1995).

BDA should harness advanced technology in order to augment the process of data exploration and exploitation. According to Sheng et al. (2019), analytics technology supports the efficiency of all stages of the BDA workflow. The technology enhances the quality of data, provides storage, increases the performance of process execution, and facilitates in-depth data analysis and data visualization. Every stage, as Hu et al. (2014) stated, has a specific technology that supports it. Big data technology is mainly divided into 3 parts those are file systems, analytics tools, and computing frameworks (Kune et al., 2016).

Big data success depends on the interplay between people, processes, and technology (Koronios et al., 2014). Suitable data analytics proficiencies enable achieving better outcomes (Klee et al., 2021). Similarly, with Big data, being close to products and business processes within the organization is essential (Davenport et al., 2012). Another research has divided the human skills required for big data analytics into two groups: technical skills and management skills (Gupta and George, 2016). It has also been indicated that technical knowledge, business knowledge relational knowledge, and business analytics knowledge are crucial for better utilizing big data technology (Mikalef et al., 2018b; Wamba et al., 2017). Therefore, having the combination of required competency, whether it is knowledge of BDA or the ability to communicate with business people to interpret BDA results, still remains the key condition (Janssen et al., 2017).

The performance of the BDA system depends not only on the skills of workers but also on the care they feel they are given. An aspect related to this topic is the working conditions of the staff that perform BDA analytics activities and execute the BDA system. For example, an enjoyable work environment (less noise, less heat, enough space, and visual comfort) can contribute to the ability to carry out processes (Górny, 2017). The working environment is broadly divided into two categories: Work and context (Raziq and Maulabakhsh, 2015). Characteristics like existing rules and regulations, weather conditions, health situations, and workload per staff's capacity apply to working conditions (Leyer et al., 2015).

2.1. Theoretical perspectives

As explained earlier in this paper, efficiency refers to information systems capability, and effectiveness means user satisfaction. Delone and McLean's (2004) success model is a widely used IS theory, which measures several variables including system quality and user satisfaction. System quality denotes the system's characteristics like response time, availability, and ease of use (DeLone and McLean, 2004). User satisfaction is indicated to be the extent users are satisfied with an information system (Gotthardt and Mezhuyev, 2022).

Another IS theory is the work system framework by Alter (2013). The work system, rephrasing Alter's definition, is a system in which human participants carry out processes using information, technology, and other resources to produce a specific output for customers. Also, big data-specific resources including data, technology, and skilled humans play a significant role in process innovation (Mikalef and Krogstie, 2020).

Measuring the performance of the BDA system, consistent with the above discussions, should have capabilities such as enabling technology, competent people, and a supportive working environment. The combination of such capabilities can strengthen the BDA system which will lead to improved performance outcomes obtained through the metrics of efficiency and effectiveness.

2.2. The BDA process

Generally, big data success is dependent on the harmony between people, technology, process, and structure which together consolidate the dynamic capability and the analytics characteristics of big data (Conboy et al., 2020). For big data, the process is about data exploration and exploitation (Koronios et al., 2014). Exploration means unlocking insights and meaningful information from data. Exploitation refers to the utilization of insights and values unlocked from data. So, the process is there, and there are more discussions about it in the existing literature.

Discussions emphasize the choice between the creation of a new BDA process that is indicated to be achievable, or to use, where appropriate, the available processes such as Cross-Industry Standard for Data Mining (CRISP-DM) and Knowledge Discovery in Database (KDD) (Saltz, 2015); two processes that belong two aspects of data science which came before big data.

The extract, transform, and load (ETL) process is also one more instance of the prevailing analytics processes (Nwokeji and Matovu, 2021). The ETL process is said to be batch-oriented (Chen et al., 2016), a quality that complicates its appropriateness to big data in which, according to Diouf et al. (2017), the speed of data processing becomes a significant factor in the quest for competitive advantage. In other terms, the agility enabled by BDA value creates a competitive advantage and organizational performance (Côrte-Real et al., 2017). The consideration of agile methods is discussed in the existing literature. Agile methodology was used for software development in the past and suggested big data analytics as a better process alternative (Ponsard et al., 2017). Unlike, the exiting process, an investigation in the literature shows that the big data analytics process or big data analytics workflow has different structures. Data acquisition, data preparation, data analysis, visualization, and interpretation are seen to be the BDA process phases. Table 1 presents the occurrences of these phases in the big data literature.

