“Big data, oriented-organizational culture, and business performance: A socio-technical approach”

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BIG DATA, ORIENTED-ORGANIZATIONAL CULTURE, AND BUSINESS PERFORMANCE: A SOCIO-TECHNICAL APPROACH

Abstract

This paper experimentally examines the impact of oriented-organizational culture that could support big data analytics (BDA) in higher education institutions (HEIs) in Saudi Arabia. Specifically, this study analyzed the effect of oriented-organizational culture (OC) on big data tasks (BDTs) toward improving decision-making (DM) and organization performance (OP). The study hinged on the theory of socio-technical systems to investigate BDA elements in higher education decision-making in Saudi Arabia. The analysis was conducted using a quantitative survey research design where data were collected from 270 IT staff working in Saudi Arabian HEIs using Qualtrics. PLS-SEM was applied to validate the research data and explore the relationship between the proposed hypotheses. The findings show that oriented-organizational culture positively affected big data tasks, i.e., storing, analyzing, and visualizing. Similarly, oriented-organizational culture positively affects improving decision-making by top management in Saudi Arabian universities. OC also positively influences the performance of Saudi Arabian universities. Improving decision-making by top management has a positive impact on enhancing the overall university's performance. However, big data tasks, i.e., storing, analyzing, and visualizing, negatively affect improving decision-making by top management in Saudi Arabian HEIs. One of the study limitations is the small sample size; future studies should include private and public universities to alter the expected outcomes. Additional technological elements, such as IT infrastructure at Saudi Arabia's private and public HEIs, are recommended to be considered in future studies to establish the competence of respective IT infrastructure.

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INTRODUCTION

In the current phase of rapid technological advancements, it has become crucial for organizations to work on big data analytics (BDA) to gain a competitive advantage. During the past few years, it has been evident that organizations worldwide are trying to adopt BDA, as they believe that it can improve overall performance and decision-making (Mikalef et al., 2019). BDA generates business advancements and allows organizations to create effective decisions, which enhance firm performance, especially for firms with a data-driven culture (Fosso Wamba et al., 2019). Although advances in BDA are most popular in developed economies, developing countries also realize the socio-economic value of leveraging big data to achieve better analysis. This leads to the development of solutions, especially in economics, public health, education, agriculture, and urban planning. Saudi Arabia, for example, is one such developing nation that has recognized the full potential of cybersecurity, agile innovation, and BDA to achieve the Kingdom's vision of 2030 (Market Studies Department, 2016). As a

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result, BDA has increasingly become the basis for Saudi Arabian technological inventions in numerous fields, particularly in educational institutions, which has improved efficiency and generated enhanced business performance (Dong & Yang, 2020). Big-data-driven decision-making is much more than having access to big data and being able to interpret it. It involves a complete set of activities, from collecting, processing, evaluating, and implementing big data for decision-making (Janssen et al., 2017).

The successful execution of all these tasks requires an effective oriented-organizational culture within higher education to maximize the significance of BDA in improving decision-making and enhancing performance. Therefore, researchers must concentrate their studies on exploring elements that define data-driven culture when making decisions, consequently enhancing their overall performances, especially in higher education institutions (Shamim et al., 2020). BDA utilization depends on an individual's understanding of socio-technical and cultural factors. Culture shapes the organization's response to innovation opportunities, including developing new technologies concerning big data (Chatterjee et al., 2018; Thirathon et al., 2017). Notwithstanding the wide range of topics covered in the earlier literature, there is still a need to thoroughly examine big data in education, especially in the Asian region and Saudi Arabia in particular. It remains to be seen how big data (BD) has been integrated by HEIs in Saudi Arabia when making management decisions and contextualizing the role of oriented-organizational culture in the technical subsystem. This study has the potential to significantly enhance the use of big data in the field of education. The restrictions that have been found and the potential paths will attract new scholars to the field. Often, the technical aspects overshadow the role of OC, which undermines understanding of the interdependencies between the social and technical components of BDA (Niederman et al., 2016). Consequently, the relationship between the big data social system and its technical system remains unexplained. The particular interest here is in the role of oriented-organizational culture on the technical subsystem, i.e., storing, analyzing, and visualizing big data to improve the decision-making by top management.

1. LITERATURE REVIEW

This section discusses the relevance of the theory of socio-technical systems in relation to the current research. Other studies in big data analytics are explored to dissect the influences on oriented-organizational culture and innovations that enhance competitiveness. Various studies have applied information system theories. However, information system theories that combine social and technical elements have limited literary backgrounds (Gupta & George, 2016). This paper uses socio-technical theory to explore BDA factors in decision-making for higher education institutes in Saudi Arabia. The socio-technical theory emerged from the Tavistock Institute. Their work combined the human and technical aspects to prevent failure while implementing information systems (Günther et al., 2017). The socio-technical theory describes prevailing technology's execution strategy to achieve organizational goals by integrating jobs, culture, and other human aspects (Makarius et al., 2020). Socio-technical systems (STS) state that an organization's success is related to optimizing social and technological systems through cooperation (Appelbaum, 1997). The reinforcement and distribution arising from the actual performance of social and technological sectors affect the combined development of these sectors, according to Sony and Naik (2020).

