

WestminsterResearch

<http://www.westminster.ac.uk/westminsterresearch>

**Drivers of Big Data Analysis Adoption and Implications on
Management Decision-Making on Financial and Non- Financial
Performance: Evidence from Nigeria's Manufacturing and Service
Industries**

Egwuonwu, A., Mendy, J. and Oruh, S.E.

This is a copy of the author's accepted version of a paper subsequently to be published in IEEE Transactions on Engineering Management.

It will be available online at:

<https://doi.org/10.1109/TEM.2023.3321426>

© 2023 IEEE . Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

The WestminsterResearch online digital archive at the University of Westminster aims to make the research output of the University available to a wider audience. Copyright and Moral Rights remain with the authors and/or copyright owners.



Drivers of Big Data Analysis Adoption and Implications on Management Decision-Making on Financial and Non-Financial Performance: Evidence from Nigeria's Manufacturing and Service Industries.

Journal:	<i>Transactions on Engineering Management</i>
Manuscript ID	TEM-22-1502
Manuscript Type:	Special Section: Application of Big Data Analysis for Trend Spotting Related to the Development and Use of Human Capital
Keywords:	Data Analytics?, Competitiveness in Technology Management, Decision Making in Technology Management, Resource Management, Capacity management.
Subject Category:	Digital Technologies and Analytics, Integrating Technology for Capability and Productivity, People and Organizations, Information Technology

Drivers of Big Data Analysis Adoption and Implications on Management Decision-Making on Financial and Non-Financial Performance: Evidence from Nigeria's Manufacturing and Service Industries.

Abstract

Despite advances in 'Big Data' utility, its adoption by contemporary organizations is yet to move beyond early capture, especially in developing countries like Nigeria. This study empirically collected and analyzed survey data from 261 professionals across Nigeria's manufacturing and service industries in 2021. This study draws on business-to-business marketing context, dynamic capabilities theory, and Technology-Organization-Environment frameworks to examine the factors affecting organizations' BDA adoption and management's policy decision making and their impact on financial and non-financial performance of firms in dynamic environments. The findings address 7 hypotheses, namely 1 and 2 which support that the anticipated organizational value and technological competence positively influence management's BDA adoption. Interestingly, hypotheses 3 and 4 confirmed that top management support and organizational readiness positively impact BDA adoption. Hypotheses 5, 6 and 7 highlight environmental contextual factors such as competitive pressure, external support, and regulatory environment as critical and positive influences for management's BDA decision adoption. However, our results found that the paths between competitive pressure and regulatory environment to management's decision for BDA adoption were both insignificant. Furthermore, the results demonstrated that management's decision to develop policy on financial and non-financial performance was positively influenced by BDA adoption. The implication and limitations are discussed.

Keywords: Big data adoption, dynamic capabilities, management, technology-organization-environment, manufacturing and service industries, Nigeria

Introduction

While big data technology is quickly advancing [14], many organizations appear not to extend its utility beyond the adoption mode. Hence, there is a need for a more in-depth investigation into organizations' adoption of Big Data Analytics (BDA) and its-associated impacts on management decision and performance opportunities, which is the focus of this study. The development of digitalized business operations has notably increased the volume, variety, and velocity of structured and unstructured information mechanisms, generally known as "Big Data" [15]. Businesses are attempting to increase the effectiveness of such data acquisition not just for themselves, but for partners and third parties. Whilst [39] observed that organizational usage of big data can successfully turn information into insights and intelligence and [115] highlighted how big data inheres to new techniques capabilities that could revolutionize business strategies and marketing, product and service development, human resources (HR), operations, and other essential processes [22], an evidence-based approach from a developing country context of such benefits has not been previously attempted.

BDA is defined as examining extensive data utilizing modern technology to reveal important information, which can aid more informed and better business decision-making [85]. Notwithstanding the success and popularity of big data, a recent industrial survey shows that most businesses have yet to capitalize on its benefits [88]. The possible explanations are that many organizations are yet to fully understand its benefits, the needed information technology (IT) and analytical capabilities and what the complexity of factorial threats are [45]. For [87], many organizations' management and leadership are struggling to understand the factors driving such big data adoption [87]. Thus, we focus on the fundamental drivers for which organizations' management decide on whether to adopt BDA and how this could impact on performance.

While previous studies database adoption [29;42], focused on individual-level adoption behaviours, research at the organizational level (of big data implementations) remains relatively scarce and needs further examination [112;139;27]. Those few studies focusing on the organizational-level, centre on adoption readiness [115;114] instead of how these impact on post adoption behaviours (i.e., usage and benefits) [144;23] to ascertain what the BDA drivers informing management decision-making are. Whilst previously studies on BDA application have

popularized the functional areas of organizational operation - including business intelligence, customer relationship management, and marketing [74], the accompanying management capabilities needed for its' adoption in developing economies is sorely missing. To address the afore gaps, this paper focuses on the following research questions below:

What are the drivers affecting management's adoption of BDA adoption and the impacts on financial and non-financial performance?

We analyze survey data from 261 management respondents from Nigeria's manufacturing and service sectors to address the key research question and the hypotheses. In doing so, we first draw on the context of business-to-business (B2B) marketing, which is a highly significant domain to examine issues related to performance, learning and development [115]. Moreover, in today's digital society, IT, and mainly BDA, play critical roles in information flows and learning [56;129]. Secondly, we use the dynamic capabilities theory of [35] to argue that BDA applications in B2B marketing situations provide substantial dynamic information processing power, which offers management the requisite knowledge to create better resource configurations and reconfigurations for competitive advantages [116;119]. We also employ the Technology-Organization-Environment (TOE) framework of [124] to examine the factors that could affect management's decision to adopt BDA because it is a holistic, robust, and flexible framework when used at the organizational level [8]. Such a TOE framework covers almost all essential aspects of an organization's internal (technology and organization) and external (environment) developmental aspects and is supported for doing so previously [57;89]. Finally, we examine the impact of management decision to adopt BDA on financial and non-financial performance as moderated by the environmental factors.

The remainder of this paper is structured as follows: the following section will explore the process and drivers of BDA and the associated financial and non-financial implications, which will follow the theoretical framework of the study and its methodology. Findings, discussion and implications are then presented and discussed.

Understanding Big Data: BDA

Although there is no universal definition of big data, it has benefited from a variety of definitional ways. For this study, we opted to draw our working definition from IT adoption literature, which defines it as high-volume (big scale), high-velocity (moving/ streaming), and high-variety (e.g., numerical, text, video, etc.) information assets that necessitate cost-effective, creative information processing for improved insight and decision-making [41]. Its significance has been shown in applying more sophisticated analytical approaches to vast data sets [23] to enable advanced analysis for organizations to automate extremely complicated choices that were previously (primarily or exclusively) based on human judgement and intuition [37;41]. However, research shows that organizations are still hesitant to adopt BDA as previous initiatives involving business intelligence gathering (often from terabytes of data) have failed [110]. Whilst firms may wonder if BDA is merely a repackaged version of old business intelligence and data mining, the extent to which it facilitates new management capabilities regarding their decision making for competitive advantages is limited [23].

To address this issue, there are distinctions between big data analytics and traditional business intelligence technologies. According to a June 2011 International Data Corporation (IDC) research, the amount of globally available data has increased by more than 50% each year since 2005, and it is predicted to approach 8,000 exabytes by 2015. (International Data Corporation Report, 2011). Unstructured data, such as online material, news feeds, social media postings, video clips, and other data that cannot be easily categorized into repeating fields, are driving this development. Big data is, therefore, an umbrella phrase for collections of data sets that are so large and complicated that they are challenging to gather, analyze, and manage promptly utilizing available data management tools and standard data processing programmes [109]. Thus, big data analytics is often seen as a dramatic departure from typical business intelligence tools [41].

Whilst big data and analytics connote various meanings to different people (Watson, 2011) and has been used in e-commerce, market intelligence, e-government, health care, and security [22], its potential for businesses has driven major improvements in BDA technologies in understanding business markets and which management choices to make [23]. However, what constitutes BDA varies for many organizations

depending on the capabilities and the applications used [23;114;74]. Therefore, we see BDA adoption as a crucial resource capacity that businesses could use to provide management with innovative understanding in dynamic environments similar to Nigeria's [43]. This warrants the use of dynamic capacities theory as a valuable lens to study BDA and show its impacts [62].

