Check for updates

https://doi.org/10.63062/trt/V24.069

THE REGIONAL TRIBUNE

Pages: 389 – 406 | Volume: 3 | Issue: 1 (Volume 2024) | ISSN (Online): 3006-8428 | DOI: 10.63062/trt/V24.069

Impact of Big Data Analytics on Organizational Performance: The Role of Business Analytics, Decision-Making Quality and Sustainability

Alisha Kamran Khan [1]
Sohaib Uz Zaman [2]
Syed Hasnain Alam [3]

[1] Master of Business Administration, Marketing, Karachi University Business School (KUBS), Faculty of Management & Administrative Sciences, University of Karachi, Karachi, Sindh, Pakistan.
Email: Alishakamran@msn.com

[2] Assistant Professor, Karachi University Business School (KUBS), Faculty of Management & Administrative Sciences, University of Karachi, Karachi, Sindh, Pakistan.
Email: sohaibuzzaman@uok.edu.pk
https://orcid.org/0000-0002-0135-3292

[3] Karachi University Business School (KUBS), Faculty of Management & Administrative Sciences, University of Karachi, Karachi, Sindh, Pakistan.
Email: hasnainalam@gmail.com
https://orcid.org/0000-0002-5008-736

Corresponding Author: Syed Hasnain Alam
hasnainalam@gmail.com

Cite this Article:
Khan, A. K., Zaman, S. U., & Alam, S. H. (2024). Impact of Big Data Analytics on Organizational Performance: The Role of Business Analytics, Decision-Making Quality and Sustainability. *The Regional Tribune,* 3(1), 35-406. https://doi.org/10.63062/trt/V24.069

ABSTRACT:
The research analyzes Big Data Analytics effects on organizational results through studies of business analytics capability improvement alongside better decision quality and sustainable product development outcomes. Organizations that utilize big data efficiently improve both their operational speed and their ability to process and utilize data which enables better decisions and innovative sustainable practices. Evidence shows that big data integration as a strategic business process component creates substantial organizational improvements which supply essential knowledge for professionals and academics alike. The research demonstrates strong evidence of performance gains yet points to the necessity for additional investigations about these relationships throughout different industry sectors.

KEY WORDS:
Big Data Analytics, Organizational Performance, Business Analytics Capacity, Decision-Making Quality, Sustainable Product Development

Introduction

The rapid change of globalization, and hyper competition has triggered the companies to adopt new practices to keep pace with the dynamic environment (Dwivedi et al., 2023; Jantunen et al., 2018; Li & Chan, 2019; Mikalef et al., 2020a). For this reason, companies have faced a massive change in the organizational practices which has not just disrupted the traditional and conventional modes of business operations but also allowed some companies to develop a competitive advantage based on it.

These practices, application, and methodologies that help businesses to maintain and manage data effectively is termed as Business Analytic which is also commonly called as Big Data (Modgil et al., 2021).

The popularity of the use of big data has been increased due to the technological advancement and digital proliferation where not just the organizations are adopting but also the institutions, different brands and companies are seen to adopt this concept more rapidly (Sena et al., 2019). Due to its massive use in the organizations it has also receive great attention by its practitioners (Fosso Wamba et al., 2015; Ke & Shi, 2014).

In the last decades, companies have seen to rely on evolving practices that are adopted by many organizations not just to evolve as an emerging market in the industry but also as an emerging economy which has greatly to contributed to its success (Lepenioti et al., 2020a).

Many organizations are engaging into the application of big data in their day-to-day tasks since it has surpassed the conventional storage of data to more advanced and sophisticated manner (Aydiner et al., 2019; Chen et al., 2019; Sena et al., 2019).

Many companies are focused on the growing importance of the use of big data in the industry, they are accessing massive amount of data which is also assisting them in proposing solutions to business problems by considering the significant data in taking strategic decisions (Frederiksen, 2009). By using Business Intelligence tools, firms can take fast-paced decisions and improve their performance (Chatterjee et al., 2024).

Businesses can use current data as well as the historical data of the companies to develop and gain huge competitive gains which overall contributes to the financial growth of the business, ultimately causing it to achieve profitability within the organization and also elevate its rank in the business industry by becoming advanced in the technology sector (Bharadwaj, et al., 2013; Luftman et al., 2015).

Hence, in this study, we will discover the factors which contributes to the importance of application of business analytics for organizations and how they can benefit from it to improve its performance, increase organizational value, build and sustain a competitive advantage.

Literature Review

Big Data Analytics

The term Big data Analytics is defined as the large volume of data that is accessible to organizations which can be used to take strategic decisions. Data varies in type, amount, and variety as referred by (Akter et al., 2016a; Mikalef et al., 2020b; Mikalef & Krogstie, 2020; Mikalef & Pateli, 2017). Whereas, according to (Grossman & Siegel, 2014), Analytics is termed as the process of assessing, managing, manipulating, and deriving valued data.

Therefore, many organizations have different setups to study the organized data to acquire more value from it (Themistocleous & Papadaki, 2020). Moreover, as per many renowned researchers, it is the organization's capability to assess the data and generate valuable information from it because if the organization failed to derive the useful data, it will not be able to integrate, assess or utilize it in obtaining desired goals (Gupta & George, 2016). Thus, data is something that assists the companies in analyzing the current scenarios and it also provides them with a valuable insight of what an ideal situation would look like if we use the appropriate data in real-time due to which big data analytics is also considered as the next big thing in future that can bring an unintended revolution in many ways (Curry et al., 2022; Kwon et al., 2014).

Hence, those organizations who gain par excellence in examining the data accurately may possess to achieve a competitive advantage in the realm of data (Kiron et al., 2015). Moreover, many researchers called the capability of analyzing the big data analytics as a tool to gain valuable insight on how to acquire a competitive advantage in future by gaining expertise in data analysis, its management, and technology (Akter et al., 2016b; Kiron et al., 2015).

Big Data Analytics Management Capacity

The management capacity of Big Data Analytics is referred as the capability of the organizations, data analysts or data scientists to manage useful data resources in such a systematic and disciplined manner that it becomes highly convenient to examine data as per the necessary requirements of organization for the purpose of delivering substantial business impact (Helfat & Winter, 2011). Therefore, BDA management capacity is absolutely necessary for the firms to maintain a significant resilient position so that no matter how severe the competition or market situations hampers (Helfat & Raubitschek, 2018).