For example, in the last decade, a clear effort has been made to solve issues related to the management of the information system by outlining the benefits of socio-technical theory. Dremel et al. (2018) discussed how the failure of a management information system (MIS) in a prominent newspaper company was resolved through the socio-technical approach. The company incorporated technical factors as well as those who interacted with the new system, resulting in an updated MIS scheme. Recently, academics and practitioners have focused their interest on BDA and are researching more on the benefits of working with socio-technical theories. The development of big data benefits has led to a shift in decision-making for many businesses in favor of data-driven approaches. Activities in the social and educational spheres are significantly impacted by the application of analytics in real-time decision-making (Sharma et al., 2014). Most of them have gained from using BDA in various ways, including organizational, operational, managerial, and strategic advantages, as well as benefits for information technology infrastructure (Wang et al., 2018). The social subsystem refers to oriented-organizational culture, presented in this study as accepting and adapting to new technological improvements that improve decision-making by top management and enhance performance in HEIs (Cronemberger, 2018). These factors are further analyzed.

The improved decision-making (IDM) technique provides a universal framework utilized by decision-makers to increase their strengths and minimize personal weaknesses. By examining decision options and the corresponding risk factors and repercussions, it tries to deliver simple solutions derived from an individual viewpoint rather than solely from rules or judgments (Janssen et al., 2017). Eisenfuhr (2011) describes organizational decision-making as a fundamental and routine management activity at all levels. As a result, it is an important management function in the administration of an organization. In today's competitive world, making fast and effective decisions are imperative. Saudi Arabian higher education, for example, is one of the pivotal public organizations that store various big data and needs to make fast and effective decisions from those big data. Encouraging staff in HEIs in Saudi Arabia to accept and adapt to new technological improvements as oriented-organizational culture is vital. Thus, oriented-organizational culture can fill the gap between the employees and the newly invented technologies within organizations to improve decision-making. According to Tjen-A-Loo (2018), educational data can be used to support the decision-making approach of the school, teachers, and student performance. However, the concern in this study is on applying BDA to improve financial and academic decision-making in Saudi Arabian universities.

The velocity of big data has increased the need for BDA to gain insights for effective decision-making by top management (Elgendy & Elragal, 2016). Nowadays, the consistency of the decisions made by top managers improves firm productivity (Adrian et al., 2018). As a result, public and private organizations realized the importance of enhancing firm performance (Shamim et al., 2020). Nowadays, improving performance means applying the latest technologies to attain such goals. BDA is one of the technologies that allow organizations to improve their performance. For instance, Bharati and Chaudhury (2019) investigated the roles of IT innovations such as big data technologies and their influence on improving firm performance. The study found that IT platforms and social capital allow organizations to implement innovative technologies, such as big data analytics, which enhance their organizations' performance.

Similarly, Fosso Wamba et al. (2019) explored the influence of technology quality, information quality, talent quality, and significant data analytics quality on enhancing an organization's performance. The findings show a positive and substantial relationship between improving decision-making and enhanced organizational performance. However, the focus of this paper is to investigate the impact of social factors, i.e., data-oriented organizational culture, to improve decision-making and enhance the performance of HEIs on technical features, i.e., BDTs. Those technical and social factors lead to improved performance by the HEIs, as established by Fosso Wamba et al. (2019).

Studies on oriented-organizational culture and IT have emphasized the role of the former in shaping organizational responses to innovation (Westrum, 2004) and IT-enabled performance (Dubey et al., 2019). Organizational culture, among other elements, is reflected in the organization's responsiveness to accept and adopt new technologies, which refers to whether organizations are willing to adapt to technology innovations in BDA (Sam & Chatwin, 2018). Furthermore, oriented-organizational culture characteristics of flexible orientation facilitate BDA for performance (Iivari & Huisman, 2007). Moreover, big data and BDA are continuously evolving, and the ability to adopt emerging BDA improvements can be associated with infrastructural requirements and advanced opportunities (Alalawneh & Alkhatib, 2021). BDTs in this study revolve around storing (source-systems feed), analyzing (tagging, classifying, categorizing, and contextualizing), and visualizing big data for better decisions. However, before one can begin to comprehend how oriented-organizational culture affects big data tasks, one must first understand the intangible components of organizational culture, such as "organizational learning," which are difficult to quantify (Mikalef et al., 2017).

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Gupta and George (2016) defined oriented-organizational culture as organizational learning, strengthening organizations' BD capacities, and giving them a competitive edge (Teece et al., 1997). The second intangible component of corporate culture regarding BD is a data-driven culture (Alharthi et al., 2017). As a result of the data-driven culture in place, management at the top tier of a company makes decisions and develops strategies to achieve the goals of big data projects. In addition, employees should understand the analytical procedures and feel competent in pre-processing large data sets. According to Nguyen and Peterson (2017), companies fail because of a mismatch between the organization's existing culture and skills and the growth strategies required to utilize analytics successfully. In addition, the company's atmosphere and internal climate should be such that they are willing to adapt to BDA tasks. At the same time, a few studies have examined the effects of oriented-organizational culture on big data's technical aspects such as BDTs.