2.3. Performance measures: Efficiency and effectiveness

A performance measure is defined as a metric used to quantify the efficiency and effectiveness of an action (Neely et al., 1995; Bourne et al., 2003). Performance efficiency is the characteristic that represents the performance relative to the number of resources used under stated conditions. It comprises "time behavior, resource utilization, and capacity as sub-characteristics" (Kaur et al., 2019). Efficiency attributes which are time and computing resource utilization are internal quality attributes (Gorla and Lin, 2010).

Table 1: BDA process phases

Authors	Acquisition/Collection	Preparation	Analysis/Analytics	Visualization	Interpretation
(Larson and Chang, 2016)	√	-	√	√	-
(Demchenko et al., 2014)	√	√	√	√	-
(Rehman et al., 2016)	√	√	√	-	-
(Gandomi and Haider, 2015; Bayrak and Kirci, 2019)	√	√	√	-	√
(Daniel, 2015)	√	-	√	√	-
(Assunção et al., 2015)	√	√	√	√	√
(Tulasi, 2013)	√	√	√	-	√
(Hussain et al., 2016)	√	√	√	-	√
(Hu et al., 2014)	√	√	√	-	-
(Jagadish et al., 2014)	√	√	√	-	√
(Sivarajah et al., 2017)	√	√	√	-	√
(Biuk-Aghai et al., 2016)	√	√	√	√	√
(Alguliyev et al., 2017)	√	√	√	-	√
(Miller and Mork, 2013)	√	√	√	√	√
(Elragal and Klischewski, 2017)	√	√	√	-	√
Total	16	14	16	6	11

From an information systems perspective, effectiveness refers to the impact of information output on supporting end-users to do their job (Heo and Haan, 2000). Measures of making data more meaningful for visualization and user interpretation fall in this category. With the help of extant big data and IS literature, the study puts forward the following measures: User satisfaction, data representation, timeliness, usefulness to business, reliability, and understandably (Pitt et al., 1995;

Grover et al., 1996; Serhani et al., 2016; DeLone and McLean, 2016; Onyeabor and Ta'a, 2018). Performance measures in terms of efficiency and effectiveness are shown in Table 2.

Table 2: Performance measures

Efficiency Measures	References
Time	(Monteiro and de Oliveira, 2011)
Capacity	(Serhani et al., 2016; Onyeabor and Ta'a, 2018; Villalpando et al., 2014; Heo and Haan, 2000)
Response time	(Serhani et al., 2016; Villalpando et al., 2014; Brunnert et al., 2014; Liu, 2014), (Onyeabor and Ta'a, 2018)
Throughput	(Serhani et al., 2016; Brunnert et al., 2014; Liu, 2014; Onyeabor and Ta'a, 2018)
Processing time	(Villalpando et al., 2014)
Accuracy	(Serhani et al., 2016)
Resource utilization	(Veiga et al., 2018; Villalpando et al., 2014; Brunnert et al., 2014)
Timeliness	(Serhani et al., 2016)
Flexibility	(Dumas et al., 2005; Leyer et al., 2015)
Provenance	(Glavic, 2012; Jagadish et al., 2014)
Effectiveness measures	
User's satisfaction	(Jagadish et al., 2014; Urbach and Müller, 2012; Petter et al., 2008; DeLone and McLean, 2016; Onyeabor and Ta'a, 2018)
Data representation	(Onyeabor and Ta'a, 2018)
Timeliness	(DeLone and McLean, 2016; Jaklic et al., 2009)
Perceived Usefulness	(Davis, 1989)
Reliability	(Pitt et al., 1995)
Understandability	(DeLone and McLean, 2016)

2.4. Factors contributing to performance

Performance is not a standalone entity. Instead, it depends on several factors, including people with specific skills, enabling technology, and supporting working conditions. The explanation of factors that contribute to the performance of the BDA process is provided in Table 3.

3. Research model and research hypothesis

Theoretically, the role of technology in enhancing performance and achieving better outcomes has been prominent. Examples, according to Heine et al. (2003), include the Technological change model, the independent effect model, the Task-technology fit model, and Technology's impact on process output and quality. The models portray that technology along with other contributing factors has a substantial impact on attaining performance objectives. Big data analytics capability is dependent on technological capability as one of the influencing factors (Adrian et al., 2017), and having the analytical capability in place can boost up firm's performance (Wamba et al., 2017).