Dynamic capabilities

One of the most important management perspectives of the last decade is "dynamic capabilities" [105], which explains how a company can maintain competitive advantages in ever-changing environments [94;119;62]. Inspired by "Schumpeterian's gale of creative destruction," [119, 1997, p. 12], dynamic capabilities help businesses adapt to ever-evolving market demands by integrating, creating, and reconfiguring their resources [119] through a collection of "identified and specified procedures" [35, 2000, p. 47]. Prior research has looked at how IT-based technology to build the internal capacities to enhance operational procedures [81;82;91;133].

BDA Adoption as a Resource Dynamic Capability

Researchers have used the term "dynamic capabilities" regarding how businesses adapt to the unpredictable situations and the internal and external competencies needed [35;116;119]. The capabilities are perceived as a set of distinctive internal procedures like integrating, reconfiguring, acquiring, and releasing resources [119;62] and these facilitate organizational, strategic resource configurations when markets form, collide, divide, change or even expire [23]. Based on these, we define BDA adoption and implementation inside organizations as the development of nimble capacities to help businesses establish routines and capacities [35;62] for knowledge generation usable in highly dynamic markets [116]. BDA may also be perceived as an internal, organizational information processing capability (Galbraith, 1973), which decreases uncertainty by increasing the generation of new insights and organizational knowledge for management's strategic decision making [116;119]. Although there have emerged "best-practices" studies on generic BDA applications [22;23], this does not guarantee uniform usage of BDA tools

across businesses and contexts [23], enterprise-level technology [116] and the way management use marketing information (such as social media marketing, e-commerce, customer relationship management, innovation, customer services, etc.) [23;119]. Consequently, perceiving and examining management's BDA adoption as a dynamic capability makes sense, and it is therefore conceptualized here in terms of how its adoption serves as a boost for management's capability development in enhancing organizational (financial) value creation.

Theoretical Framework and Hypotheses Development

This study's theoretical framework focuses on Dynamic Capabilities [9] to examine how specific businesses' unique pasts [119] create competitiveness [116]. The idea of route dependence implies that the factors that shape an organization's capacities vary [35] depending on setting/context [119] and contextual forces: technical and external fitness [48]. In line with these, we use the technological, organizational, and environmental (TOE) framework [126;1] from the IT management literature to pinpoint the specific factors explaining why management are more likely to adopt BDA within a marketing domain than others. The TOE framework proposes technical, organizational, and environmental aspects that determine why BDA may be implemented in a business [8]. Our conceptual model for management's BDA adoption is grounded on dynamic capabilities and the TOE framework for deeper understanding of the variables that encourage or discourage BDA [1] (see Fig. 1). Our theoretical framework is developed from measurable hypotheses that are applicable to assess the impact of management's BDA adoption and their financial and non-financial performance implications. Based on research, we examine the various technological (anticipated value and technology compatibility), organizational (top management support and organizational readiness), and environmental (competitive pressure, external support from vendors, and government regulation) factors that influence management's BDA adoption. We also investigated the moderating effects of environmental dynamism on the relationship between financial and non-financial performance, two essential components of the business value provided by BDA adoption in marketing contexts. The justifications for the selection of the hypotheses are provided below.

Technological factors

Anticipated value: Anticipated value is a term used to indicate the advantages expected operationally and strategically when companies adopt new technology [128]. Direct advantages include lower operating costs and improved internal efficiency arising from less data re-entry, lower mistake rates [79] and novel products and services and individualized customer care [18]. Similarly, indirect advantages especially in marketing environments [14], include enhanced customer service, process reengineering [24;122] and increased collaboration and information exchange within organizations [128].

[Insert Figure 1, Conceptual Model about here]

Assuming the management of a focused firm has a high opinion of the usefulness of BDA, they should proceed to adopt full usage of BDA to meet their requirements [23]. Hence, we hypothesize the following:

Hypothesis 1: Anticipated value positively influences management's BDA adoption.

Technological competence: According to [124], the ability to use contemporary technologies effectively is a well sought after reason for adopting innovations, whose compatibility with a firm highlights “the degree to which the innovation is perceived as consistent with the existing values, past experiences [path dependence], and needs of the potential adopter” [97, 1983, p. 223;35;119]. Applying this definitional construct within an organization, suggests “compatibility of an innovation may refer to its congruence with (1) the value systems (e.g., culture), and (2) the business practices of an organization” [23, p. 17]. As outlined by [119], and validated in recent studies [52], both cognitive and operational compatibility, have been shown to be positively associated with the acceptance and implementation of innovations although differentiating such a distinction is sometimes contextually problematic [128].

As a result, we propose that business decision-makers will be more inclined to include BDA in their marketing if it is consistent with company's values (which, in turn, are a reflection of its history) and standard operating procedures. Thus, we hypothesize:

Hypothesis 2: Technological compatibility positively influences management's BDA adoption.

Organizational factors

Top management support: Top management support is the extent to which upper-level management supports modern IT-based systems (e.g., BDA) and recognizes that the variability of capabilities of these systems and the data they create are key indicators of success [103]. Empirical research suggests that when senior managers have optimistic expectations of IT system's potential benefits, they are more likely to adopt it [67]. Through management support (e.g., advocating and campaigning for the IT-based adoption within the organization), this functions as a driver for changes in organizational norms, values, and cultures, allowing others to adopt and adapt new technologies [53;55;69] and develop network-based adoptions within organizations [6;20;67]. Thus, we hypothesize that:

Hypothesis 3: Top management support positively influences management's BDA adoption.

Organizational readiness: Organizational readiness reflects firm-level capacity and propensity to embrace technological change [37]. It is a measure of the company's technical IT capacity and experience, showing ability to manage and invest in new technology [118;138]. Field commentators on big data business analytics contend that an organization's readiness is key for BDA adoption and implementation [37;98]. According to [7] and [40], in the marketing field, organizational readiness has a strong and favourable association for such adoption. Thus, we hypothesize that:

Hypothesis 4: Organizational readiness positively influences management's BDA adoption.

Environmental factors

Competitive pressures: The term "competitive pressure" describes the environmental threat posed by a company's rivals in the same market [83], which may force them to embrace new technology to gain advantage [86]. According to [86], similarly, rival firms can think about using big data tactics to win over customers in a competitive market by incorporating cutting-edge technological advancements [144]. Organizations in the same sector are under increasing pressure to mimic the practices of market leaders for market advantage during volatility [69]. According to [2], the fear of being seen as unique compared to competitors within the same sector may be a motivating factor in adopting newer technologies, thereby acting as a driving force [86;97]. When there is a lot of rivalry in an industry, it may slow down new business starts and the spread of innovative technologies. Thus, we hypothesize that:

Hypothesis 5: Competitive pressure positively influences management's BDA adoption.

External support: External support is defined as extended support from a vendor or third party to encourage enterprises to innovate and implement a new strategy [12;37]. It is a critical driver of innovation adoption and success [40;101]. Access to vendor support is crucial for management's BDA adoption since it enables learning from suppliers and open-source platforms, thereby expanding management's innovative capacity [37]. As [23] noted, outsourcing from external parties and suppliers works effectively for an organization's marketing division, especially in new start-ups lacking technical expertise. Thus, we hypothesize that:

Hypothesis 6: External support positively influences management's BDA adoption.

Regulatory environment: A favourable regulatory environment is one whereby a government promotes enterprises utilizing big data technologies by providing a suitable infrastructure, legal framework, regulatory directives, and assistance [144]. For instance, with government support, legal steps can be taken to address people's worries about information leakage and illegal data trading, which can make it more difficult for big data adoption [58;135]. Thus, we hypothesize:

Hypothesis 7: Regulatory environment positively influences BDA adoption

BDA adoption and financial and non-financial performance

Empirical research shows that the benefits of management's BDA adoption substantially affects financial and non-financial performance [4;46;131]. With the use of BDA techniques, organizations may boost their sales and revenue by increasing their ROI [4] or facilitate the completion of e-commerce purchasing [51]. [48] argued that businesses would benefit financially from adopting BDA solutions whilst [97] highlighted that BDA adoption has a positive relationship with a firm's financial performance even under high levels of market turbulence and environmental changes.