According to Lunde et al. (2019), there are several reasons why firms remain ineffective in using big data despite possessing technology. One such factor is the unsupportive organizational culture. A culture of organizations affects all levels of decision-making: strategic, tactical, and operational (Attar, 2020). A good decision-making process is based on how individuals are educated about the values, practices, and beliefs that are prevalent in the organization's culture, as well as how they understand the views and frames of mind of others in the decision-making process. Dasgupta and Gupta (2019) underlined the importance of cultural concerns in information systems, adaptation, and use. They stressed that daunting IS studies consider individual cultural values while studying culture and IT management. Transnational, national, and professional organizational cultures impact an individual's performance of daily tasks. All these cultures are not equally prevalent in the workplace. Higher education, for example, is one of the contexts that is rapidly growing. Saudi universities need an oriented-organizational culture to accept and adapt to new BDA technological improvements.

The first stage of big data tasks is data storage. It refers to various types of data that can be kept in various formats after being collected from various sources. It runs multiple tasks concurrently to optimize the process. Aggregation, duplication, and archiving of data are all necessary tasks for completing the storing stage of big data management. There are numerous valuable solutions for storing large amounts of data, including Hbase, NoSQL, Gluster, HDFS, and GFS. The second step of the data task is data analysis, which includes analyzing collected data using different types of analytics. Data analysis involves algorithmic approaches used to the data; it consists of various key features such as a problem to be solved, a decision to be made, and various conclusions drawn from data. According to Saggi and Jain (2018), analyzing big data collected from various sources and creating insights from those data will improve decision-making and create business values. Similarly, Wamba et al. (2017) claimed that most organizations started implementing big data analytics to cover new insights that could assist them in better understanding their business and market and making timely and effective business decisions.

In recent years, many universities have developed many technological opportunities and solutions to improve the quality of their services. Pawirosumarto et al. (2017) identified the impact of oriented-organizational culture on enhancing university performance by using remote workers and virtualization technology. Their results indicated a positive effect of oriented-organizational culture on implementing remote workers and virtualization technology in Iranian universities. For this reason, it can be concluded that given the suitable conditions for its use, remote workers and virtualization technology can be used as one of the most essential tools for increasing productivity in universities. The velocity of big data has increased the need for BDA to gain insights for effective decision-making by top management (Elgendy & Elragal, 2016). Nowadays, the consistency of the decisions made by top managers improves the firm's productivity (Adrian et al., 2018). Aldholay et al. (2018) argued that job and decision-making performance is affected by system quality and information quality. Providing good information quality means storing, analyzing, and visualizing that data to help top managers make the best decisions from the analyzed data.

Value creation is a crucial part of a company's overall strategy. This includes but is not limited to profit maximization, client retention, and business goals. To gain this value creation successfully, big data analytics has to be implemented by organizations. Likewise, the notion of big data analytics as a company-level innovation is developed to create company uniqueness, which provides greater value to the financial sectors, supply chain management, IT firms and contributes directly to their overall performance in creating business values (Foster, 2019). BDA is a "significant differentiator" because it encourages companies to act proactively and ahead of the competition. In this manner, BDA saves firms from making unnecessary investments and boosts company revenue by approximately 8% (Wamba et al., 2017). The literature presents the example of a target corporation that applies BDA to track consumers' shopping habits and estimate future buying trends via the usage of a loyalty card program, "value creation" (Wamba et al., 2017). Segooa and Kalema (2018) suggest that there are three main factors affecting universities' adoption and implementation of BDA. The first is the importance of data-driven decision-making stemming from the need for improved performance; the second is some key characteristics of data-driven decision-making based on knowledge management, which is essential for organizational success; the third is a strong culture needed to support data-driven decision-making in university management.

The other imperative aspect of this study is the technical subsystem. The technical subsystem is shaped in this study as big data tasks. In a big data environment, one looks at big data tasks as a critical aspect of the technical subsystem, and it often revolves around storing big data from various reliable resources, analyzing those stored big data, and visualizing them to improve the decision-making by top management in HEIs in Saudi Arabia (Tjen-A-Loo, 2018). Besides this, storage is the first task of big data tasks, and it refers to how various types of data can be stored in various formats after being collected from various sources. It runs multiple tasks concurrently to optimize the storage process. Aggregation, duplication, and archiving of data are necessary tasks for completing the storing stage of big data management (Siddiqa et al., 2016). Data analysis is the second stage of big data tasks, which includes analyzing collected data using different types of analytics. Data analysis involves algorithmic approaches used for concluding the data. It consists of various key features, such as a problem to be solved, a decision to be made, and various conclusions that must be drawn from data. The organization must combine its strategy with the analysis to value data (Bishop, 2019). Data visualization is the last stage of big data tasks, which leads to data visualizations enhancing the effectiveness of certain decisions. Data visualization can greatly influence decision-making processes if managers view data analytics as valuable and use it to support their decisions (Thirathon et al., 2017). These steps of "big data task" were proposed in this study as the main factors in improving the decision-making approach.

Taking a socio-technical systems approach, Figure 1 proposes that big data's impact on top managers' decision-making is based on a combination of social factors (oriented-organizational culture) and technical factors (big data storage, analysis, and visualization). Oriented-organizational culture and BDTs were discussed first, followed by oriented-organizational culture and IDM. Then, the impact of BDTs on IDM was explored. Lastly, the influence of improving decision-making on enhancing the performance of HEIs was addressed.