Table 3: Performance contributing factors

Factor	Item	Reference
Technology	Availability	(Mneney and Van Belle, 2016)
	Suitability	(Statz, 2005; Lněnička, 2015)
	Volatility	(Statz, 2005)
	Maturity	(Morabito, 2015)
Competency	Qualification	(Mikalef et al., 2018a)
	Technical skills	(Mikalef et al., 2017; Gupta and George, 2016)
	Communication skills	(Akter et al., 2016; Davenport et al., 2012; Mikalef and Krogstie, 2019)
	Process knowledge	(Blasini and Leist, 2013; Amaravadi and Lee, 2005)
	Business knowledge	(Mikalef et al., 2018b; Wamba et al., 2017), (Debortoli et al., 2014)
Working Conditions	Motivation	(Lazaroiu, 2015; Latham and Pinder, 2005)
	Workload per staff's capacity	(Leyer et al., 2015; Rouse et al., 1993)
	Comfortability of work environment	(Górny, 2017; Leyer et al., 2015)

The performance, therefore, can be as broad as the technology-organization level, or as specific as the technology-process level. The latter is of important consideration since this study purports that technology positively supports BDA process performance. The BDA literature shows that advanced technological tools improve the efficiency of BDA workflow.

To illustrate, these techniques can help achieve better data quality, adequate storage space, faster access and process speed, deeper analysis, and more concise results presentation (Sheng et al., 2019). Hence, the following hypotheses are proposed:

Hypothesis 1: Technology has a positive influence on the efficiency of the BDA Process.
Hypothesis 2: Technology has a positive influence on effectiveness.

Competency is defined as "the underlying attributes of individuals such as their knowledge, skills or abilities" (Hoffmann, 1999). Regarding big data, the need for the right people is one of the mainly raised issues (Morabito, 2015). From a resource-based view perspective, human capital which pertains to technical and business skills or company-specific knowledge has been perceived as an essential input for information systems capabilities (Ravichandran et al., 2005). Such big data capabilities drive inputs into greater values (Wade and Hulland, 2004), and lead to dynamic capabilities which leverage both internal and external competencies to address the requirement of unstable environments (Mikalef et al., 2019b). It was also reported (Blasini and Leist, 2013) that individual competencies, such as business knowledge, technical knowledge, methodological and product knowledge, communication skills, process knowledge, and company-specific knowledge, are key success factors for process performance management. In BDA literature, technical knowledge, business domain knowledge, and relational knowledge are essential to better exploit big data tools and technology (Mikalef et al., 2018b; Wamba et al., 2017). The existing literature also shows the relationship between knowledge of tasks and performance and how this can increase production, minimize errors, and help achieve objectives (Bravo et al., 2015).

The BDA process consists of a number of phases. Some phases (data acquisition, data preparation, and data analysis) are internally accomplished; others (visualization and interpretation) involve interactions with the users. Efficiency measures apply to the first part of the phase while effectiveness measures examine the second part. For both, different skill sets are required. Analytical skills, statistical skills, programming skills, etc. are necessary for a successful BDA system. Also, communication skills to impart the results to the user, and domain knowledge are required for securing optimum result utilization and achieving better customer satisfaction. In this regard, previous studies highlighted the need for technical skills for harnessing new technologies to extract insights from big data, and managerial skills which pertain to the competence of employees in understanding and interpreting data in a business context (Mikalef et al., 2017).

Hypothesis 3: Competency has a positive influence on the efficiency of the BDA Process.
Hypothesis 4: Competency has a positive influence on the effectiveness of the BDA Process.

Performance is not a standalone entity. There are always factors that contribute to performance improvement. It encompasses the working condition of the staff that performs process tasks. For this purpose, a prior study by Górny (2017) proposed the presumption that working conditions significantly determine staff's ability to operate in a working environment and perform tasks. The study also pointed out that more emphasis should be put on the significance of working environment parameters for examining the ability of staff to work in conditions that guarantee their safety and their ability to perform work efficiently. Other studies highlighted the implications of contextual factors (environmental factors and internal factors) on process performance (Leyer et al., 2015). The interplay among data, people, and technology didn't work well for many low-performing organizations because they fail to consider the characteristics of the context in which they work (Mikalef et al., 2019a). Accordingly, the study posits the following hypotheses:

Hypothesis 5: Working conditions have a positive influence on the efficiency of the BDA Process.
Hypothesis 6: Working conditions have a positive influence on the effectiveness of the BDA Process.