Although BDA adoption investment might be pricey, it increases business productivity [80]. [84], [83], and [65] and has been found to have beneficial impacts on innovative capabilities that boost financial performance [101;97;131]. [136] studies have all revealed that BDA's predictive capabilities allow firms to provide business models that increase profits. [131] found a positive effect of BDA on essential determinants of financial performance, including market performance, organizational performance and operational performance [10;51]. [137] went further by saying that BDA tends to improve a firm's financial performance rather than market performance. The current study posits that organizations' management that adopt BDA will gain higher levels of both financial and non-financial performance. Thus, we hypothesize as follows:

Hypothesis 8: Management's BDA adoption positively influences firm financial performance.

Hypothesis 9: Management's BDA adoption positively influences firm's non-financial performance

The Moderating Role of Environmental Dynamism

To ascertain whether other (external) factors influence management's decision to adopt BDA, we examine environmental dynamism, which is described as the unpredictability of external environmental changes [142;35], view it as a fundamental situational component in dynamic

capabilities theory, indicating that the variance of competitive advantage provided by an organizational capability is dependent on environmental dynamism. Some earlier studies argued that the effects of dynamic capabilities in a volatile market are uncertain [77:79]. In a moderately dynamic market, according to [35], organizations often proceed along linear and predictable paths (with these markets characterized by stable industry structures with defined market boundaries) thereby warranting dependence on usage of prior information [79]. On the other hand, high-velocity markets are characterized by non-linear, less predictable and volatile industry structures and developments [76].

Although some academics have expressed concerns about the unexpected nature of environmental dynamism on organizational outcomes [3;79], we argue that such an environment presents more opportunities for organizations to benefit from management's decision to adopt BDA. [3] study uncovered that a volatile external environment may either boost or degrade a firm's most valuable skills especially in high-velocity markets, see [77;46]. Existing research supports the hypothesis that information sharing might lead to increased variation in financial performance results in dynamic circumstances [72]. Environmental dynamism adds enormous pressure on organizations to use organizational knowledge to drive their actions [31;54;113] as key organizational decision-makers (management) must analyze events quickly and act effectively [17]. However, market volatility might increase management stress and cognitive demands, potentially hindering their ability to make sense of events and execute critical ideas [17]. This undermines management confidence and their strategic decision-making capability on how to improve organizations' financial and non-financial performance [19]. Thus, when faced with such an environment, the necessity for BDA becomes critical for corporate decision-makers (management). Additionally, in volatile markets, dynamic capabilities depend less on existing information and much more on swift innovation and situation-specific new knowledge [35;119].

Given that BDA is supposed to enhance an organization's potential of finding new knowledge and insight, the following explanation shows that its value is most prominent in highly dynamic contexts [22]. This is especially important in marketing, as enormous volumes of data are routinely gathered from many departments and locations across an organization (e.g., advertising, social media marketing, content marketing etc. – [35]. Such data have to be processed, integrated, analyzed and understood holistically so that management could make strategic choices

more effectively in a highly dynamic market [72]. With BDA, insights may be generated rapidly and efficiently across all core marketing operations, which can lead to significant savings or revenue development. Research has shown that managers' confidence increases in high-velocity markets when they gain new information and insights since this boosts their ability to deal with the psychological challenges of uncertainty [46], allowing them to swiftly recognize and respond to changing situations [72]. Thus, we hypothesize the following:

Hypothesis 10a: Environmental dynamism positively moderates the impact of management's BDA adoption on organizations' financial performance.

Hypothesis 10b: Environmental dynamism positively moderates the impact of management's BDA adoption on organizations' non-financial performance.

Methodology

The methodical predilection covers the various harmonized techniques in conducting a research study [104]. Hence, the method, sample frame, and preliminary analysis are presented in this section.

Method and sample frame

This study is underpinned by a positivist research philosophy, which is based on a scientific and structured approach using quantitative data. Thus, the research adopts a survey methodology, often referred to as a primary but critical data-gathering method, which can help to provide a broader and generalized insight into a research inquiry using a relatively massive number of participants [104]. Before (survey) data collection, the survey questions were pilot tested (across the manufacturing and service sectors in Nigeria), with 10 management experts in August 2021. Pilot studies enhance survey quality by offering input from a variety of viewpoints to prevent any problems that may develop during the real data-gathering process [104]. As [104] intimate, the construct questions were deemed appropriate for inclusion in the final survey after undergoing several proposed modifications based on the pilot study's results and respondents' comments (see construct items and their symbols in Appendix A).

Approximately 870 randomly chosen Nigerian management professionals from various organizations received the final survey between September and November of 2021. This respondent sample was chosen as the most knowledgeable about big data in the firms, given that not all organizations employ big data specialists. The survey was sent both in paper and electronic forms. The hard copies were distributed directly to the professionals in different organizations for completion. The soft copies were designed using Google Forms and distributed by sending invitations, including a link to the Google Form via LinkedIn and WhatsApp. A total of 286 responses were received, representing a 32.8% response rate. [38] stated that the appropriate minimum sample size for structural equation modelling in management information systems research is about 200 participants when developing moderately complex models. Moreover, a sample size of 200 gives an acceptable error rate of less than 10% within the available time, effort, and resources [47]. Accordingly, an acceptable sample size of more than 200 was chosen, and the final sample size was 261 usable management responses.

Of the 261 respondents, 55.9% were CEO/manager-owners, and 44% were senior managers. Their firms were mainly food and beverages 21%, online and offline retailers 12.6%, internet service providers 17.2%, and machinery and equipment, among others, made up the remaining percentage (see Table 1 for the demographic profile of the study's participants).

Table 1

Demographic profile (n – 261)

[Insert table 1 about here]

Preliminary analysis

Prior to data analyzing, we performed a preliminary analysis of the dataset, comprising a missing data analysis, a non-response bias check, and a common method bias check. We evaluated our data set to see whether it satisfied the assumption of missing data at random using

Little's MCAR test (MCAR). The findings showed that the missing data occurred completely randomly ($2(1012) = 1017.114$, $p = .564$). We substituted the missing data with a simple mean even though the missing data was little and unpredictable [71;74].

Using t-tests, non-response bias was investigated by comparing early and late responders in terms of annual revenues, big data experience, and the number of employees [71]. According to the findings, there were no statistically significant differences between these groups. As a result, we concluded that non-response bias did not constitute concern for this research.

Because the independent and dependent variables were from the same source and self-reported by the respondents [93], common method bias might be a threat to this study. We thus examined this bias by using two seminal methods. First, following the guidelines by [93], we protected respondent-researcher anonymity, provided clear directions, used other variables and items not relevant to this study, and proximally separated independent and dependent variables both at the design and data collection stages [93]. We then used the statistics to test for bias. Harman's one-factor test [44] was used to examine if common method bias threatened the validity of our findings. The unrotated factor solution revealed that no component accounted for 50% or more of the variation. We repeated [70] test, which employed a marker-variable approach in the model by introducing an irrelevant marker variable to corroborate these results. The largest shared variance with other variables was 0.035 (3.5%), suggesting that there was no common method bias in this study, implying that any common method bias that may have occurred did not pose a substantial danger to its validity.

Measurement

We adapted previously validated survey measurement items to collect data (see Appendix A for sources). Following the arguments from previous studies [32;107;108], this study utilized a seven-point Likert scale with anchors ranging from 1 (strongly disagree) to 7 (strongly agree) except for financial and non-financial performance. The two performance constructs were measured using a seven-point Likert-type scale ranging from 1 ('worse than major competitors') to 7 ('much worse than major competitors').