2. AIM AND HYPOTHESES

The study aimed to investigate the influence of oriented-organizational culture on improving decision-making and organizational performance of the upper management of higher educational institutions (HEIs) in Saudi Arabia. The research hypotheses were to assess big data's impact on top managers' decision-making of HEIs based on social factors, such as the oriented-organizational culture, and technical factors, such as big data storage, analysis, and visualization. The study objectives are to establish the role of big data and oriented-organizational culture in improving decision-making by the decision-makers in higher educational institutions in Saudi Arabia. There is a gap in understanding big data applications in enhancing educational and management policies in HEIs in Saudi Arabia. This study seeks to assess this from an oriented-organizational culture perspective. In addition, the paper empirically establishes a correlation between big data tasks, improving decision-making, and improving university performance and adoption of innovation. The following hypotheses are proposed:

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H1: *Oriented-organizational culture of accepting and adapting technological improvements positively affects BDTs.*

H2: *Oriented-organizational culture of accepting and adapting technological improvements has a positive effect on enhancing university performance.*

H3: *Storing, analyzing, and visualizing big data have a positive effect on the financial, strategic, and academic decisions of top management.*

H4: *Oriented-organizational culture of accepting and adapting technological improvements has a positive effect on enhancing university performance.*

H5: *Improving the decision-making by top management has a positive impact on OP.*

3. METHODOLOGY

The study adopted a quantitative survey research design and was approved by the Human Research Ethics Committee of the University of Technology, Sydney, with study number UTS HREC ETH19-4262. The study population included 29 public universities in Saudi Arabia (Ministry of Education, 2020). The paper relied on primary data collected from a representative sample of the respondents using a questionnaire hosted online using Qualtrics, and disseminated using WhatsApp and email. From this list, six government-owned universities volunteered to contribute to the study. The criteria for selecting the respondents were based mainly on their job functions. The study primarily targeted the IT staff of HEIs and included academic and non-academic staff that deal with IT in some capacity. Academic and non-academic staff of HEIs were selected because they usually hold higher degrees and are more experienced than non-IT staff. The data collection period was from November 1, 2020, to March 31, 2021. The survey questionnaire was sent to 350 respondents. After sorting the responses and eliminating the incomplete questionnaire data and outliers, the responses from two hundred seventy (270) respondents were considered valid and analyzed. The information was collected online, and the hypotheses were evaluated using PLS-SEM. The final sample size was based on the recommendations of Ringle et al. (2020).

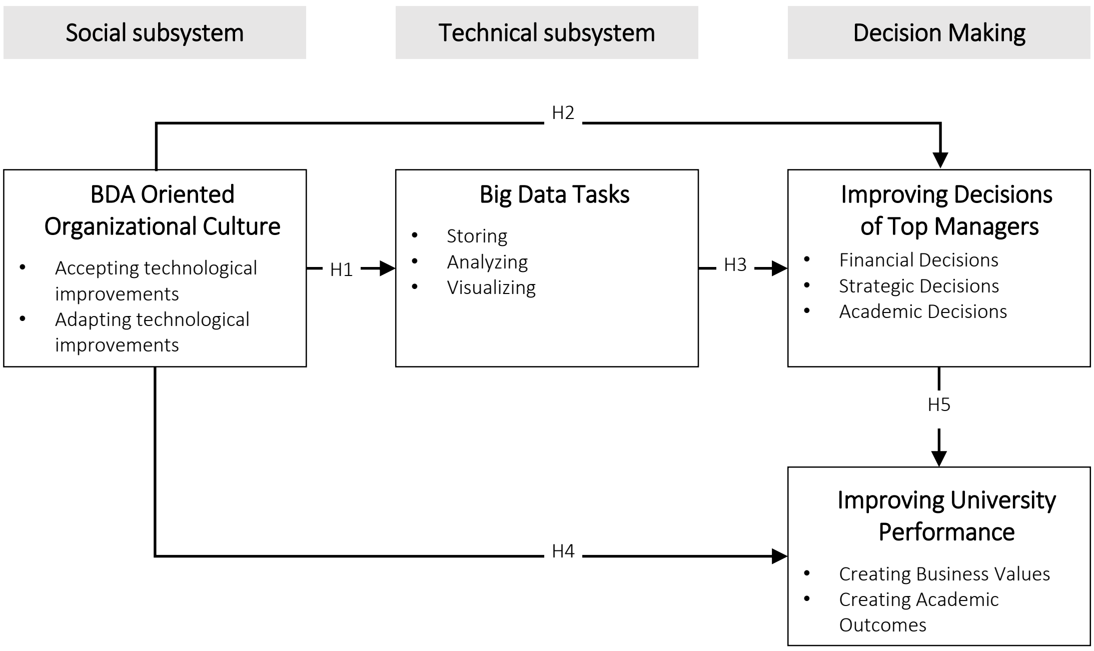

Figure 1. Research model showing the relationship between social subsytem, technical subsytem and improved decision making

4. RESULTS

The demographic information of the respondents presented in Table 1 revealed that out of 270 respondents, 53% were male, 37% were female, and 10% preferred not to say. A significant difference in the percentage of male-to-female participants was expected since only 20.4% of Saudi Arabia's labor force is female, based on data from the World Bank (2021). The majority of respondents were aged 26-35 (55%), while the least represented respondents were 18-25 (7%). Furthermore, most respondents have a Master's degree (43%), while many others have a Ph.D. (22%), a Bachelor's Degree (22%), or a Diploma (11%). The majority were Saudi nationals (81%), while a few were non-Saudi who were either born in Saudi Arabia (6%) or born outside Saudi Arabia (12%).