Theoretical Framework and Conceptual Model

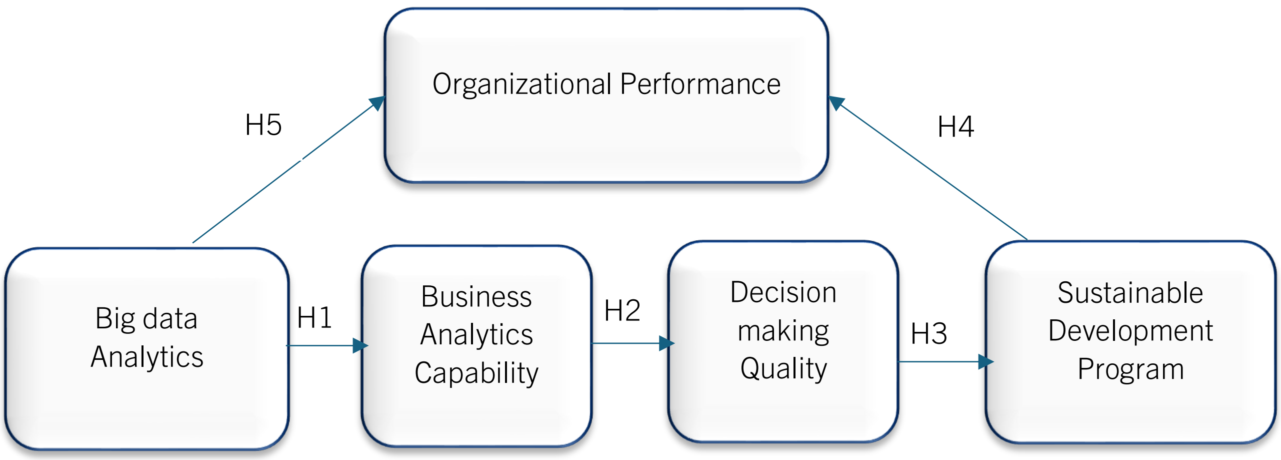
The concept of big data analytics having a positive relation on organizational performance prevails with some important constituents. However, the past studies and research done on big data have been explicitly done and recognized by many researchers at a great scale. But, right now the observed research work has been at an elementary stage where it is believed that big data means only huge amount of databases regardless of how it impact other important factors (Ferraris et al., 2019).

Hence, the connection between big data and organizational performance has been significantly studied by many renowned researchers but the Resource Based Review (RBV) remains a primary aspect to examine. Many researches constitute a great amount on how big data is capable of influencing organizational performance and how it is related (Erevelles et al., 2016; Viaene, 2013).

Business Analytics Capacity

Figure 1

Research Framework



Business analytics is the practice followed by organizations of storing huge amounts of valuable data in company's database management system where they can access it in order to regulate their decision making effectively. This data is about the company's clients, resources, and the products and services they offer. This enables the company to keep track of their essential information to draw necessary insights when they are taking decisions regarding the company's valuable assets or resource mobilization (Zhan & Tan, 2020).

Big Data and Business Analytics Capacity

Therefore, many organizations are following Business Analytics as a practice in their workplaces and also instructing its entire workforce to follow the same in order to drive efficient decision-making, streamlined processes, enhanced automation, and reduce data errors (Phillips-Wren & Hoskisson, 2015). Furthermore, companies are taking initiatives to observe Business Analytics in their functional areas such as HR, Marketing, Finance, POM etc because it has the capability to predict and assess the data wherever it's necessary as it will improve the organizational performance alongside it will also provide different ways to explore more prospects (Bayrak, 2015).

H1: Big Data Analytics has a positive influence on Business Analytics Capacity

Decision Making Quality

It is important that the companies maintain a good understanding of how big data, business analytics, asset, and resource management are connected whilst possessing strong technical knowledge and a proficient team of data scientists that have enough potential to comprehend different prerequisites of a task. If they managed to form such insights then the decision making quality of the organizations can be improvised (Agustí et al., 2024). Moreover, the success of the organization is rooted in efficient resource planning, asset allocation, and resource maximization by identifying the strengths of the internal dynamics while grasping the external context (Davenport, 2018; Vidgen et al., 2017).

Business Analytics Capacity and Decision-Making Quality

However, the main aspect of following Business Analytics in a firm is to address the intricacies and complexities involved in order to analyze the current organizational situation, predict the future potential of the firm where its capable to undergo, and the necessary change which needs to implemented abruptly (Lepenioti et al., 2020b). This whole operation is done to reduce human interaction as much as they can and enhance the decision making process on a daily basis (Kesavan & Kushwaha, 2020).

This enables the company to strive in emerging competition of digitalization where all the data analytical tools need to be studied effectively (Luoma, 2016). Many researchers also proposed that in order to make strategic decisions, it is necessary to evaluate real-time data to draw conclusions by using different statistical and hypothetical models to provide accurate reasoning (Volberda et al., 2021).

Furthermore, the ability of Business Analytics to support the decision-making process, it is significant that the company should know how to effectively observe data, utilize the resources, and incorporate necessary technical skills that are relevant to pursuing each task successfully. This will also ensure that the task management activities are in coordination because in many companies, those decisions that are taken at different levels within a large size organization, are considered as a primary component (López-Muñoz & Escribá-Esteve, 2017). Considering the above, we can formulate another hypothesis:

H2: Business Analytics capacity has a positive influence on Decision-making quality.

Sustainable Product

Organizations that are often involved in big data analytics used to produce and offer sustainable goods and services. Within a constantly evolving environment, business analytics serves as a basis in building foundational knowledge and information to follow a systematic approach (Salehan & Kim, 2016), which is usually uncommon in many firms. But those companies which are dedicated to pursue business analytics turn out to produce sustainably viable products which also allows to establish a competitive advantage in the long run as a result of analyzing big data (Zhan & Tan, 2020).