Management's BDA adoption was conceptualized as a second-order construct, and it relates to the four business values (strategic value, transactional value, transformational value, and informational value) for organizations. The items in this section were adapted from [97], where strategic value refers to the degree to which the organization perceives strategic advantages, and transactional value refers to the degree to which the user feels that BDA offers operational benefits. Transformational value, on the other hand, relates to the degree of perceived changes in a firm's structure and capabilities as a future consequence, whilst informational value refers to the degree to which the user of BDA solutions benefits from improved knowledge [97].

We leveraged 'Technology-Organization-Environment' (TOE) constructs, which comprise technological, organizational, and environmental factors. The technological factors are anticipated value and technological competency. The items for anticipated value were adapted from [24;50;124;122], respectively, while technological competence was adapted from [124;128] respectively. On the other hand, two organizational factors, namely top management support and organizational readiness, were included in this study to ascertain their influence on management decision making. The measurements of these items were adapted from [23;64,95]. The environmental factors consist of competitive pressure, external support, and government regulation. The items were adapted [40;46;64].

The study also includes the dimensions of financial and non-financial performance to measure management respondents' perception of the effect of BDA adoption on financial and non-financial performance improvement. The measures of these two constructs originated from [96;101]. All items of this study and their sources are shown in Appendix A.

Data analysis of results

Structural equation model (SEM) was considered more appropriate for our research than other analytic approaches such as linear regression due to the benefits derived by investigating the hypothesized causal paths among the constructs [38]. The IBM Amos 22 software package was used to evaluate the data.

Descriptive statistics, reliability, and validity

The means, standard deviations, Cronbach's alphas, composite CR, AVEs, and construct correlations are shown in Table 2. The range of Cronbach's alphas between 0.868 and 0.925 indicates solid internal consistency [13]. Construct reliability was evaluated based on composite construct reliabilities (CR) computed using the formula: $p = (\sum \lambda_i)^2 / ((\sum \lambda_i)^2 + \sum \theta_i)$, where λ_i refers to the i th factor loading and θ_i refers to the i th error variance [47, p. 687]. As shown in Table 2, the CRs range from 0.844 and 0.925, with all being greater than the commonly accepted cut-off value of 0.70 [38], thereby demonstrating reliability.

Table 2: Descriptive statistics, correlations, Cronbach's alpha, and the square root of the AVE

[Insert table 2 about here]

Table 2 presents the inter-construct correlation matrix. To evaluate discriminant validity, the square root of the average variance extracted (AVE) for each construct (on the diagonal) is compared to the inter-construct correlation. When the square root of the AVE is greater than the equivalent inter-construct correlation estimates, this indicates that the indicators have more in common with the concept they are related with than with other constructs, providing evidence of discriminant validity [47]. As each square root of the average variance extracted (AVE) is greater than the corresponding inter-construct correlations, we can assume that the measures' divergent validity is acceptable based on the data.

To evaluate construct validity, an exploratory component analysis with varimax rotation was performed on all constructions, and the factor loadings for each construct are provided in Appendix A. All items are loaded on a separate construct, and their factor loadings are all more than 0.5, indicating high convergent validity. These findings demonstrate discriminant validity by confirming the presence of eight observed constructs with eigenvalues greater than 1.0.

Structural model assessment

The goodness-of-fit of the structural model was examined, and the R² value for BDA adoption is 0.787. The model chi-square is statistically significant ($\chi^2(511) = 989.673$, $p < .001$), indicating that the exact fit hypothesis is rejected. The value of χ^2/df is 2.079, which indicates a good model fit. However, as this test is highly sensitive [100], we also examined other measures of goodness-of-fit by using a combination of one of the relative fit indexes and root mean square error of approximation (RMSEA) [49]. This revealed a comparative fit index (CFI) of 0.902 and an incremental fit index (IFI) of 0.903, with both exceeding the cut-off value of 0.80 (Byrne, 2001). The RMSEA is 0.060 [16], further indicating that our data adequately fit the measurement model. Variance inflation factors (VIFs) for the independent variables were also checked for evidence of multicollinearity concern [92]. The results ranged from 1.299 to 2.218. None of the VIF exceeds 5, indicating that multicollinearity is not an issue in our study.

Table 3: Structural equation modelling results

[Insert modelling result table about here]

Hypotheses testing (direct effects)

The first two hypotheses state that the elements of technology context, namely anticipated value and technological competence, will all positively influence BDA adoption. As shown in Table 3, the paths from anticipated value ($\beta = 0.172$, $p = .003$) and technological competence ($\beta = 0.374$, $p < .005$) to management's BDA adoption are all significant. Thus, our results support these hypotheses. Hypotheses 3 and 4, state that top management support, organizational readiness will positively influence BDA adoption. As demonstrated below, the path from top management support to BDA adoption is significant ($\beta = 0.406$, $p < .000$), and the path from organizational skills to BDA adoption are also significant ($\beta = 0.342$, $p < .005$). Thus, hypotheses 3 and 4 were supported. Hypotheses 5, 6 and 7 state that in the environmental context factors

such as competitive pressure, external support, and regulatory environment all positively influence BDA adoption. Although our results found support for external support ($\beta = 0.271$, $p = .002$), the paths between competitive pressure ($\beta = 0.172$, $p = .213$), and regulatory environment ($\beta = 0.005$, $p = .783$) to BDA adoption were both not significant. Hence, the findings support hypotheses 6, but not hypotheses 5 and 7. Furthermore, the results demonstrated that financial performance ($\beta = 0.096$, $p = .031$) and non-financial performance ($\beta = 0.095$, $\beta = 0.018$) were positively influenced by management's BDA adoption.

Test of moderation (indirect effects)

In addition to the direct relationship of our model, we examined two moderating effects: H10a and H10b, respectively, and posit that environmental dynamism positively moderates the degree to which management's decision to use BDA influences financial and non-financial performance. Testing moderating effects involves a comparison of a main effect model with a moderating effect model, we conducted our analyses by creating interaction variables directly within the CB-SEM. Interaction terms were computed using the standardized scores, thus limiting potential multicollinearity between the main and interaction variables. In each of the interaction models, the interaction terms are significant with the addition of each of the interaction variables. We observe that, as hypothesized, the path coefficient for H10a is positive (0.312, significant at 0.003). However, the moderation effect of H10b was not statistically significant with a path coefficient of -0.122 (significant at 0.415). Concentrating on the significant path, our findings imply that when management use BDA it has a stronger influence on the organization's financial performance especially in a dynamic environment. See Table 3 for a summary of the moderation test results.

Discussion

In this section, we address the research question addressed in this study: *'What are the drivers affecting management's adoption of BDA adoption and the impacts on financial and non-financial performance?'* To address the research question, the TOE framework was employed to examine the

impact of technological, organizational, and environmental factors on BDA adoption in organizations. The technological factor (anticipated value and technological competence), organizational factors (top management support and organizational readiness), and most of the environmental factors (competitive pressure, external support, and regulatory environment) were found to have a significant positive influence on organizational BDA adoption. However, the impacts of one environmental factor (external support) BDA adoption were not supported by the findings of this study. We also examined the influence of organizational BDA adoption on their financial and non-financial performance. The findings of this study supported these relationships. Moreover, we tested the moderating effect of environmental dynamism on the relationship between BDA adoption on both financial and non-financial performance. Our result found support for the moderating effect between environmental dynamism and financial performance. However, the path between environmental dynamism and financial performance and non-financial performance was not supported.

These findings are discussed further in the following sub-sections, which reflect on previous studies to highlight the study's contributions.

Technological factor

Our data analysis results show that both technological components in our model (anticipated value and technology compatibility) directly influence BDA adoption. Our hypothesis is supported by these results, which are also usually in line with the TOE framework. Moreover, these results provide new insight into how the BDA's implementation might ultimately pay dividends. In particular, we find that it is not the technical components themselves but rather the actual use of the technologies (BDA) that has a significant effect on the performance of an organization. The ultimate impact of big data on organizational outcomes is mediated by BDA adoption. As a result, the TOE variables are required antecedents to promote BDA adoption, which will eventually be the crucial component that contributes to enhanced business performance.