Table 1. Demographic information of respondents

Items		Frequency	%
Gender	Female	99	37
	Male	142	53
	Prefer not to say	29	10
Age	18-25	20	7
	26-35	149	55
	36-45	78	29
	45 and above	23	9
Education	Diploma	30	11
	Bachelor	59	22
	Master	116	43
	Doctorate	59	22
	Other	6	2
Nationality	Saudi	219	81
	Non-Saudi-born in Saudi	17	6
	Non-Saudi	34	12
Years of Experience	Less than one year	9	3
	One year	19	7
	2-3 years	54	20
	4-5 years	46	17
	More than 5 years	142	53
Role at the University	University Deanship of IT	16	6
	Dean of Information Technology College	5	2
	IT executive level\IT managers	30	11
	IT Academic Staff	127	47
	Programmer-Developer	75	28
	IT Technician	17	6
Has experience in big data	Yes	203	75
	No	67	25

Note: Total Sample = 270.

Before examining the measurement model, the paper considered ruling out the common method bias (CMB). Consistent with the suggestion of Kock et al. (2021), VIF values were checked to be less than 3.3 for each block of exogenous and endogenous variables. VIF values beyond 3.3 are not only an indication of pathological collinearity but also an indication of model contamination with common method bias (Kock et al., 2021). The VIF values were 1.316, 1.406, 1.449, and 1.356 for all four blocks of measured and latent variables. Thus, the data met the criteria, except for one block, marginally exceeded, and therefore, ruled out the CMB.

Regarding factor loadings, the measure is considered reliable when the factor loadings (FL) are above 0.50 (Hair et al., 2017). Ferrando (2021) highlights the range of factor loadings quality, i.e., excellent (0.71), very good (0.63), good (0.55), fair (0.45), and poor (< 0.32). Most of the study scale factor loadings were above 0.65 (see Table 2 and Figure 2), so the basis for the reliability of the study measures was established.

Regarding internal consistency, the threshold for the reliability of the measure is > 0.7 scores of Cronbach's α for each of the measures (Hair et al., 2017); the research estimations met the criteria as indicated in Table 2 and Figure 2. However, owing to the underestimation problem with Cronbach's α, there is a need for a greater estimation of true reliability (Memon et al., 2021). As shown in Table 2, the study model adequately met the acceptable values of CR, i.e., > 0.7 for confirmatory purposes (Hair et al., 2017).

Convergent validity is the extent of agreement in several trials at quantifying the same theory using varied approaches (Bagozzi, 1980). The AVE (average variance explained) for convergent validity should be greater than 0.5. The AVE values in Table 3 are well within the limits to prove the convergent validity of the constructs (Memon et al., 2021).

The eminence quality of the measurement model is assured through its predictive validity, which is calculated by utilizing the values of communality (H2); all of those values were positive for all blocks (Table 2), ensuring the predictive validity and eminence quality of the measurement model.

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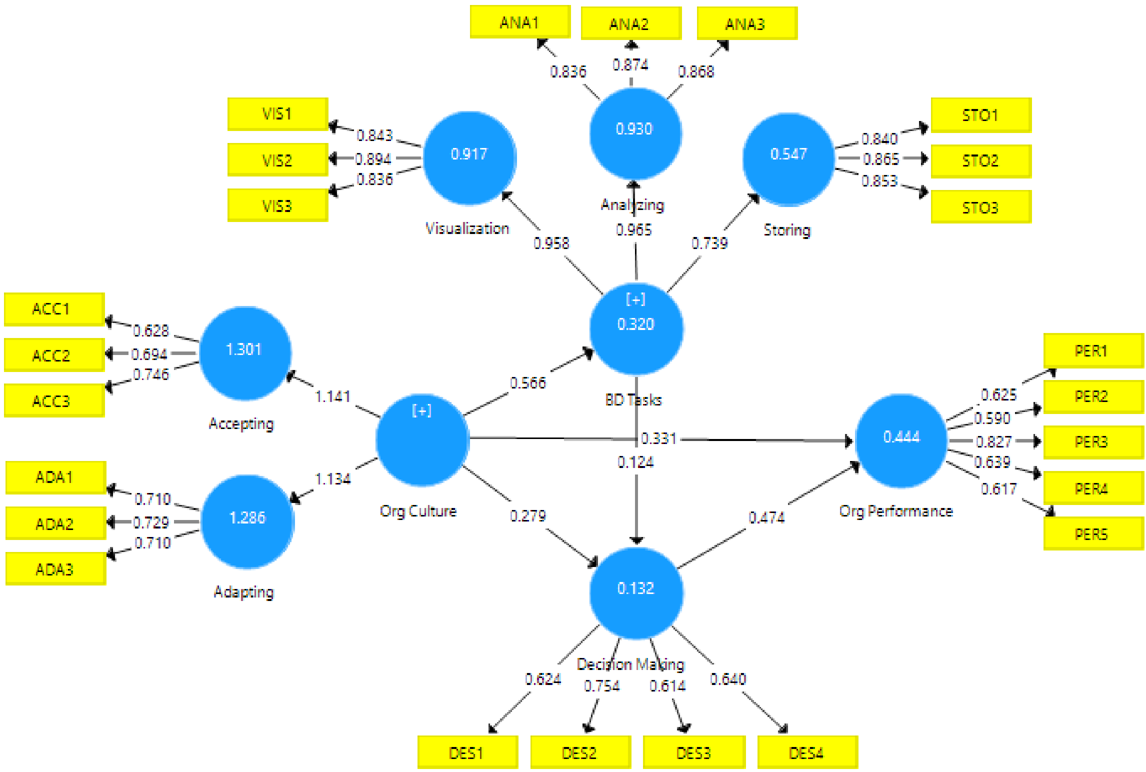