Decision-Making Quality and Sustainable Product

There are three fundamental aspects of developing such products, which are social, economic, and environmental factors (Ali et al., 2020; Kesavan & Kushwaha, 2020; Maliha, 2023). Environmental factors may include all those factors which needs to be studied before analyzing the data and drawing conclusions or else companies may face its respective challenges. This study requires the analysis of rules and regulations followed in order to support in the manufacturing of sustainable goods (Oliveira et al., 2020). Social factors may involve the realization of the social factors where the company is residing (Ali et al., 2020). This is mostly important when company is taking prior decisions solely based on the nature of its work and not considering how much it has the potential to impact the environment. Lastly, economic factors are mostly related to those parameters which should be assessed while devising strategies and plans in the development of sustainable products (Ahmad et al., 2016). Hence, companies are using big data analytics to observe value-based decision-making, reduce the time-span of incorporating product design, and curtail costs (Zhan & Tan, 2020). In the context of this, we can develop the hypothesis below:

H3: Decision-making quality has a positive influence on Sustainable Product Development

Organizational Performance

It is very common for organizations to consider performance as their main desirable goal to achieve. In this way, most companies set up their Key Performance Indicators (KPIs) which are used to predict how much competent an organization is in acquiring its targets in short run so that it can help them succeed in the long run (Kanwal et al., 2024). Principally, companies tend to measure its performance by analyzing the financial data, but it is now considered as less valuable because there are also some other factors which need to be studied.

Sustainable Product and Organizational Performance

These factors involve both financial and non-financial data because the financial data is only limited to funding aspects or cost analysis but the non-financial data provides the companies with a more vivid picture of what the customer actually is demanding and where are they lacking. Not only this, companies will also be able to evaluate if they can address those problems or not (Masa'deh et al., 2016).

H4: Sustainable Product Development has a positive influence on organizational performance

Big Data Analytics and Organizational Performance

Big data analytics greatly impact organizational performance with the mediating support of Business Analytics Capability, Decision-making quality, and Sustainable Product Development. Hence, with crucial prediction and analysis of data, firms will be able to observe the practice of business analytics with the help of recognizing the value of technology and HR. Moreover, they can engage in effective decision-making which will result in developing sustainable products. This significant relationship has the potential to positively influence organizational performance (Al-Ansaari et al., 2015).

H5: Big data analytics has a positive impact on organizational performance.

Research Methodology

Research Design

Based on the research above, a conceptual framework has been developed. The research comprises Big Data Analytics as an independent variable which includes BDA Management Capacity involving four steps namely, planning, financing, integration, and supervision. Organizational performance is taken as a dependent variable, and Business Analytics Capability, Decision Making Quality, and Sustainable Product Development as direct relations.

The research adopts a quantitative research technique and the purpose of choosing a quantitative research design is to collectively figure out the behavior of organizations that how big data analytics particularly influence organizational performance. (research design confirmatory factor analysis CFA mention) The Quantitative research design matches the purpose of my research as it aims to address how many firms follows the same practice. For this purpose, we are using a cross-sectional survey design to study the impact of BDA on organizational performance with business analytics, decision-making quality and sustainability. This design is commonly preferred and used by researches carrying out research on business and management studies which specifically addresses technological adoption gaps (Akter et al., 2016b).

By using cross-sectional method, we can study and study the trend that is prevailing, which will eventually allow us to evaluate the influence of big data analytics on organizational performance (Bitmiş & Ergeneli, 2015;

Rahman et al., 2013). This technique enables us to observe, measure, and validate data effectively (F. Hair Jr et al., 2014). By employing this method, the performance can also be assessed effectively which will reduce data biases and give us an evident opportunity for conducting a transparent research as responses are collected in the meantime (Fosso Wamba et al., 2015; Gupta & George, 2016).

This study mostly involves integrated constructs, hence, we are using PLS-SEM technique. It is particularly essential to be used for handling small-sized samples and abnormal data distributions that often occur in big data analytics (F. Hair Jr et al., 2014; Giovanis & Athanasopoulou, 2018). We tested the hypothesis using the partial least square structural equation modelling (PLS-SEM) (Van Kollenburg et al., 2020). It allows us to examine cause-effect relationship and to study complex data.

Sampling Approach

In this study, we have employed judgmental sampling technique as the data that needs to be collected from among organizational firms in Pakistan were large in number and it was big enough to be covered. So, by using this method, we can choose to target specific working bodies, executives, and managers that have direct involvement in using big data analytics in their firms to improve organizational performance by implementing business analytics capabilities, eventually allowing them to carry out effective decision making and develop

sustainable products as its offering to customers (F. Hair Jr et al., 2014).

The sample chosen acts as relevant to obtain the research objectives and collect results accordingly (Gupta & George, 2016). Hence, the rationale of using PLS-SEM was to work with small sample size to handle complex models ((Bitmiş & Ergeneli, 2015; F. Hair Jr et al., 2014; Rahman et al., 2013). Big data analytics involves multiple constructs (Akter et al., 2016a; Giovanis & Athanasopoulou, 2018). For this purpose, cross-sectional survey also works well as it is significantly employed to study variables separately (Bitmiş & Ergeneli, 2015), which provided a necessary approach to assess causal relationship between BDA and organizational performance effectively (F. Hair Jr et al., 2014). This survey technique also enables the companies to study and gather data in a way which provides opportunity of improving their decision making capabilities and observe sustainable practices efficiently (Fosso Wamba et al., 2015).

Data Collection and Analysis

The sample data was collected from those organizations that actively use big data analytics. The data was conducted in the form of a questionnaire as a survey instrument which is developed by using the relevant constructs and items as per the research topic that how Big data analytics impacts organizational performance; Business Analytics Capability, Decision Making Quality, and Sustainable Product Development.

The study involved judgmental sampling technique to choose those managers, executives, and working bodies that are highly engaged in the practice of employing big data analytics in their workplace (Jantunen et al., 2018). This study was verified by adopting measurement scale to ensure content validity in order to refine the questionnaire from experts given by (Bitmiş & Ergeneli, 2015; Rahman et al., 2013). As a result, data was assessed by using Smart PLS 3.0 of PLS-SEM modeling to study and manage complicated constructs.

Measurement Constructs

The data was initially collected in sections where section one comprises of independent variable being used in this research, section two collects data for all the variables used, and final stage three gathered the data for the dependent variable. This strategy was in view of the practice to obtain transparent results and avoid data biases (Zhang et al., 2023).

However, the measurement scales used in this research was collectively taken from different renowned researchers for given constructs (Bitmiş & Ergeneli, 2015; Rahman et al., 2013). It provided useful scales forBig data Analytics and its dimensions (Akter et al., 2016b; Gupta & George, 2016; Modgil et al., 2021). The variables were measured by using scales suggested by Fosso Wamba et al., 2015 and Ghasemaghaei et al., 2017. The dependent variable as organizational performance was measured by using Venkatraman & Ramanujam's (1986) framework.