Organizational factors

Both organizational factors (top management support and organizational readiness) were shown to have an impact on BDA adoption. Top management support is commonly identified as a significant factor in organizations' adoption of various forms of technology, such as ICT, cloud computing, e-commerce, CRM, and ERP [5;7;28;40]. The major decision-makers in organizations are the owners/managers, and their vision impacts the extent of support for BDA implementation. Top management support is critical for establishing a favourable environment for enterprises to embrace new technology (7;106). Top-level management drives organizational transformation by conveying and fostering values via a clear vision for the company [28]. Top-level management assistance may help speed up learning and spreading technology across the organization [7]. As such, they play an important role in the various phases of BDA adoption.

The significant relationship between organizational readiness and BDA adoption is consistent with past technology adoption studies [37;28;58;64]. Without enough technical, financial, and qualified human resources, organizations find it difficult to implement BDA. An organization is unlikely to implement BDA if it has the necessary resources and competencies. Outsourcing BDA requires financial and early technology resources, and qualified people are critical in the implementation stage [37].

Environmental factors

Among the three environmental factors (competitive pressure, external support, and government regulation), only external support plays a substantial role in BDA adoption among organizations. The insignificant impact of competitive pressure contradicts the results of [40]. A lack of multi-national rivals and low levels of BDA among local competitors in the Nigerian market are plausible factors for the minimal influence of competitive pressure in Nigeria. Nigerian institutions, for example, are less impacted by globalization than their counterparts in other countries because of sanctions that have prevented major investments by international corporations in the Nigerian market (Nwanga et al., 2022). Competitive pressure is reduced since local businesses are slow to embrace BDA. Consequently, this consideration is negligible when business owners and managers decide whether to implement BDA [23].

The predicted significant relationship between external support and organizational BDA adoption is consistent with the results of [40;37]. According to [40], if a firm's CEOs understand that an Information System (IS) service provider can meet their IS adoption requirements, they are more likely to adopt it. Training and technical assistance provided by BDA service providers may alleviate managers' concerns over the lack of technical skills required for BDA implementation. Organizations grappling with a shortage of knowledge rely heavily on external assistance for decision-making.

In contrast to the results of [64] and [40], the findings of this research demonstrate that government regulations do not influence organization BDA adoption. A possible explanation for the insignificance of this correlation is that organizations see BDA adoption as a substantial investment and that government incentives are inadequate to justify the expenditure. Moreover, the rapid changes in government regulations in Nigeria negatively impact the degree to which managers' actions depend on government regulations, particularly in the case of BDA. The impact of government regulations on organizations' decisions to invest in BDA in Nigeria is insignificant [].

The findings demonstrated that BDA adoption significantly impacts organizations' financial and non-financial performance. [77;82;97] have shown that BDA adoption produces commercial value for enterprises and enhances their capabilities. According to [83], BDA favours enterprises' marketing success because it helps them create goods and services that provide clients with higher value and separate them from rivals. [101 and [97] both claimed that BDA might boost enterprises' capacity to raise sales profitability and acquire and retain consumers. BDA helps organizations to see their surroundings through the lens of data, resulting in increased competitive advantage, a well-perceived brand image, and a positive reputation [91].

Finally, we examined the moderating effects of environmental dynamism on the relationship between management's BDA adoption and financial and non-financial performance. Based on our data, we discovered that management's BDA adoption, which the literature has affirmed as a critical organizational information processing skill, has a beneficial influence on organizational level financial and non-financial performance. Although these results support the existing literature [132;18] as information processing is confirmed as a dynamic competence that provides

organizations with a competitive benefit [35], we added the moderating effects of environmental dynamism to examine the interaction between management's decision to adopt BDA and what impacts it had on both financial and non-financial performance. Our findings indicate that environmental dynamism moderates the relationship between management's BDA adoption and financial success. However, our data's findings highlighted that the moderating influence of environmental dynamism on the relationship between management's choice to adopt BDA and their organizations' non-financial performance was not significant.

Contributions, Implications, limitations, and future research direction

This research is unique – given that it is one of fewest studies to employ a large-scale field questionnaire to produce an integrated conceptual model that examines the factors influencing management's decision to adopt BDA and the effects of its utilization within marketing environments of Nigeria. The findings extend the existing body of research on organizational IT-based adoption of BDA by highlighting the evidence on which management make operational and strategic organizational choices.. The research framework is widely transferable and generalizable to future studies on the value and knowledge creation of how enterprises at the managerial, organizational-level develop competences via dynamic capabilities theory and the TOE framework. We posit that management's decision to apply BDA as a dynamic organizational information processing tool accords them the capability to affect critical, strategic organizational performance outcomes [119]. Our study also extends the TOE framework [8;1] by discovering a range of anticipated value, technological competence, top management support, organizational readiness, and external support which all directly impact management's BDA adoption choice. Future research should investigate the impact of firm-level use of BDA (or other knowledge systems) on other dimensions of organizational performance.

Our results contradict earlier research that found competitive pressure and government regulation to be key drivers of management's BDA adoption [37;40;64] as there were no significant testable associations between these concepts. Despite earlier studies' concerns, our research shows that management's choice to adopt big data significantly impacts organizational level financial and non-financial performance thereby

[80]. [131], management's values-based choices in adopting BDA. Moreover, the way we integrated dynamic capabilities theory with the TOE framework establishes an earlier missing theoretical connection between the major drivers/antecedents of management's BDA adoption and requisite organizational outcomes of such choices. Future research can include other complimentary theoretical viewpoints into our framework .

The outcomes of this research also have significant management practice implications. First, we have shown evidence of how management's BDA adoption has a direct impact on the financial and non-financial performance of an organization although previous research has only hinted at the potential benefits of big data analytics [62]. As many businesses are still hesitant to make such commitments, we extend [119] potential return on investment by deepening understanding of how to do so efficiently. Our results should serve as "proof of concept" that using BDA practices could benefit management's decision-making capability and organizational success. Our research also helps managers better understand how to weigh the risks associated with external variables like volatility in their decision-making about resource identification, prioritization and allocation. Therefore, decision-makers in organizations need to realize that the extent to which BDA adoption influences specific organizational outcomes should be done by critically understanding their organization's setting. Additionally, the present research reveals the significant managerial levers to do so. Therefore, our study dispels earlier myths that labelled businesses as 'big data laggards' because of management's lack of understanding of which choices optimize business success [62].

Although a combination of organizational, environmental, and technological factors could impact on management's choices regarding BDA adoption, our study found that management decision to implement BDA in Nigeria is primarily organizational and environmental rather than technological (Esomonu et al., 2020). We highlighted how top management and external support are two of the most important elements influencing management's BDA strategic adoption decisions (Ihechu and Ugwuoji 2017). We add that top management should enhance BDA adoption by ensuring the necessary financial and technical support, hiring employees with the requisite skills and capabilities and offering the

relevant training to maximize success [28]. The government should develop initiatives to enhance management's support and optimization capacity.

While this study has demonstrated significant strengths, we also acknowledge numerous possible limitations. First, the theories we used are based on causal concepts to characterize the interactions in the study's model. Second, the cross-sectional research approach we used does not entirely allow for definite findings of correlation. Longitudinal research could be conducted in future to give more evidence for causal interactions. A longitudinal study might give more insight into the varying nature of how management's BDA adoption affects not only organizational performance but other aspects such as cultural nuances and staff's potential resistance to BDA adoption. Longitudinal research would also give a more detailed knowledge of how the TOE variables could impact on the various interacting internal and external factors impacting on the process and outcomes of managerial decision-making potentials. Third, the research concentrated on Nigeria, a developing country with little infrastructural and institutional development. Nigeria's weak infrastructures and institutions have a substantial influence on the competitive character of the markets in which the selected organizations were located and the government's ability to encourage enterprises' and their management's adoption of BDA. More research is needed to put the conceptual framework to the test in both developing and developed nations beyond marketing contexts. Furthermore, future research might benefit from the study's conceptual framework by examining other elements including organizational and individual culture, market pressure, and technological infrastructures [14;32].