Figure 2. Measurement model highlighting factor loadings

Table 2. Measurement model assessment showing data validity

Variables	Cronbach	CR	AVE	H²	Factor Loading
Organizational Culture	0.820	0.870	0.528	0.338	>.65
Accepting	0.728	0.847	0.649	0.305	>.73
Adapting	0.759	0.862	0.676	0.347	>.78
BD Tasks	0.883	0.907	0.523	0.403	>.76
Storing	0.888	0.931	0.818	0.601	>.88
Analyzing	0.894	0.934	0.825	0.612	>.88
Visualization	0.893	0.933	0.824	0.610	>.90
Decision-Making	0.752	0.843	0.575	0.298	>.68
Organizational Performance	0.794	0.859	0.550	0.328	>.68

A structural model shows the relationship between constructs and related theories based on existing literature (Hair et al., 2017). The socio-technical theory drives the structure of relationships defined in Figure 1 to explain the impact of OC on BDTs, strategic decision-making, and organizational performance. To assess the structural model, the study considered the significance and relevance of path coefficients, R2, f^2, and Q2. The paper used bootstrapping to analyze the importance of path coefficients. Hair et al. (2017) indicated that the minimum number of bootstrap samples must be at least as large as the number of valid observations. Therefore, the study used 500 bootstrap samples, drawing inferences from Cohen (1998), and f^2 values of 0.02, 0.15, and 0.35 indicate an exogenous construct's small, medium, or large effect on an endogenous construct (Hair et al., 2017). A 5% significance level is assumed when testing the proposed relationships; it is concluded that an effect was significant at a p-value smaller than 0.05. Therefore, it was also assumed that the commonly applied critical t value for the two-tailed tests at that significance level is 1.96. The hypotheses outcomes are presented in Table 3.

In Hypothesis 1, it was proposed that OC would also positively affect BDT. As shown in Table 3, OC has a significantly positive impact on BDTs ($\beta = 0.484$, $t = 6.914$, $p < 0.001$). The value of f^2 =