This research approach constituting all constructs employed the 5-point likert scale which was taken to ensure data validation, reliability and consistency (Schuberth et al., 2023). With the use of likert scale, the data was assessed by representing (1=strongly disagree, and 5=strongly agree) for a thorough analysis of the results (Howard & Rose, 2019).

Results and Findings

Respondents Profile

A total of 235 responses were collected from the working bodies of different organizations where executives, managers, officers, and entry-level persons were involved. These people belonged to different industries such as Banking/Finance, IT, Education, Health, and Retail. Most of them were designated at different positions including Marketing, IT Specialist, Data Analyst, HR, and Finance officers. The questionnaire was disseminated through Social Media including WhatsApp, Facebook, and LinkedIn where people took part actively.

Reliability and Validity Analysis

Table 1

Constructs Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
BAC	0.819	0.820	0.695
BDA	0.845	0.847	0.649
DMQ	0.881	0.881	0.712
OP	0.894	0.894	0.738
SPD	0.866	0.867	0.685

Table 1 illustrates the construct reliability and validity from the study on big data analytics and organizational performance. The measurement model test results consisting of Cronbach Circle, Composite Reliability (CR), and Average Variance Extracted (AVE) are key indicators to know the reliability and validity of the research model.

Cronbach's Alpha values of all constructs fall between 0.819 and 0.894, more than acceptable cut-off point of 0.70 suggesting good internal consistency. Likewise, the Composite Reliability (CR) values lie above 0.70 for every construct, which further guarantees the reliability of the scale.

Likewise, the AVE values from 0.649 to 0.738 exceed the 0.50 cut-off value, providing a valid evidence of convergent validity (Fornell & Larcker, 1981). The Results of the Measurement Model These results indicate the fact that the measurement model is reliable and valid to study the impact of big data analytics on the organizational performance.

Discriminant Validity – Heterotrait-Monotrait (HTMT) Ratio

HTMT stands for Heterotrait-Monotrait Ratio, which is a type of discriminant validity. Discriminant validity is important because we want to be sure that different constructs in our model are not too closely related to each other. According to Henseler et al. (2015), an HTMT value lower than 0.85 suggests that the constructs are not too highly correlated and capture different aspects of reality.

Table 2

HTMT Ratio for Discriminant Validity

	BAC	BDA	DMQ	OP	SPD
BAC					
BDA	0.808				
DMQ	0.600	0.703			
OP	0.792	0.698	0.646		
SPD	0.787	0.805	0.827	0.603	

Table 2 results reveal that all values in the last row is lower than the 0.85 threshold, thus verifying that the constructs utilized in this study hold discriminant validity. The HTMT for example, indicates the value as per BAC and BDA is 0.808, and that of DMQ and OP is 0.646, which means these constructs can be clearly distinguished. The max HTMT value in this table is 0.827 between SPD and DMQ, but still within the acceptable range.

These findings confirm the measurement model, revealing that the constructs do not overlap excessively with each other, and thus minimizing fears of multicollinearity. Consequently, it validates the constructs, confirming that the constructs measure varying dimensions of big data analytics and organizational performance.

Variance Inflation Factor (VIF)

Table 3

Variance Inflation Factor

Indicator	VIF
BAC1	1.923
BAC2	1.923
BDA2	2.859
BDA3	1.849
DMQ1	2.108
DMQ2	2.739
DMQ3	2.789
OP1	3.040
OP2	3.554
OP3	2.228
SDP1	1.980
SDP2	2.406
SDP3	2.602
BDA1	2.159

The table 3 shows the Variance Inflation Factor (VIF) values of indicators. Generally, the variance inflation factor (VIF) is used to measure the multicollinearity, and the larger the value of VIF, the higher the suspicion of multicollinearity problem. Both the VIF values for BAC1 and BAC2 are equal to 1.923 in this case, well within acceptable limits, hence no significant multicollinearity detected. Similarly, for BDA2 (2.859), DMQ1 (2.108), and DMQ3 (2.789), all are below the common threshold of 5, indicative of shared common variance thus multicollinearity is not a problem for these indicators.

Close the original and translate it to create Another one to adjust to a tenth...but OP2 has a VIF of 3.554, his score is OK but not a particular good one compared to other indicators. None of the VIF values exceed the common threshold of 5, which means that there is no high multicollinearity in the model. Therefore, VIF values indicate low multicollinearity, as all remain below a threshold of concern.

Summary of Reliability and Validity Analysis

The reliability and validity analysis indicates that the measurement model has a good robustness. Therefore, the strong internal consistency is confirmed by Cronbach's Alpha (0.819–0.894) and Composite Reliability (CR) (above 0.70). Convergent validity was good based on AVE (0.649–0.738) values. The Heterotrait-Monotrait Ratio (HTMT) of all constructs below 0.85 confirms its discriminant validity. VIF values that are reasonably far below 5, indicating no multicollinearity issues. The model is considered reliable, valid, and itself not subject to multicollinearity issues.

Structural Model Evaluation

Table 4

Significance of Path Coefficients

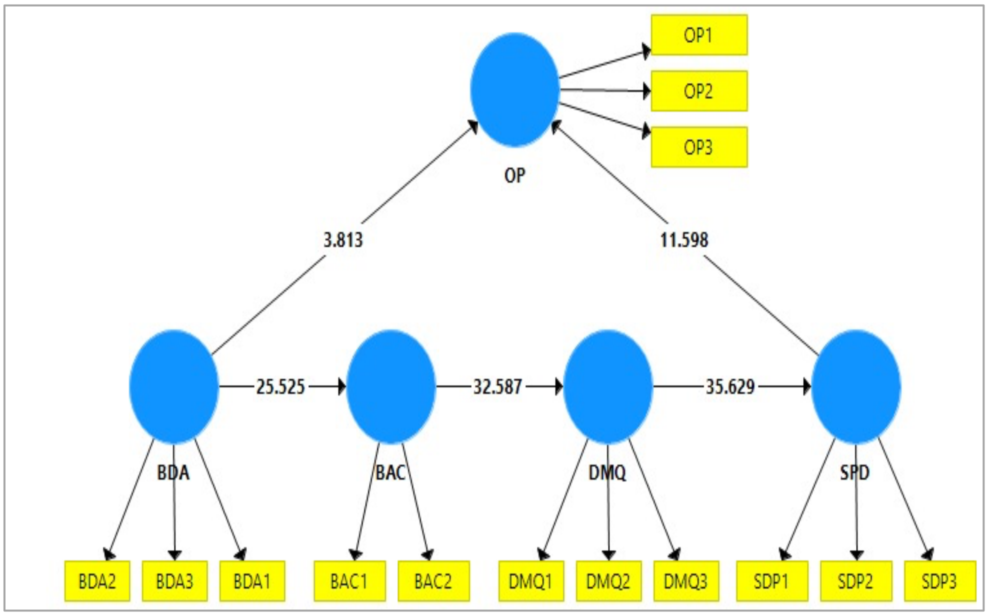
Constructs	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BAC -> DMQ	0.847	0.846	0.026	32.587	0.000
BDA -> BAC	0.780	0.781	0.031	25.525	0.000
BDA -> OP	0.228	0.230	0.060	3.813	0.000
DMQ -> SPD	0.847	0.846	0.024	35.629	0.000
SPD -> OP	0.682	0.681	0.059	11.598	0.000

The results confirm that organizations that utilize big data analytics can improve their performance by improving their analytical capabilities, decision-making, product development, independence and sustainability.