References:

1. Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. *International Journal of Information Management*, 34(5), 639–651.
<https://doi.org/10.1016/j.ijinfomgt.2014.05.002>
2. Abrahamson, E., & Rosenkopf, L. (1993). INSTITUTIONAL AND COMPETITIVE BANDWAGONS: USING MATHEMATICAL MODELING AS A TOOL TO EXPLORE INNOVATION DIFFUSION. *Academy of Management Review*, 18(3), 487–517.
<https://doi.org/10.5465/amr.1993.9309035148>
3. Afuah, A. (2001). DYNAMIC BOUNDARIES OF THE FIRM: ARE FIRMS BETTER OFF BEING VERTICALLY INTEGRATED IN THE FACE OF A TECHNOLOGICAL CHANGE? *Academy of Management Journal*, 44(6), 1211–1228. <https://doi.org/10.2307/3069397>
4. Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). 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>
5. Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the north east of England. *Journal of Enterprise Information Management*, 26(3), 250–275. <https://doi.org/10.1108/17410391311325225>
6. Armstrong, C. P., & Sambamurthy, V. (1999). Information Technology Assimilation in Firms: The Influence of Senior Leadership and IT Infrastructures. *Information Systems Research*, 10(4), 304–327. <https://doi.org/10.1287/isre.10.4.304>

7. Asiaei, A., & Ab. Rahim, N. Z. (2019). A multifaceted framework for adoption of cloud computing in Malaysian SMEs. *Journal of Science and Technology Policy Management*, 10(3), 708–750. <https://doi.org/10.1108/jstpm-05-2018-0053>
8. Baker, J. (2011). The Technology–Organization–Environment Framework. *Information Systems Theory*, 231–245. https://doi.org/10.1007/978-1-4419-6108-2_12
9. Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1), 99–120.
<https://doi.org/10.1177/014920639101700108>
10. Bendickson, J. S., & Chandler, T. D. (2019). Operational performance: The mediator between human capital developmental programs and financial performance. *Journal of Business Research*, 94, 162–171. <https://doi.org/10.1016/j.jbusres.2017.10.049>
11. Berraies, S., & Hamouda, M. (2018). Customer empowerment and firms' performance. *International Journal of Bank Marketing*, 36(2), 336–356.
<https://doi.org/10.1108/ijbm-10-2016-0150>
12. Biney, I. K. (2019). Unearthing entrepreneurial opportunities among youth vendors and hawkers: challenges and strategies. *Journal of Innovation and Entrepreneurship*, 8(1). <https://doi.org/10.1186/s13731-018-0099-y>
13. Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, 110(2), 305–314. <https://doi.org/10.1037/0033-2909.110.2.305>

14. Buhl, H. U., Röglinger, M., Moser, F., & Heidemann, J. (2013a). Big Data. *Business & Information Systems Engineering*, 5(2), 65–69.
<https://doi.org/10.1007/s12599-013-0249-5>
15. Buhl, H. U., Röglinger, M., Moser, F., & Heidemann, J. (2013b). Big Data. *Business & Information Systems Engineering*, 5(2), 65–69.
<https://doi.org/10.1007/s12599-013-0249-5>
16. Byrne, B. M. (2001). Structural Equation Modeling With AMOS, EQS, and LISREL: Comparative Approaches to Testing for the Factorial Validity of a Measuring Instrument. *International Journal of Testing*, 1(1), 55–86. https://doi.org/10.1207/s15327574ijt0101_4
17. Cannella, A. A., Park, J. H., & Lee, H. U. (2008). Top Management Team Functional Background Diversity and Firm Performance: Examining The Roles of Team Member Colocation and Environmental Uncertainty. *Academy of Management Journal*, 51(4), 768–784.
<https://doi.org/10.5465/amr.2008.33665310>
18. Cao, Q., Jones, D. R., & Sheng, H. (2014). Contained nomadic information environments: Technology, organization, and environment influences on adoption of hospital RFID patient tracking. *Information & Management*, 51(2), 225–239.
<https://doi.org/10.1016/j.im.2013.11.007>
19. Carmeli, A., Schaubroeck, J., & Tishler, A. (2011). How CEO empowering leadership shapes top management team processes: Implications for firm performance. *The Leadership Quarterly*, 22(2), 399–411. <https://doi.org/10.1016/j.leaqua.2011.02.013>

20. Chatterjee, D., Grewal, R., & Sambamurthy, V. (2002a). Shaping up for E-Commerce: Institutional Enablers of the Organizational Assimilation of Web Technologies. *MIS Quarterly*, 26(2), 65. <https://doi.org/10.2307/4132321>
21. Chatterjee, D., Grewal, R., & Sambamurthy, V. (2002b). Shaping up for E-Commerce: Institutional Enablers of the Organizational Assimilation of Web Technologies. *Management Information Systems Quarterly*, 26(2), 65. <https://doi.org/10.2307/4132321>
22. Chen, Chiang, & Storey. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36(4), 1165. <https://doi.org/10.2307/41703503>
23. Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of Management Information Systems*, 32(4), 4–39. <https://doi.org/10.1080/07421222.2015.1138364>
24. Chwelos, P., Benbasat, I., & Dexter, A. S. (2001a). Research Report: Empirical Test of an EDI Adoption Model. *Information Systems Research*, 12(3), 304–321. <https://doi.org/10.1287/isre.12.3.304.9708>
25. Chwelos, P., Benbasat, I., & Dexter, A. S. (2001b). Research Report: Empirical Test of an EDI Adoption Model. *Information Systems Research*, 12(3), 304–321. <https://doi.org/10.1287/isre.12.3.304.9708>
26. Chwelos, P., Benbasat, I., & Dexter, A. S. (2001c). Research Report: Empirical Test of an EDI Adoption Model. *Information Systems Research*, 12(3), 304–321. <https://doi.org/10.1287/isre.12.3.304.9708>
27. Clarke, R. (2015). Big data, big risks. *Information Systems Journal*, 26(1), 77–90. <https://doi.org/10.1111/isj.12088>

28. Cruz-Jesus, F., Pinheiro, A., & Oliveira, T. (2019). Understanding CRM adoption stages: empirical analysis building on the TOE framework. *Computers in Industry, 109*, 1–13. <https://doi.org/10.1016/j.compind.2019.03.007>
29. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319. <https://doi.org/10.2307/249008>
30. Diffusion of Innovations. (1983). In *Rogers, E.M.* New York: Free Press.
31. Droge, C., Jayaram, J., & Vickery, S. K. (2004). The effects of internal versus external integration practices on time-based performance and overall firm performance. *Journal of Operations Management, 22*(6), 557–573. <https://doi.org/10.1016/j.jom.2004.08.001>
32. Dwivedi, Y. K., Kapoor, K. K., Williams, M. D., & Williams, J. (2013). RFID systems in libraries: An empirical examination of factors affecting system use and user satisfaction. *International Journal of Information Management, 33*(2), 367–377. <https://doi.org/10.1016/j.ijinfomgt.2012.10.008>
33. Dwivedi, Y. K., Wade, M. R., & Schneberger, S. L. (2011). *Information Systems Theory: Explaining and Predicting Our Digital Society*, Vol. 2. Springer Publishing Company, Incorporated eBooks, 470.
34. Dynamic Capabilities: Understanding Strategic Change in Organizations. (2007). In *Helfat et al., 2007 Helfat, C.; Finkelstein, S.; Mitchell, W.; Peteraf, M.A.; Singh, H.; Teece, D.J.; and Winter, S.G.* Oxford: Blackwell.

35. Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal*, 21(10–11), 1105–1121.
[https://doi.org/10.1002/1097-0266\(200010/11\)21:10/11](https://doi.org/10.1002/1097-0266(200010/11)21:10/11)
36. Galbraith, J. R. (1973). *Designing Complex Organizations* (0 ed.). Addison-Wesley Pub. Co.
37. Gangwar, H. (2018). Understanding the Determinants of Big Data Adoption in India. *Information Resources Management Journal*, 31(4), 1–22.
<https://doi.org/10.4018/irmj.2018100101>
38. Gefen, Rigdon, & Straub. (2011). Editor's Comments: An Update and Extension to SEM Guidelines for Administrative and Social Science Research. *MIS Quarterly*, 35(2), iii. <https://doi.org/10.2307/23044042>
39. George, G., Osinga, E. C., Lavie, D., & Scott, B. A. (2016). Big Data and Data Science Methods for Management Research. *Academy of Management Journal*, 59(5), 1493–1507. <https://doi.org/10.5465/amj.2016.4005>
40. Ghobakhloo, M., Arias-Aranda, D., & Benitez-Amado, J. (2011). Adoption of e-commerce applications in SMEs. *Industrial Management & Data Systems*, 111(8), 1238–1269. <https://doi.org/10.1108/02635571111170785>
41. Gillon, K., Aral, S., Lin, C. Y., Mithas, S., & Zozulia, M. (2014). Business Analytics: Radical Shift or Incremental Change? *Communications of the Association for Information Systems*, 34. <https://doi.org/10.17705/1cais.03413>
42. Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, 19(2), 213.
<https://doi.org/10.2307/249689>

43. Grant, R. M. (1996). Prospering in Dynamically Competitive Environments: Organizational Capability as Knowledge Integration. *Organization Science*, 7(4), 375–387. <https://doi.org/10.1287/orsc.7.4.375>
44. Greene, C. N., & Organ, D. W. (1973). An Evaluation of Causal Models Linking the Received Role with Job Satisfaction. *Administrative Science Quarterly*, 18(1), 95. <https://doi.org/10.2307/2391931>
45. Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems*, 26(3), 191–209. <https://doi.org/10.1016/j.jsis.2017.07.003>
46. Gupta, S., Drave, V. A., Dwivedi, Y. K., Baabdullah, A. M., & Ismagilova, E. (2020). Achieving superior organizational performance via big data predictive analytics: A dynamic capability view. *Industrial Marketing Management*, 90, 581–592. <https://doi.org/10.1016/j.indmarman.2019.11.009>
47. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/ebr-11-2018-0203>
48. Hofmann, E. (2015). Big data and supply chain decisions: the impact of volume, variety and velocity properties on the bullwhip effect. *International Journal of Production Research*, 55(17), 5108–5126. <https://doi.org/10.1080/00207543.2015.1061222>
49. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>

50. Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic Data Interchange and Small Organizations: Adoption and Impact of Technology. *MIS Quarterly*, 19(4), 465. <https://doi.org/10.2307/249629>
51. Jayanand, M., Kumar, M. A., Srinivasa, K. G., & Siddesh, G. M. (2015). Big Data Computing Strategies. *Handbook of Research on Securing Cloud-Based Databases With Biometric Applications*, 72–90. <https://doi.org/10.4018/978-1-4666-6559-0.ch004>
52. Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R., & Childe, S. J. (2016). Modelling quality dynamics, business value and firm performance in a big data analytics environment. *International Journal of Production Research*, 55(17), 5011–5026. <https://doi.org/10.1080/00207543.2016.1154209>
53. Karahanna, E., & Preston, D. S. (2013). The Effect of Social Capital of the Relationship Between the CIO and Top Management Team on Firm Performance. *Journal of Management Information Systems*, 30(1), 15–56. <https://doi.org/10.2753/mis0742-1222300101>
54. Karimi, J., & Walter, Z. (2015). The Role of Dynamic Capabilities in Responding to Digital Disruption: A Factor-Based Study of the Newspaper Industry. *Journal of Management Information Systems*, 32(1), 39–81. <https://doi.org/10.1080/07421222.2015.1029380>
55. Kearns, G. S., & Sabherwal, R. (2006). Strategic Alignment Between Business and Information Technology: A Knowledge-Based View of Behaviors, Outcome, and Consequences. *Journal of Management Information Systems*, 23(3), 129–162. <https://doi.org/10.2753/mis0742-1222230306>

56. Kohli, A. K., & Jaworski, B. J. (1990). Market Orientation: The Construct, Research Propositions, and Managerial Implications. *Journal of Marketing*, 54(2), 1–18. <https://doi.org/10.1177/002224299005400201>
57. Kuan, K. K., & Chau, P. Y. (2001a). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management*, 38(8), 507–521. [https://doi.org/10.1016/s0378-7206\(01\)00073-8](https://doi.org/10.1016/s0378-7206(01)00073-8)
58. Kuan, K. K., & Chau, P. Y. (2001b). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management*, 38(8), 507–521. [https://doi.org/10.1016/s0378-7206\(01\)00073-8](https://doi.org/10.1016/s0378-7206(01)00073-8)
59. Kuan, K. K., & Chau, P. Y. (2001c). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management*, 38(8), 507–521. [https://doi.org/10.1016/s0378-7206\(01\)00073-8](https://doi.org/10.1016/s0378-7206(01)00073-8)
60. Kuan, K. K., & Chau, P. Y. (2001d). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management*, 38(8), 507–521. [https://doi.org/10.1016/s0378-7206\(01\)00073-8](https://doi.org/10.1016/s0378-7206(01)00073-8)
61. Kuan, K. K. Y., & Chau, P. Y. K. (2001). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management*, 38(8), 507–521. [https://doi.org/10.1016/s0378-7206\(01\)00073-8](https://doi.org/10.1016/s0378-7206(01)00073-8)
62. Laaksonen, O., & Peltoniemi, M. (2016). The Essence of Dynamic Capabilities and their Measurement. *International Journal of Management Reviews*, 20(2), 184–205. <https://doi.org/10.1111/ijmr.12122>

63. Laaksonen, O., & Peltoniemi, M. (2018). The Essence of Dynamic Capabilities and their Measurement. *International Journal of Management Reviews*, 20(2), 184–205. <https://doi.org/10.1111/ijmr.12122>
64. Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management. *The International Journal of Logistics Management*, 29(2), 676–703. <https://doi.org/10.1108/ijlm-06-2017-0153>
65. Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., & Seidel, S. (2018). How Big Data Analytics Enables Service Innovation: Materiality, Affordance, and the Individualization of Service. *Journal of Management Information Systems*, 35(2), 424–460. <https://doi.org/10.1080/07421222.2018.1451953>
66. Lei, Y., Jia, F., Lin, J., Xing, S., & Ding, S. X. (2016). An Intelligent Fault Diagnosis Method Using Unsupervised Feature Learning Towards Mechanical Big Data. *IEEE Transactions on Industrial Electronics*, 63(5), 3137–3147. <https://doi.org/10.1109/tie.2016.2519325>
67. Liang, Saraf, Hu, & Xue. (2007a). Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management. *MIS Quarterly*, 31(1), 59. <https://doi.org/10.2307/25148781>
68. Liang, Saraf, Hu, & Xue. (2007b). Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management. *MIS Quarterly*, 31(1), 59. <https://doi.org/10.2307/25148781>
69. Lim, J. H., Stratopoulos, T. C., & Wirjanto, T. S. (2013). Sustainability of a Firm's Reputation for Information Technology Capability: The Role of Senior IT Executives. *Journal of Management Information Systems*, 30(1), 57–96. <https://doi.org/10.2753/mis0742-1222300102>

70. Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121. <https://doi.org/10.1037/0021-9010.86.1.114>
71. Little, G. L., & Robinson, K. D. (1987). One-Day Dropouts from Correctional Drug Treatment II. *Psychological Reports, 60*(2), 454–454. <https://doi.org/10.2466/pr0.1987.60.2.454>
72. Mandal, S. (2018). An examination of the importance of big data analytics in supply chain agility development. *Management Research Review, 41*(10), 1201–1219. <https://doi.org/10.1108/mrr-11-2017-0400>
73. Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2022). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*. <https://doi.org/10.1108/imds-11-2021-0695>
74. Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020a). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management, 54*, 102190. <https://doi.org/10.1016/j.ijinfomgt.2020.102190>
75. Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020b). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management, 54*, 102190. <https://doi.org/10.1016/j.ijinfomgt.2020.102190>

76. McCarthy, I. P., Lawrence, T. B., Wixted, B., & Gordon, B. R. (2010). A MULTIDIMENSIONAL CONCEPTUALIZATION OF ENVIRONMENTAL VELOCITY. *Academy of Management Review*, 35(4), 604–626. <https://doi.org/10.5465/amr.2010.53503029>
77. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019a). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *British Journal of Management*, 30(2), 272–298. <https://doi.org/10.1111/1467-8551.12343>
78. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019b). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, 98, 261–276. <https://doi.org/10.1016/j.jbusres.2019.01.044>
79. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2021.103434>
80. 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>
81. 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>