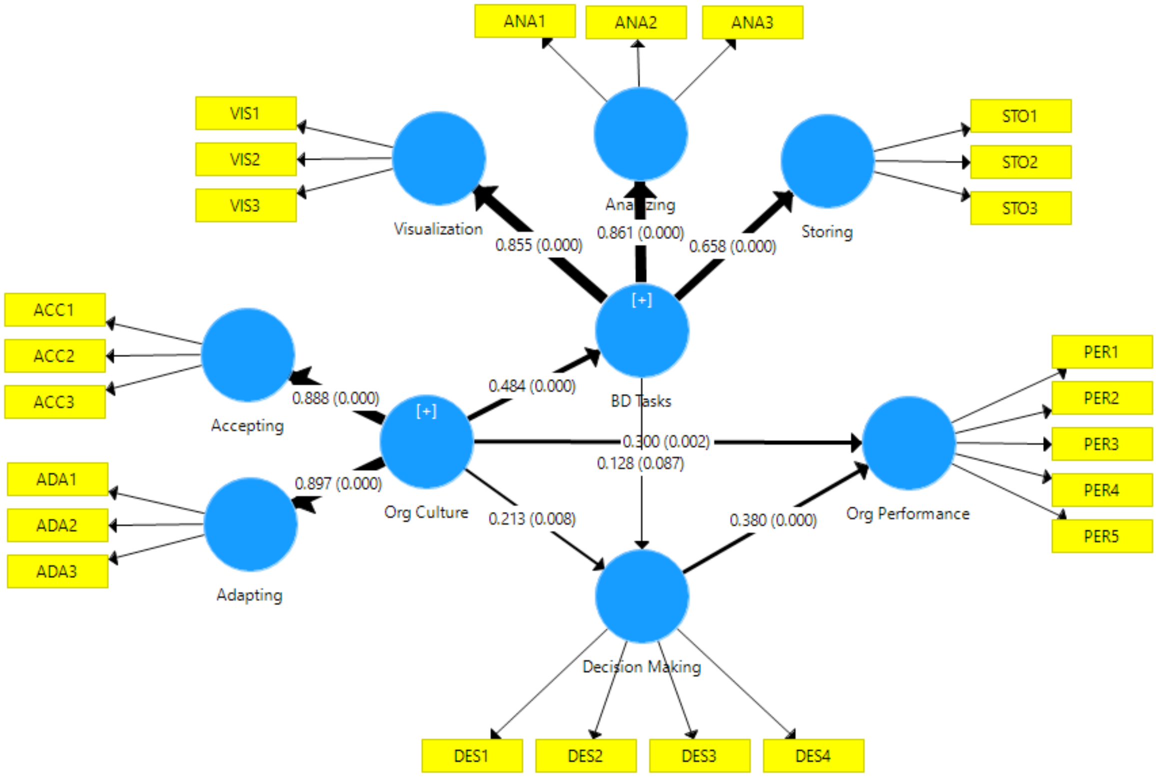

Figure 3. Structural model based PLS-SEM analysis

Table 3. Hypotheses testing

Path	β	SE	t	p	F²	Result
OC → BDT	0.484	0.070	6.914	0.000	0.307	H1: Supported
OC → DM	0.213	0.080	2.662	0.008	0.038	H2: Supported
OC → OP	0.300	0.101	2.977	0.003	0.118	H3: Supported
BDT → DM	0.128	0.079	1.628	0.104	0.014	H4: Not Supported
DM → OP	0.380	0.094	4.042	0.000	0.189	H5: Supported

0.307 suggests that OC had a medium effect on BDT, which confirmed that Hypothesis 1 was supported. Similarly, in Hypothesis 2, the study proposed that OC has a significantly positive impact on DM. The findings stated that OC has a positive and significant impact on DM ($\beta = 0.213$, $t = 2.662$, $p = 0.008$), with a large effect i.e., $f^2 = 0.038$. Hence, Hypothesis 2 was supported.

Hypothesis 3 proposed that OC would have a positive impact on OP. These results indicate that OC has a significantly positive impact on OP ($\beta = 0.300$, $t = 2.977$, $p = 0.003$). The impact size of OC on OP was also small at $f^2 = 0.118$. Hence, the results also confirmed the support for Hypothesis 3. Hypothesis 4 postulated that BDT would positively affect DM. The findings show that BDT have a significantly positive impact on DM ($\beta = 0.128$, $t = 1.628$, $p = 0.104$) with a very small effect size ($f2 = 0.014$). On this basis, Hypothesis 4 was not supported by the findings of the study. Hypothesis 5 proposed that DM would have a positive impact on OP. The results indicate that DM has a significantly positive impact on OP ($\beta = 0.380$, $t = 4.042$, $p < 0.001$). The impact size of OC on OP was also considerable at $f^2 = 0.189$. Hence, the results also confirmed the approval of Hypothesis 5.

The eminence quality, or the predictive relevance for each endogenous block, was measured by the cross-validated redundancy index (CVRI: Stone–Geisser's Q2), R2, and goodness of fit (GOF). Q2 is used to measure the eminent quality of the structural model. The positive values of Q2 (> 0) are acceptable for the good quality/predictive relevance of a structural model (Figure 3). R2 is the measure of overall effect size, as indicated in Table 4 that 32% of OC, 26% of BDT, 23.7% of DM, and 30.7%

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Table 4. Structural model assessment of eminence quality

Variables	Q^2	R^2	AVE	GOF	VIF
OC	.333	.320	.528	0.411	1.316
BDT	.121	.260	.523	0.369	1.406
DM	.045	.237	.575	0.369	1.449
OP	.153	.307	.550	0.411	1.356

of DM are explained by the overall model. GOF is measured by combining effect size and convergent validity (Bozionelos & Simmering, 2022) with an acceptable limit of 0 to 1. GOF was calculated by the square root of the product of commonality and R2. The GOF values were well within the acceptable range, confirming the structural model's overall fitness. Moreover, multicollinearity for the structural model was also assessed. Hair et al. (2017) suggest that multicollinearity has the possibility of inflating the bootstrap standard type II errors or failing to detect that an effect is present in the research. VIF values beyond 3.3 are not the only indication of pathological collinearity (Kock et al., 2021); VIF values (Table 4) showed that the structural model was well-fitted (Bozionelos & Simmering, 2022).

5. DISCUSSION

Together with the social and technical subsystems, BDA is essential in improving decision-making and gaining a competitive advantage. This requires a deep understanding of the significance of providing social and technical models such as BDA through technical and oriented-organizational culture lenses in the higher education context. Previous studies have examined the social subsystem in the era of BDA, precisely the oriented-organizational culture aspect (Sam & Chatwin, 2018; Thirathon et al., 2017). The findings indicated that the social factor-oriented-organizational culture, i.e., accepting and adapting to new BDA technological improvements, positively affects BDATs. Additionally, the study hypothesized that oriented-organizational culture positively impacts improving decision-making by top management (H2). The results show that OC has positively affected decision-making by executives in Saudi Arabian universities. In this study, it is hypothesized that big data tasks positively influence and improve the decision-making by executives. It was found that BDATs positively impact and improve the decision-making by executives.