Efficiency, as a measurable concept, is an internal performance measure that shows how well the process transforms inputs into outputs. Effectiveness is an external performance measure that shows the extent to which a process achieves the needs of various stakeholders. This conforms to the description that internal quality influences external quality which in turn influences quality in use (Merino et al., 2016). From the information systems' perspective,

efficiency is concerned with the utilization of resources to operate the information systems' users' benefit. On the other hand, effectiveness is related to how users use information systems to accomplish an organization's mission (Hamilton and Chervany, 1981). The notion that system quality is a major participant in user satisfaction is also very common in the existing information systems literature (Petter et al., 2008; DeLone and McLean, 2016; Pak et al., 2010). Based on the terms of this research, the relationship between efficiency and effectiveness lies in that effectiveness is a measure of good output, while efficiency is a measure of the resources required to achieve the output. Therefore, we propose the following hypotheses. The whole concept is also presented in Fig. 1.

Hypothesis 7: Efficiency has a positive influence on effectiveness.

4. Methodology

4.1. Scale development

The questionnaire used in this survey was developed based on the factor and items extracted from the reviewed literature. The survey questionnaire was chosen because it demonstrates a causal relationship among research variables and enables the generalization of the research findings (Wamba et al., 2017). The quality determinants of software systems are also measured using organizational, individual, and technological measures (Gorla and Lin, 2010), whether efficiency and effectiveness measures are performance attributes of information systems.

The distributed questionnaire consisted of the following sections: The first section was related to the user's demographic information. Information about gender, age group, academic qualifications, users' understanding of BDA, and, the positions they occupy in their organizations is featured in this section. In the second section, the respondents were asked to provide their perceptions about the BDA process. For the third section, the respondents were asked to rate the performance of the BDA process based on efficiency and effectiveness measures. The fourth section of the survey is about performance-contributing factors of the BDA process.

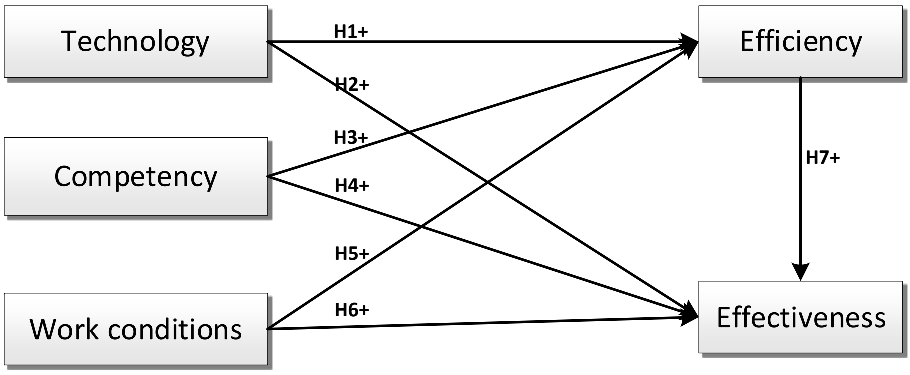

Fig. 1: Research model

4.2. Sample and data collection

In this research, purposive sampling was employed to determine the respondents to the research instrument. The use of purposive sampling is appropriate "when the researcher already knows something about the specific cases and deliberately selects specific ones because they are likely to produce the most valuable data" (Rowley, 2014). Purposive sampling is the process where a group of respondents is chosen because of certain characteristics they have (Chua, 2012). The selection process is decided by the researcher based on a range of criteria including knowledge about the research area, availability, and willingness to participate (Oliver and Jupp, 2006).

To collect data, 200 copies of the questionnaire were distributed among the participants of the NextBigTech Asia conference and exhibition. Only 120 copies were returned. Finally, 100 properly filled-in copies of the survey were chosen for analysis. Table 4 shows that the respondents were 56% of male and 44% of female, and were in different age groups. The majority of them received a bachelor's degree and had various qualifications in computing. The respondents work in public, private, and semi-private sectors and possess prior knowledge of big data analytics.

Table 4: Respondents' demographics

Variable	Frequency	Percentage
Gender		
Female	44	44%
Male	56	56%
Age		
20-30	28	28%
31-40	40	40%
41-50	27	27%
Above 50	5	5%
Academic qualification		
Bachelor	64	64%
Diploma	2	2%
Master	28	28%
PhD	4	4%
Network Security	1	1%
Software Engineering	1	1%
Organization category		
Private	46	46%
Public	39	39%
Semi-public	15	15%
Very Good Knowledge of Big Data	20	20%
Good knowledge of Big Data	80	80%
Knowledge of performance measurement		
Yes	52	52%
Somehow	31	31%
No	17	17%

5. Analysis and results

The data was analyzed using SPSS and SmartPLS 3.0 software tools. The SPSS software is used to analyze the demographic data. SmartPLS 3.0 is used to generate the measurement model and the structural model for this research. The measurement model is related to examining the reliability and validity of model constructs and the structural model scrutinizes the relationships among them.