The statistical interpretation in Table 4.4 proves that Big Data Analytics positively affected on Business Analytics Capacity (O = 0.780, p = 0.000). This shows that institutions that invest to BDA have higher analytical capabilities and are able to use data in order to improve faster and at a larger scale. Consequently, companies capable of advanced analytics are in a stronger position to make informed decisions. For example, it is showcased in the positive relation of Business Analytics Capacity to Decision-Making Quality, high path coefficient (O = 0.847, p = 0.000) confirm that with increased analytics capacity improved and data-based decision-making processes are practiced.

Figure 2

SEM Model of the Study

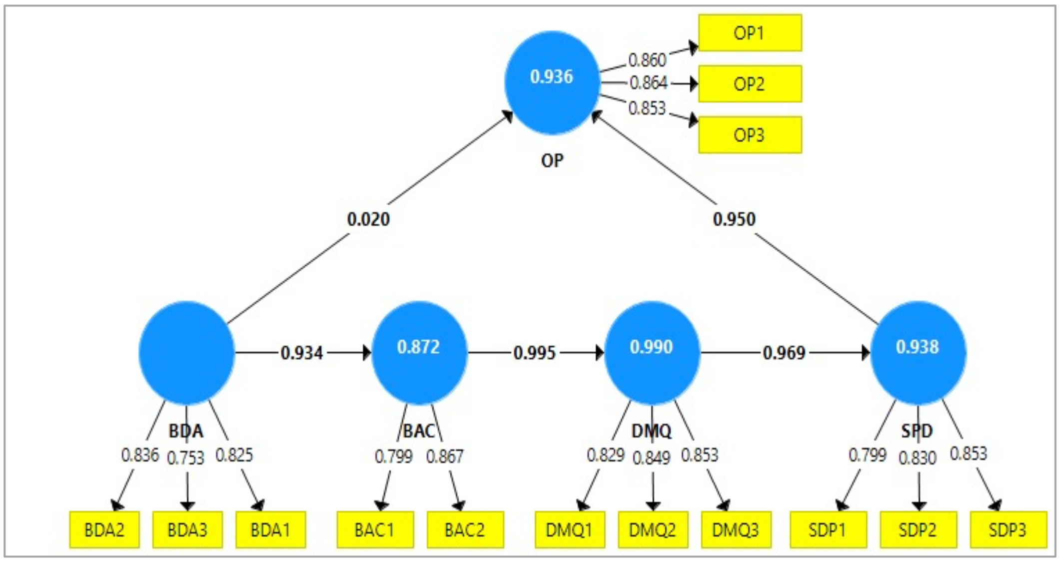


The findings also reveal that improved decision-making associates with Sustainable Product Development (O = 0.847, p = 0.000). It implies that data-driven decision-making organizations are likely to provide innovative and sustainable products that are in line with long-term business objectives and environmental values. Thus, Sustainable Product Development has a positive influence on Organizational Performance (O = 0.682, p = 0.000). This should serve as a powerful reminder that sustainability is now a business imperative, not just an ethical touchstone or regulatory box to tick.

Notably too, Big Data Analytics were found to have a direct effect on Organizational Performance (O = 0.228, p = 0.000). Nonetheless, this impact is lower than the indirect antecedential influence of Business Analytics Capacity, Quality of Decision-Making and Sustainable Product Development. Although big data can directly improve performance, building analytics capability can be a powerful indirect lever on performance, as can better organizational decision-making and a focus on sustainable innovation.

Figure 2

SEM Model of the Study



Data from this study was examined in SmartPLS 3 and shows that Big Data Analytics has a positive effect on organizational performance (direct) and analytics capacity, decision-making, and sustainable product development (indirect). The SEM model presented in Figure 4.1 and 4.2 was constructed by establishing latent constructs and measuring reliability and validity measures (Cronbach' Alpha, Composite Reliability, AVE, and discriminant validity). In summary, the analysis illustrates the coalescence of data-driven capabilities and sustainability-centric strategies toward improved organizational outcomes.

Coefficient of Determination

Table 5

Coefficient of Determination (R^2 Values)

Variable	R Square	R Square Adjusted
BAC	0.872	0.872
DMQ	0.990	0.990
OP	0.936	0.935
SPD	0.938	0.938

Results showed that Business Analytics Capacity (BAC) demonstrated a high R^2 of 0.872, indicating that Big Data Analytics plays a major role in creating the analytical properties of an organization. DMQ also performs extremely well, yielding an even higher R^2 of 0.990, which suggests that almost all the observed variations in decision-making can be explained by DMQ predictors, supporting the claim that analytics enhances decision-making behavior.

The R^2 value for each of the Sustainable Product Development (SPD) and Organizational Performance (OP) have strong R^2 values of 0.938 and 0.936, respectively, both of which demonstrate the model effectively explains how decision-making and sustainability work together to bring about organizational success. The slight variations in R^2 and Adjusted R^2 indicate the stability of the model and its reliability for predictions. These results underscore that big data analytics, science-based decision-making, and green strategies improve organizational performance.

Final Result Summary

Data collected for PLS-SEM analysis also confirms that BDA is significantly improving organizational performance both directly and indirectly. We found that organizations with BDA create a solid BAC and reach a better DMQ. Better decision-making enables SPD, and ultimately delivers OP.

The results supported all hypotheses, supporting the idea that data-driven decision-making and sustainability-oriented strategies can greatly contribute to the success of the business. Psychologically, Building Dynamic Analysis capability directly impacts Sustainability Practices.