Hypothesis 3 positively affirmed the significant impact of oriented-organizational culture on organizational performance and is supported by the literature (Saggi & Jain, 2018; Wamba et al., 2017). It demonstrates how an oriented cultural paradigm can be harnessed as a growth and development indicator, which HEIs in Saudi Arabia can leverage to build a sustainable model. A culture that promotes a data storage culture in an optimized setting will place itself at a competitive advantage when considering the economic implications of its culture as it relates to data tasks. The essence of data storage is not to keep it to oneself but for the idea of analyzing and turning the raw information into visual and abstract data that can drive policy and developmental decision-making. The data agglutination paints a clearer picture of what problem the stored data addresses and how to use the data to improve decision-making. According to Saggi and Jain (2018), the analysis of big data gathered from diverse sources and the production of insights from such data will enhance the decision-making process and produce commercial value. Correspondingly, Wamba et al. (2017) asserted that most businesses have begun applying big data analytics to gain new insights to enhance efficiency and make decisions favorable to the business in the long run.

The interpretation of Hypothesis 4, which revealed that BDTs do not positively improve decision-making, eschews the limitations of BDTs as being beneficial in improved decision-making in the higher education system of Saudi Arabia. The results do not agree with the views of Pawirosumarto et al. (2017), who were able to identify the impact of oriented-organizational culture and how this can be applied in the scenario of the education system. The coronavirus disrupted the education flow globally, forcing many institutions to realign and consider eLearning as a core component of instruction either as a standalone course or in a blended environment where the learning is shared to incorporate both classroom and online learning. This has increased the need for the consumption of BDA and their adoption toward improving decision-making. Recognizing this, Elgendy and Elragal (2016) informed that BDA has increased in velocity affording managers the laxity of effective decision-making. Adrian et al. (2018) recognized that while BDA improves decision-making, the consistency of decisions ultimately sustains the process. Drawing back from the arguments by Aldholay et al. (2018), system quality and information quality have an impact on how well people perform at work and in making decisions. To provide senior managers with the finest information quality, it is paramount to store, analyze, and visualize the data to support their decision-making and ensure other stakeholders are keyed into the vision of the decision-makers.

Furthermore, it was hypothesized that decision-making by top management would positively impact university performance (H5). The study results indicate that improving decision-making will affect university performance by creating business values and academic outcomes. Overall knowledge of the BDA model demonstrates how the social and technical subsystems contribute to enhancing the decision-making approach by executives and, subsequently, enhancing the universities' performance in Saudi Arabia.

This study adds to the pool of knowledge in the higher education sector by investigating the constructive role of social and technical subsystems in enhancing decision-making by top managers within Saudi universities. Thus, this study has various theoretical implications. First, the social subsystem in the current study is represented as the impact of oriented-organizational culture on BDTs, IDM, and OP. This impact has not been explored by previous research either in Saudi Arabia or in the higher education context. Merging such constructs allows Saudi Arabia to higher education programs. Second, the technical aspects of the current study are shaped by BDTs, including storing, analyzing, and visualizing big data to improve decision-making. Those technical factors have not been investigated in previous big data research. However, previous studies investigated the significance of information and system quality leading to a firm's improved work efficiency (Ji-fan Ren et al., 2017), data security and quality (Abouelmehdi et al., 2017; Bandarupalli & Parveen Sultana, 2019; Lombardo, 2018). Third, the proposed model is the first model that merges the power of social and technical aspects in higher education sectors, which gives it the uniqueness of BDA in the Saudi Arabian higher education setting and developing countries. Lastly, this paper adds to the pool of knowledge of socio-technical theory and its applications. This contribution could enhance the current stage of BDA in Saudi Arabian higher education and other public firms.

CONCLUSION

The impact of focused organizational culture that may promote big data analytics (BDA) in Saudi Arabian higher education institutions is thoroughly analyzed. To improve decision-making (DM) and organizational performance, this study specifically examined the impact of oriented organizational culture (OC) on big data tasks (BDTs). The study looked into BDA factors in Saudi Arabian higher education decision-making using the theory of socio-technical systems. The results showed that both social and technical aspects impact BDA, leading to improved decision-making by executives and enhanced university performance. Besides, through the lens of the social subsystem, oriented-organizational culture plays an imperative role in big data tasks, i.e., storing, analyzing, and visualizing big data. This impact can influence the way of practicing those big data tasks by the whole staff within Saudi universities. The findings also suggest that oriented-organizational culture has a crucial impact on improving decision-making and enhancing university performance by creating business values and academic outcomes for the whole university.

The study pinpoints some areas for further studies. First, the sample size should be more significant and include private and public universities. Therefore, some variations in the results can be obtained regarding social and technical aspects. Second, more private and public universities should be included in other developing countries when exploring similar research studies. The researchers will then be able

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to better understand the social and technical angles within developing countries and how to apply the variables. Third, more technical factors should be included, such as IT infrastructure with private and public universities in Saudi Arabia. These added variables will allow future research to determine the capability of IT infrastructure within Saudi Arabian universities.

AUTHOR CONTRIBUTIONS

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