The measurement model was evaluated reflectively using 3 main criteria those are internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2021). Fig. 2 shows the criteria used to evaluate the measurement model. The results of the internal consistency and validity assessment are presented in Tables 5-7. As the results indicate, the questionnaire is finely developed and the data is ready for further analysis.

5.1. Structural model assessment

The structural model analysis provides the assessment of the hypotheses which were proposed earlier in this paper. The researchers used a bootstrapping approach to assess the path coefficient. The path coefficient is said to be the relationship between the constructs in the structural model (Hair et al., 2021). There are seven hypothetical relationships of model constructs and their respective paths. To assess the path coefficients, P-values are used, which are taken to be equal to or less than 0.05 (Cohen, 1992). Table 8 and Table 9 present the results of path analysis. The results show that all paths are significantly using the one-tailed test, except three paths are Working Conditions to Effectiveness (WC→EFFEC), Working Conditions to Efficiency (WC→EFFIC), and Competency to Effectiveness (Comp→EFFEC).

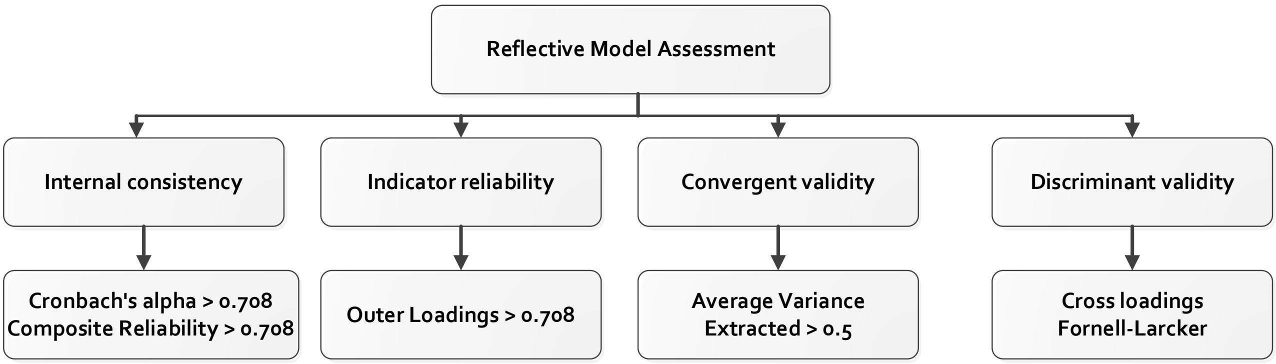

Fig. 2: Reflective assessment criteria (Dalvi-Esfahani et al., 2020)

R^2 is indicated to be a measure of the model's predictive accuracy ranges between 0 and 1. R^2 values should be bigger enough for the model to attain a minimum level of explanatory power (Urbach and Ahlemann, 2010). As was reported (Chin, 1998), the value of 0.670 is substantial, values around 0.333 on average and that of 0.190 and below are considered weak. Accordingly, R^2 of EFFEC is 0.493 which signifies that there is 49.3% of the variance explained for EFFEC by the independent variables, namely: TECH, COMP, WC, and EFFIC. The R^2 of EFFIC is 0.278 which indicates there is a 27.8% of variance explained for EFFIC by the independent variables: TECH, COMP, and WC. With reference to Chin's Criteria, the relationship between influential factors (TECH, COMP, WC, and EFFIC) and EFFEC is substantial (0.493>0.33). Conversely, the relationship between EFFIC and its influencing inferential factors is moderate (0.33>0.278>0.190). Conclusively, the model being examined has substantial predictive accuracy for the dependent variable of effectiveness and substantial predictive accuracy for the dependent variable of efficiency.

The F square value represents the level of effect in case the independent variable is dropped from the structural model. Values of 0.020, 0.150, and 0.350, respectively denote the independent variable's small, medium, or large impact on the structural model (Hair et al., 2021). The results indicate that EFFIC has a medium to a large effect (0.209) on EFFEC. The results also show COMP has a low impact on both EFFEC and EFFIC. Similarly, the effect size of WC on EFFEC and EFFIC is considered to be below, 0.027 and 0.004, respectively. Lastly, the effect of TECH on EFFEC and EFFIC can be interpreted as a medium to low impact.