Hypothesis Testing Results

Table 6

Hypotheses Testing Summary

Hypothesis	Path	Status
H1	BDA → BAC	Supported
H2	BAC → DMQ	Supported
H3	DMQ → SPD	Supported
H4	SPD → OP	Supported
H5	BDA → OP	Supported

The findings in Table 4.6 illustrates that organizations need to implement not only Big Data Analytics but to build their analytical capabilities and decision-making schemas to derive its true benefits.

Limitations of the Study

A few limitations of this study should be noted. First, it used a cross-sectional quantitative design using a 5-point Likert scale, limiting the ability to capture changes over time and restricting causal inferences. Data were gathered by means of Google Forms and social networks, and a judgmental sampling technique was used in that data collection method, which can introduce selection bias and affect the generalizability of findings. Furthermore, participants were from specific industries—like Banking/Finance, IT, Education, Health, and Retail—and selected from limited categories for designation, viz. executives, managers, officers, and entry-level staff. Such sampling from people within specific industries and roles may not reflective the broader organizational picture and may leave out how other sectors or executive-level thought players are shaping the topics at hand.

In addition, the use of self-reported data enhance vulnerability to common method bias, since the respondents might want to give socially acceptable answers or misunderstand survey items. While very practical, it might also limit the richness of aversion as the 5-point Likert scale limits the amount of responses that can be given and thus how detailed the construct can be. These contribute its applicability across wide ranges of settings but are still challenged by the limitations of CFA and PLS-SEM which rely on the quality of the input data and underlying assumptions of the model that may oversimplify the complex phenomenon of big data analytics in unique environmental contexts.

Moreover, due to the cross-sectional design of the study, no conclusions can be drawn about causality and dynamic developments within organizations. The lack of exploration of factors such as organizational culture, the maturity of the organization's technological capabilities, the prevailing external market conditions—factors that might have been roadblocks or enablers, respectively—may have added depth to a more nuanced understanding of the relationships between big data analytics and organizational performance.

Discussion

Finding and Contributions

Based on data until October 2023, this study investigates the influence of Big Data Analytics BDA on Organizational Performance OP considering Business Analytics Capacity BAC, Decision-Making Quality DMQ, and Sustainable Product Development SPD variables. Employing a quantitative and cross-sectional research strategy with PLS-SEM, this research corroborates that BDA has a considerable and positive impact on organization success directly and indirectly.

The findings support the Resource-Based View (RBV) theory, which states that organizations achieve competitive advantage through the effective utilization of resources like big data (Barney, 1991). Notably, the study results verify that when BDA increases BAC, it leads to an increase in DMQ and SPD, which further contributes to improved OP. This provides further support for previous studies that found data analytic as a strategic resource that facilitates even decision-making and innovation (Fosso Wamba et al., 2015). Yet, even though all the findings give a good measure to the indispensable nature of analytics, some studies criticize that in the absence of a proper data governance and integration, the rewards which can be given to BDA, they will be unfeasible for those famous organizations (Zhang et al., 2023).

Similar results were found in past studies that present BDA as a driver of decision-making and influence on a firm performance (Gunasekaran & Spalanzani, 2012). It supports the positive relation between BAC and DMQ as it states that with the advanced analytical capabilities the accuracy of decision increases (Davenport, 2018). However, various scholars claim that organizations face difficulty in converting big data insights into real performance progression owing to skill gaps and reluctance to adjust (LaValle et al., 2011).

The need for decision making through enhanced analytics capabilities must be an immediate-fix in the long-term sustainable innovation journey. Investment in data-driven strategies can be rewarding for organizations working in enterprises across finance, IT, healthcare, etc. Nonetheless, problems related to data quality, infrastructure works, and employee training have to be solved to maximize BDA (Fosso Wamba et al., 2015).

Conclusion

The present study finds strong evidence throughout the literature review that BDA improves organizational performance. Nevertheless, the findings illuminate that utilizing BIG DATA ANALYTICS (BDA) has a supportive role in augmenting performance both directly and indirectly through the implications of enhancing Business Analytics Capacity (BAC) and Decision-Making Quality (DMQ) on Sustainable Product Development (SPD). These relationships exemplify the role of BDA which allows businesses to make smarter decisions, create innovative and environmentally sustainable products, and become overall more efficient and competitive.

By gathering data from professionals from diverse industries—banking, IT, education, health, and retail—and applying advanced methods like PLS-SEM analysis in an insightful way, the study demonstrates how important it is for firms to devote efforts to employ BDA strategically. A rigorous quantitative methods enable concrete instructions for data collection and analysis, and the considerations of reliability and validity provide assurance of the measures used to capture the constructs of interest.

Though the study is confined to some occupations and industries, and relies on judgmental sampling, it provides insights that should interest members of the business, analytical, and policy-making fields who want to harness the power of data to enhance organizational performance. This paper is also a starting point for future research which could examine these relationships in other contexts and over longer time frames.

In addition, the paper establishes that Big Data Analytics is not only a technical instrument but a tactical resource whose proper integration can significantly enhance the way organizations perform and thrive.

Future Research Directions

Future research should consider a longitudinal design for maintaining a better understanding of big data analytics and organizational performance. Realizing this technique would help researchers to explore trends over time and establish stronger causal relationships between constructs.

Furthermore, using probability sampling methods for selection would increase the representativeness of the sample, and having a wider variety of industries and designations would present a holistic outlook towards the phenomena across multiple organizational contexts.

Finally, researchers may also consider more nuanced measurement scales that would more precisely capture complex attitudes and behaviors. Finally, a triangulation between subjective data and objective performance metrics is likely to strengthen the robustness and validity of the findings, enabling a more holistic view of how big data analytics drives organizational success.

References

Agustí, M. A., Aguilar-Caro, R., Galán, J. L., & Acedo, F. J. (2024). Dynamic resource management and slack resources. *Management Decision, 62(*13), 223–242. https://doi.org/10.1108/MD-01-2023-0119

Ahmad, M. A., Asaad, M. N., Saad, R., Iteng, R., & Rahim, M. K. I. A. (2016). Mediating effect of sustainable product development on relationship between quality management practices and organizational performance: Empirical study of Malaysian automotive industry. 020010. https://doi.org/10.1063/1.4960850

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016a). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics, 182*, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016b). How to improve firm performance using big data analytics capability and business strategy alignment*? International Journal of Production Economics, 182,* 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Al-Ansaari, Y., Bederr, H., & Chen, C. (2015). Strategic orientation and business performance: An empirical study in the UAE context. *Management Decision, 53*(10), 2287–2302. https://doi.org/10.1108/MD-01-2015-0034

Ali, S., Poulova, P., Yasmin, F., Danish, M., Akhtar, W., & Usama Javed, H. M. (2020). How Big Data Analytics Boosts Organizational Performance: The Mediating Role of the Sustainable Product Development. *Journal of Open Innovation: Technology, Market, and Complexity, 6*(4), 190. https://doi.org/10.3390/joitmc6040190

Aydiner, A. S., Tatoglu, E., Bayraktar, E., & Zaim, S. (2019). Information system capabilities and firm performance: Opening the black box through decision-making performance and business-process performance. *International Journal of Information Management, 47,* 168–182. https://doi.org/10.1016/j.ijinfomgt.2018.12.015

Barney, J. (1991). Resources, firm resources, and sustained competitive advantage*. Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Bayrak, T. (2015). A Review of Business Analytics: A Business Enabler or Another Passing Fad. Procedia - *Social and Behavioral Sciences, 195*, 230–239. https://doi.org/10.1016/j.sbspro.2015.06.354

Bharadwaj, Anandhi, Bharadwaj, A., El Sawy, O. A., University of Southern California, Pavlou, P. A., Temple University, Venkatraman, N., & Boston University. (2013). Digital Business Strategy: Toward a Next Generation of Insights. *MIS Quarterly, 37*(2), 471–482. https://doi.org/10.25300/MISQ/2013/37:2.3

Bitmiş, M. G., & Ergeneli, A. (2015). How Psychological Capital Influences Burnout: The Mediating Role of Job Insecurity. *Procedia - Social and Behavioral Sciences, 207*, 363–368. https://doi.org/10.1016/j.sbspro.2015.10.106

Chatterjee, S., Rana, N. P., & Dwivedi, Y. K. (2024). How does business analytics contribute to organisational performance and business value? A resource-based view. *Information Technology & People, 37*(2), 874–894. https://doi.org/10.1108/ITP-08-2020-0603

Chen, Y., Jin, Q., Fang, H., Lei, H., Hu, J., Wu, Y., Chen, J., Wang, C., & Wan, Y. (2019). Analytic network process: Academic insights and perspectives analysis. *Journal of Cleaner Production, 235*, 1276–1294. https://doi.org/10.1016/j.jclepro.2019.07.016

Curry, E., Auer, S., Berre, A. J., Metzger, A., Perez, M. S., & Zillner, S. (Eds.). (2022). Technologies and Applications for Big Data Value. *Springer International Publishing*. https://doi.org/10.1007/978-3-030-78307-5

Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics, 1*(2), 73–80. https://doi.org/10.1080/2573234X.2018.1543535

Davenport, T. H. & Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Harvard Business Press.

Dwivedi, R., Nerur, S., & Balijepally, V. (2023). Exploring artificial intelligence and big data scholarship in information systems: A citation, bibliographic coupling, and co-word analysis. *International Journal of Information Management Data Insights, 3*(2), 100185. https://doi.org/10.1016/j.jjimei.2023.100185

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897–904. https://doi.org/10.1016/j.jbusres.2015.07.001

Hair Jr, J., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review, 26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2019). Big data analytics capabilities and knowledge management: Impact on firm performance. *Management Decision, 57*(8), 1923–1936. https://doi.org/10.1108/MD-07-2018-0825

Fosso, W. S., Akter, S., Edwards, A., Chopin, G., & Gnanzou D. (2015). How 'big data' can have big impact. *Journal of Business Research, 70,* 356–365.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics, 165,* 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

Frederiksen, A. (2009). Competing on analytics: The new science of winning. *Total Quality Management & Business Excellence, 20*(5), 583–583. https://doi.org/10.1080/14783360902925454

Ghasemaghaei, M., Hassanein, K., & Turel, O. (2017). Increasing firm agility through the use of data analytics: The role of fit. *Decision Support Systems, 101*, 95–105. https://doi.org/10.1016/j.dss.2017.06.004

Giovanis, A., & Athanasopoulou, P. (2018). Understanding lovemark brands: Dimensions and effect on Brand loyalty in high-technology products. *Spanish Journal of Marketing - ESIC, 22*(3), 272–294. https://doi.org/10.1108/SJME-07-2018-0035

Grossman, R. L., & Siegel, K. P. (2014). Organizational Models for Big Data and Analytics. *Journal of Organization Design, 3*(1), 20. https://doi.org/10.7146/jod.9799

Gunasekaran, A., & Spalanzani, A. (2012). Sustainability of manufacturing and services: Investigations for research and applications. *International Journal of Production Economics, 140*(1), 35–47. https://doi.org/10.1016/j.ijpe.2011.05.011

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*, 308-317. https://doi.org/10.1016/j.jbusres.2016.08.004

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

Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy, 47*(8), 1391–1399. https://doi.org/10.1016/j.respol.2018.01.019

Helfat, C. E., & Winter, S. G. (2011). Untangling Dynamic and Operational Capabilities: Strategy for the (N)ever-Changing World. *Strategic Management Journal, 32*(11), 1243–1250. https://doi.org/10.1002/smj.955

Howard, M. C., & Rose, J. C. (2019). Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct. *Information & Management, 56*(6), 103134. https://doi.org/10.1016/j.im.2018.12.002

Jantunen, A., Tarkiainen, A., Chari, S., & Oghazi, P. (2018). Dynamic capabilities, operational changes, and performance outcomes in the media industry. *Journal of Business Research, 89*, 251–257. https://doi.org/10.1016/j.jbusres.2018.01.037

Kanwal, S., Al Mamun, A., Wu, M., Bhatti, S. M., & Ali, M. H. (2024). Corporate social responsibility: A Driver for green organizational climate and workplace pro-environmental behavior. *Heliyon, 10*(19), e38987. https://doi.org/10.1016/j.heliyon.2024.e38987

Ke, M., & Shi, Y. (2014). Big Data, Big Change: In the Financial Management. *Open Journal of Accounting, 03*(04), 77–82. https://doi.org/10.4236/ojacct.2014.34009

Kesavan, S., & Kushwaha, T. (2020). Field Experiment on the Profit Implications of Merchants' Discretionary Power to Override Data-Driven Decision-Making Tools. *Management Science,* 66(11), 5182–5190. https://doi.org/10.1287/mnsc.2020.3743