5.2. Discussion

The goal of this discussion is to interpret and explain the significance of research findings regarding what was previously known about the research issue, and the insights and understandings discovered based on empirical study. The following are aspects being discussed in this Section.

There is an enormous need to enhance the chance of success for big data initiatives. This is at least to minimize the overwhelming rate of failure, which was reported to be 50% higher than other IT projects (Lai and Leu, 2017). This is even though 93% of businesses reported cost-saving after successfully investing in big data (Côrte-Real et al., 2020). It is rational to look at both systems' perspectives where the internal capability of the system is scrutinized and users' perspectives where their satisfaction and needs are observed.

Another important aspect is knowing where to contribute and what the determinants of success are. Similarly, how to make sure that our big data system is performing well or whether it is necessary to make improvements to the existing settings. Performance measurement meets all these needs. It assists identification of problems before they deteriorate, and it also reveals existing opportunities.

Table 5: Assessment of the internal consistency

Constructs	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Competency	0.817	0.878	0.644
Effectiveness	0.853	0.888	0.532
Efficiency	0.917	0.929	0.503
Technology	0.749	0.859	0.673
Working Conditions	0.786	0.875	0.701

Table 6: Discriminant validity (cross-loadings)

Constructs / Indicators	COMP	EFFEC	EFFIC	TECH	WC
COMP1	**0.704**	0.208	0.221	0.283	0.478
COMP2	**0.825**	0.386	0.383	0.467	0.425
COMP4	**0.861**	0.355	0.323	0.395	0.402
COMP5	**0.811**	0.373	0.316	0.365	0.431
EFFEC1	0.197	**0.748**	0.497	0.520	0.389
EFFEC2	0.299	**0.805**	0.524	0.483	0.302
EFFEC3	0.532	**0.722**	0.462	0.447	0.371
EFFEC4	0.376	**0.773**	0.424	0.358	0.228
EFFEC5	0.226	**0.716**	0.389	0.340	0.193
EFFEC6	0.278	**0.651**	0.444	0.344	0.384
EFFEC7	0.211	**0.679**	0.340	0.451	0.363
EFFIC10	0.458	0.505	**0.749**	0.373	0.338
EFFIC11	0.226	0.473	**0.784**	0.298	0.247
EFFIC12	0.322	0.363	**0.731**	0.399	0.245
EFFIC13	0.131	0.368	**0.745**	0.448	0.188
EFFIC14	0.352	0.419	**0.664**	0.314	0.186
EFFIC15	0.454	0.561	**0.762**	0.388	0.252
EFFIC16	0.121	0.489	**0.667**	0.460	0.274
EFFIC3	0.272	0.406	**0.613**	0.343	0.151
EFFIC4	0.056	0.353	**0.695**	0.354	0.187
EFFIC5	0.136	0.243	**0.650**	0.412	0.231
EFFIC6	0.287	0.450	**0.654**	0.272	0.286
EFFIC7	0.193	0.439	**0.748**	0.447	0.254
EFFIC9	0.467	0.446	**0.736**	0.287	0.308
TECH1	0.325	0.501	0.433	**0.880**	0.360
TECH2	0.476	0.430	0.481	**0.877**	0.380
TECH3	0.382	0.504	0.357	**0.691**	0.429
WC1	0.540	0.410	0.309	0.450	**0.864**
WC2	0.551	0.395	0.299	0.421	**0.875**
WC3	0.192	0.302	0.261	0.307	**0.768**

Table 7: Discriminant validity (Fornell-Larcker)

Constructs	COMP	EFFEC	EFFIC	TECH	WC
COMP	**0.802**	-	-	-	-
EFFEC	0.425	**0.729**	-	-	-
EFFIC	0.397	0.610	**0.709**	-	-
TECH	0.481	0.584	0.519	**0.821**	-
WC	0.530	0.445	0.348	0.475	**0.837**

Table 8: Results of path analysis

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-value
COMP→ EFFEC	0.056	0.0555	0.122	0.457	0.324
COMP → EFFIC	0.167	0.192	0.99	1.686	0.046
EFFIC→ EFFEC	0.389	0.395	0.108	3.607	0.00
TECH → EFFEC	0.287	0.296	0.126	2.288	0.011
TECH → EFFIC	0.407	0.394	0.112	3.626	0.00
WC→ EFFEC	0.144	0.139	0.112	1.426	0.077
WC → EFFIC	0.066	0.073	0.132	0.499	0.309