Kim, G., Shin, B., & Kwon, O. (2012). Investigating the Value of Sociomaterialism in Conceptualizing IT Capability of a Firm. *Journal of Management Information Systems, 29*(3), 327–362. https://doi.org/10.2753/MIS0742-1222290310

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management, 34*(3), 387–394. https://doi.org/10.1016/j.ijinfomgt.2014.02.002

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics && the journey from insights to value. *MIT Sloan Management Review, 52* (2), 21-32. https://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value/

Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020a). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management, 50,* 57–70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003

Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020b). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management, 50*, 57–70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003

Li, T. (Carol), & Chan, Y. E. (2019). Dynamic information technology capability: Concept definition and framework development. *The Journal of Strategic Information Systems, 28*(4), 101575. https://doi.org/10.1016/j.jsis.2019.101575

López-Muñoz, J. F., & Escribá-Esteve, A. (2017). An upper echelons perspective on information technology business value. *European Research on Management and Business Economics, 23*(3), 173–181. https://doi.org/10.1016/j.iedeen.2017.02.003

Luftman, J., Derksen, B., Dwivedi, R., Santana, M., Zadeh, H. S., & Rigoni, E. (2015). Influential it Management Trends: An International Study. *Journal of Information Technology, 30*(3), 293–305. https://doi.org/10.1057/jit.2015.18

Luoma, J. (2016). Model-based organizational decision making: A behavioral lens. *European Journal of Operational Research, 249*(3), 816–826. https://doi.org/10.1016/j.ejor.2015.08.039

Maliha, R. (2023). The big data analytical capability and firm performance: Mediating role of supply chain performance. *The Asian Bulletin of Big Data Management, 2*(1), 36–48. https://doi.org/10.62019/abbdm.v2i1.23

Masa'deh, R., Obeidat, B. Y., & Tarhini, A. (2016). A Jordanian empirical study of the associations among transformational leadership, transactional leadership, knowledge sharing, job performance, and firm performance: A structural equation modelling approach. *Journal of Management Development, 35*(5), 681–705. https://doi.org/10.1108/JMD-09-2015-0134

Mikalef, P., & Krogstie, J. (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems, 29*(3), 260–287. https://doi.org/10.1080/0960085X.2020.1740618

Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research, 70*, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and E-Business Management, 16*(3), 547–578. https://doi.org/10.1007/s10257-017-0362-y

Mikalef, P., Pappas, I. O., Krogstie, J., & Pavlou, P. A. (2020a). Big data and business analytics: A research agenda for realizing business value. *Information & Management, 57*(1), 103237. https://doi.org/10.1016/j.im.2019.103237

Mikalef, P., Pappas, I. O., Krogstie, J., & Pavlou, P. A. (2020b). Big data and business analytics: A research agenda for realizing business value. *Information & Management, 57*(1), 103237. https://doi.org/10.1016/j.im.2019.103237

Modgil, S., Gupta, S., Sivarajah, U., & Bhushan, B. (2021). Big data-enabled large-scale group decision making for circular economy: An emerging market context. *Technological Forecasting and Social Change, 166*, 120607. https://doi.org/10.1016/j.techfore.2021.120607

Oliveira, R. D., Leitão, J., & Alves, H. (2020). Corporate Governance and Sustainability in HEIs. In E. Sengupta, P. Blessinger, & T. S. Yamin (Eds.), Innovations in Higher Education Teaching and Learning (pp. 177–191). Emerald Publishing Limited. https://doi.org/10.1108/S2055-364120200000022016

Phillips-Wren, G., & Hoskisson, A. (2015). An analytical journey towards big data. *Journal of Decision Systems, 24*(1), 87–102. https://doi.org/10.1080/12460125.2015.994333

Rahman, I. A., Memon, A. H., & Karim, A. T. A. (2013). Examining Factors Affecting Budget Overrun of Construction Projects Undertaken through Management Procurement Method Using PLS-sem Approach. *Procedia - Social and Behavioral Sciences, 107*, 120–128. https://doi.org/10.1016/j.sbspro.2013.12.407

Salehan, M., & Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems, 81*, 30–40. https://doi.org/10.1016/j.dss.2015.10.006

Schuberth, F., Hubona, G., Roemer, E., Zaza, S., Schamberger, T., Chuah, F., Cepeda-Carrión, G., & Henseler, J. (2023). The choice of structural equation modeling technique matters: A commentary on Dash and Paul (2021). Technological Forecasting and Social Change, *194*, 122665. https://doi.org/10.1016/j.techfore.2023.122665

Sena, V., Bhaumik, S., Sengupta, A., & Demirbag, M. (2019). Big Data and Performance: What Can Management Research Tell us? *British Journal of Management, 30*(2), 219–228. https://doi.org/10.1111/1467-8551.12362

Themistocleous, M., & Papadaki, M. (Eds.). (2020). Information Systems: 16th European, Mediterranean, and Middle Eastern Conference, EMCIS 2019, Dubai, United Arab Emirates, December 9–10, 2019, Proceedings (Vol. 381). Springer International Publishing. https://doi.org/10.1007/978-3-030-44322-1

Van Kollenburg, G. H., Van Es, J., Gerretzen, J., Lanters, H., Bouman, R., Koelewijn, W., Davies, A. N., Buydens, L. M. C., Van Manen, H.-J., & Jansen, J. J. (2020). Understanding chemical production processes by using PLS path model parameters as soft sensors. *Computers & Chemical Engineering, 139,* 106841. https://doi.org/10.1016/j.compchemeng.2020.106841

Viaene, S. (2013). Data Scientists Aren't Domain Experts. *IT Professional, 15*(6), 12–17. https://doi.org/10.1109/MITP.2013.93

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research, 261*(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Volberda, H. W., Khanagha, S., Baden-Fuller, C., Mihalache, O. R., & Birkinshaw, J. (2021). Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms. *Long Range Planning, 54*(5), 102110. https://doi.org/10.1016/j.lrp.2021.102110

Zhan, Y., & Tan, K. H. (2020). An analytic infrastructure for harvesting big data to enhance supply chain performance. *European Journal of Operational Research, 281*(3), 559–574. https://doi.org/10.1016/j.ejor.2018.09.018

Zhang, S., O'Connor, P., & Gardiner, E. (2023). Some rules should be broken: Developing a measure of constructive rule beliefs. *Personality and Individual Differences, 207,* 112145. https://doi.org/10.1016/j.paid.2023.112145