Table 9: Summary of hypothesis testing

3	Path	P-value	Decision
H1	TECH →EFFIC	0.00	Supported
H2	TECH →EFFEC	0.011	Supported
H3	COMP →EFFIC	0.046	Supported
H4	COMP →EFFEC	0.324	Not supported
H5	WC →EFFIC	0.077	Not supported
H6	WC → EFFEC	0.309	Not supported
H7	EFFIC → EFFEC	0.00	Supported

This research pertains to measuring the performance of the BDA process. Efficiency (EFFIC), effectiveness (EFFEC), technology (TECH), competency (COMP), and working conditions (WC) have been found to be the factors that partake in the performance evaluation of the said process.

The study supported that efficiency, as an internal measure of the BDA process, leads to effectiveness as a strong hypothetical relationship has resulted between the two constructs. It means that if the process is internally capable, it will be externally useful for users. This conforms to the description that internal quality influences external quality which in turn influences quality in use (Merino et al., 2016). Other studies also indicate that the system's characteristics (e.g., better resource utilization) enhance process output quality, which in turn could lead to better business outcomes (Davamanirajan et al., 2006). The pre-existing performance literature also shows that resource utilization, flexibility, as well as innovation are the determinants of performance (Fitzgerald et al., 1991). It was also noted that performance efficiency embodies three measures, namely 1) time behavior,

2) resource utilization, and 3) capacity (Villalpando et al., 2014). The role of having efficient systems is evident from the above explanation.

Effectiveness focuses on user satisfaction and the usefulness of BDA process output. It is measured using seven items and it observably scored high in the reliability testing and the factor loading. However, the role of the endogenous variable should also be looked at from the perspective of its relationship with other influencing exogenous variables. The results exhibited a remarkable, positive influence of efficiency on effectiveness. This means an emphasis on efficiency which, as mentioned before, is related to the system's capability, leads to effectiveness which focuses on user satisfaction like timely delivery, ease of understanding, reliable output, and process optimization. This agrees with the existing performance measurement literature where effectiveness is defined as whether the process is achieving adequate results (Leyer et al., 2015), and how the information provided assists users to perform their work (Heo and Haan, 2000). Effectiveness has also a substantial relationship with the performance-contributing factors in the proposed model. Therefore, effectiveness can be regarded as an anchor variable that sits at a pivotal point in the relationship of the research model's constructs.

Three performance influencing factors for BDA process performance are technology (TECH), competency (COMP), and working conditions (WC). Competency represents the know-how, technology the means, and working conditions of the state of ecosystems in which work takes place. Regarding relationships among research constructs, 4 hypotheses were supported, and 3 were rejected. For technology, the results concur with the fact that technological support enhances the efficiency of BDA workflow which was stated as data generation, data acquisition, data storage, data processing, and data analysis (Sheng et al., 2019; Hu et al., 2014). It has also been reported that technology is one of the catalysts in overall BDA implementation success (Adrian et al., 2017).

For competency, the reviewed literature has evidenced that having proper skills and knowledge are instrumental in big data analytical capability. The skills vary from technical skills and know-how in big data analytics to domain knowledge and communication skills in organizational settings. Studies in this regard are available in Mikalef et al. (2017), Gupta and George (2016), Wamba et al. (2017), and Mikalef and Krogstie (2019). For big data, being close to products and processes within the organization also is necessary (Davenport et al., 2012), even though the technical work is most commonly related to big data scientists. Consistent with this, the hypothetical relationship between competency and efficiency was supported by the study. However, the relationship between competency and effectiveness was not significant.

It should be noted that effectiveness is related to how the output provided by the system, that is to say, the BDA system, supports users to perform their work (Heo and Haan, 2000). The relationship between human skills and competency with effectiveness can be in terms of the business knowledge and communication skills that data analytics professionals should possess to become close to products and processes within the business. The importance of such knowledge and skills are massively discussed in the existing literature (Davenport et al., 2012; Akter et al., 2016; Debortoli et al., 2014; Mikalef et al., 2018b). However, it is a common misconception that data scientists are more associated with technical competency, or the know-how necessary to harness technology to extract insights from big data (Mikalef et al., 2017).

Caring for staff's working conditions is ideally appealing, but the presumption that work condition, as a construct, has an influence on staff's ability to operate and perform process tasks (Górny, 2017), was not hypothetically supported. Working condition, in a proud sense, is a factor that pertains to the welfare of employees of the entire organization, not necessarily for a part of it. Likewise, one can perceive the need for specific tools and skills needed by the BDA process, but not particular work conditions that cater for BDA process performance.

Fig. 3 shows the performance measurement flow for the BDA process. The flow begins with obtaining the required competent people to perform BDA tasks and activities and then equipping them with the required technology or tools to use. Regarding the work condition, make sure that workers are happy and motivated. Next, assess the performance using efficiency measures and effectiveness measures.

5.3. Conclusion

Performance measurement in the n big data Analytics process is designated to achieve two objectives: Achieving the functional capability of big data systems and achieving the satisfaction of users who interact and use the analytics results. The first is achieved using efficiency measures and the second is achieved through effectiveness measures. Performance is also influenced by a number of factors including technology, competency, and work conditions. The BDA process facilitates the exploration and exploitation of big data. It consists of several phases extending from data acquisition, data preparation, analysis, and processing, to visualization and interpretation of results. Unlike developer-centered approaches, users need a stake in performance measurement to continuously measure the performance of their big data systems. In this regard, performance metrics should be application-independent. This is because individual applications can be out of use but performance measures, such as response time, throughput, and accuracy, to name a few, are relevant at all times for successful systems. Therefore, the model presented in this study provides such a performance measurement approach to the big data body of knowledge.

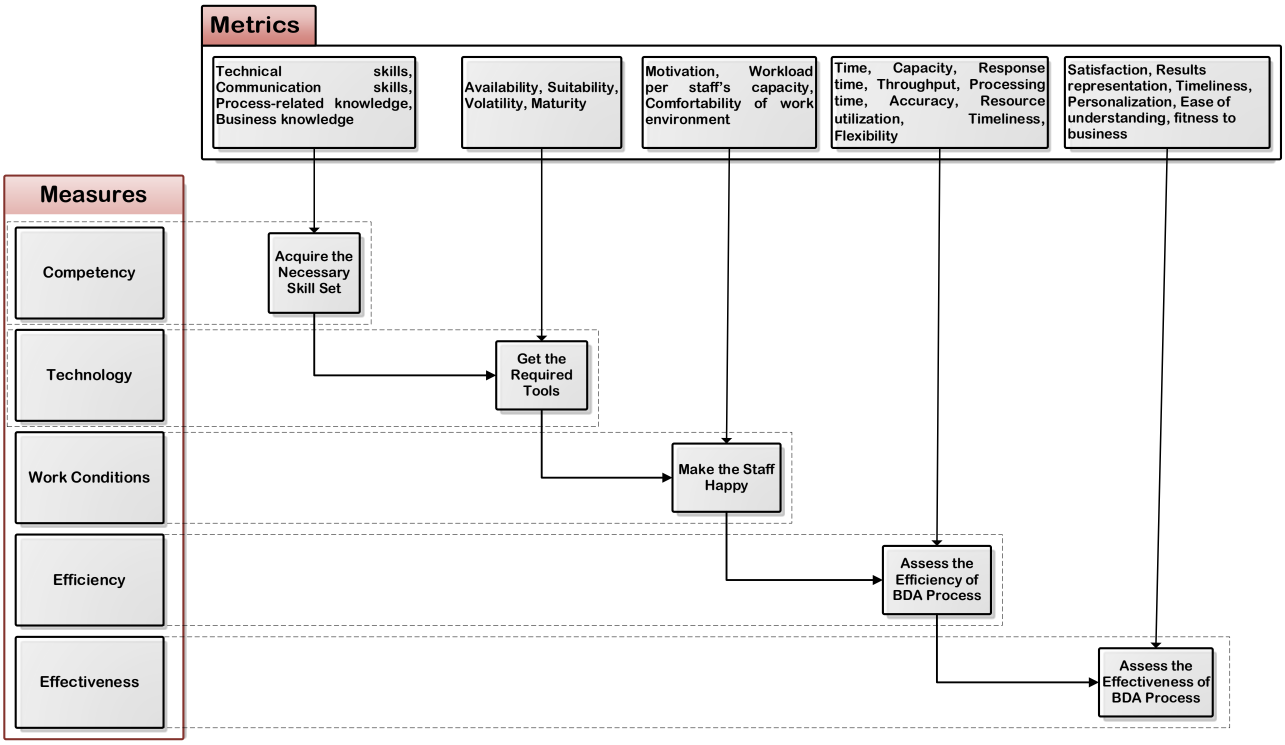

Fig. 3: The performance measurement flow for the BDA process

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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