82. Mikalef, P., Pateli, A. G., & Van De Wetering, R. (2016). IT FLEXIBILITY AND COMPETITIVE PERFORMANCE: THE MEDIATING ROLE OF IT-ENABLED DYNAMIC CAPABILITIES. *European Conference on Information Systems*.
83. Müller, O., Fay, M., & vom Brocke, J. (2018a). The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. *Journal of Management Information Systems*, 35(2), 488–509.
<https://doi.org/10.1080/07421222.2018.1451955>
84. Müller, O., Fay, M., & vom Brocke, J. (2018b). The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. *Journal of Management Information Systems*, 35(2), 488–509.
<https://doi.org/10.1080/07421222.2018.1451955>
85. Müller, O., Fay, M., & vom Brocke, J. (2018c). The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. *Journal of Management Information Systems*, 35(2), 488–509.
<https://doi.org/10.1080/07421222.2018.1451955>
86. Obal, M. (2017). What drives post-adoption usage? Investigating the negative and positive antecedents of disruptive technology continuous adoption intentions. *Industrial Marketing Management*, 63, 42–52. <https://doi.org/10.1016/j.indmarman.2017.01.003>
87. Olivera, P., Danese, S., Jay, N., Natoli, G., & Peyrin-Biroulet, L. (2019). Big data in IBD: a look into the future. *Nature Reviews Gastroenterology & Hepatology*, 16(5), 312–321. <https://doi.org/10.1038/s41575-019-0102-5>

88. Oussous, A., Benjelloun, F. Z., Ait Lahcen, A., & Belfkih, S. (2018). Big Data technologies: A survey. *Journal of King Saud University - Computer and Information Sciences*, 30(4), 431–448. <https://doi.org/10.1016/j.jksuci.2017.06.001>
89. Park, S. Y., & Pan, B. (2018a). Identifying the next non-stop flying market with a big data approach. *Tourism Management*, 66, 411–421. <https://doi.org/10.1016/j.tourman.2017.12.008>
90. Park, S. Y., & Pan, B. (2018b). Identifying the next non-stop flying market with a big data approach. *Tourism Management*, 66, 411–421. <https://doi.org/10.1016/j.tourman.2017.12.008>
91. Pavlou, P. A., & El Sawy, O. A. (2006). From IT Leveraging Competence to Competitive Advantage in Turbulent Environments: The Case of New Product Development. *Information Systems Research*, 17(3), 198–227. <https://doi.org/10.1287/isre.1060.0094>
92. Petter, Straub, & Rai. (2007). Specifying Formative Constructs in Information Systems Research. *MIS Quarterly*, 31(4), 623. <https://doi.org/10.2307/25148814>
93. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
94. Priem, R. L., & Butler, J. E. (2001). Is the Resource-Based “View” a Useful Perspective for Strategic Management Research? *Academy of Management Review*, 26(1), 22–40. <https://doi.org/10.5465/amr.2001.4011928>

95. Priyadarshinee, P., Raut, R. D., Jha, M. K., & Gardas, B. B. (2017). Understanding and predicting the determinants of cloud computing adoption: A two staged hybrid SEM - Neural networks approach. *Computers in Human Behavior*, 76, 341–362.
<https://doi.org/10.1016/j.chb.2017.07.027>
96. Qian, C., Cao, Q., & Takeuchi, R. (2012). Top management team functional diversity and organizational innovation in China: The moderating effects of environment. *Strategic Management Journal*, 34(1), 110–120. <https://doi.org/10.1002/smj.1993>
97. Raguseo, E., & Vitari, C. (2018). Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects. *International Journal of Production Research*, 56(15), 5206–5221. <https://doi.org/10.1080/00207543.2018.1427900>
98. Ramanathan, R., Philpott, E., Duan, Y., & Cao, G. (2017). Adoption of business analytics and impact on performance: a qualitative study in retail. *Production Planning & Control*, 28(11–12), 985–998. <https://doi.org/10.1080/09537287.2017.1336800>
99. Ramdani, B., Chevers, D., & Williams, D. A. (2013). SMEs' adoption of enterprise applications. *Journal of Small Business and Enterprise Development*, 20(4), 735–753. <https://doi.org/10.1108/jsbed-12-2011-0035>
100. Raykov, T., Tomer, A., & Nesselroade, J. R. (1991). Reporting structural equation modeling results in Psychology and Aging: Some proposed guidelines. *Psychology and Aging*, 6(4), 499–503. <https://doi.org/10.1037/0882-7974.6.4.499>
101. Ren, S. J. F., Ngai, E., & Cho, V. (2009). Examining the determinants of outsourcing partnership quality in Chinese small- and medium-sized enterprises. *International Journal of Production Research*, 48(2), 453–475. <https://doi.org/10.1080/00207540903174965>

102. Salarzadeh Jenatabadi, H., Babashamsi, P., Khajeheian, D., & Seyyed Amiri, N. (2016). Airline Sustainability Modeling: A New Framework with Application of Bayesian Structural Equation Modeling. *Sustainability*, 8(11), 1204. <https://doi.org/10.3390/su8111204>
103. Sanders, N. R. (2007). Pattern of information technology use: The impact on buyer-supplier coordination and performance. *Journal of Operations Management*, 26(3), 349–367. <https://doi.org/10.1016/j.jom.2007.07.003>
104. Saunders, M. N., & Bezzina, F. (2015). Reflections on conceptions of research methodology among management academics. *European Management Journal*, 33(5), 297–304. <https://doi.org/10.1016/j.emj.2015.06.002>
105. Schilke, O. (2013). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic Management Journal*, 35(2), 179–203. <https://doi.org/10.1002/smj.2099>
106. Scupola, A. (2009). SMEs' e-commerce adoption: perspectives from Denmark and Australia. *Journal of Enterprise Information Management*, 22(1/2), 152–166. <https://doi.org/10.1108/17410390910932803>
107. Shareef, M. A., Dwivedi, Y. K., Kumar, V., & Kumar, U. (2017). Content design of advertisement for consumer exposure: Mobile marketing through short messaging service. *International Journal of Information Management*, 37(4), 257–268. <https://doi.org/10.1016/j.ijinfomgt.2017.02.003>
108. Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management*, 44, 65–75. <https://doi.org/10.1016/j.ijinfomgt.2018.09.013>

109. Snijders, C., Matzat, U., & Reips, U. (2012). "Big Data" : big gaps of knowledge in the field of internet science. *International Journal of Internet Science*, 7(1), 1–5.
110. So, are the geeks inheriting the earth? (2013). *Strategic Direction*, 29(9), 12–15. <https://doi.org/10.1108/sd-08-2013-0051>
112. Son, J. Y., & Benbasat, I. (2007). Organizational Buyers' Adoption and Use of B2B Electronic Marketplaces: Efficiency- and Legitimacy-Oriented Perspectives. *Journal of Management Information Systems*, 24(1), 55–99. <https://doi.org/10.2753/mis0742-1222240102>
113. Song, M., Droge, C., Hanvanich, S., & Calantone, R. (2005). Marketing and technology resource complementarity: an analysis of their interaction effect in two environmental contexts. *Strategic Management Journal*, 26(3), 259–276. <https://doi.org/10.1002/smj.450>
114. Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2016). Understanding the Factors Affecting the Organizational Adoption of Big Data. *Journal of Computer Information Systems*, 58(3), 193–203. <https://doi.org/10.1080/08874417.2016.1222891>
115. Sun, S., Hall, D. J., & Cegielski, C. G. (2020). Organizational intention to adopt big data in the B2B context: An integrated view. *Industrial Marketing Management*, 86, 109–121. <https://doi.org/10.1016/j.indmarman.2019.09.003>
116. Tallon, P. P. (2007a). A Process-Oriented Perspective on the Alignment of Information Technology and Business Strategy. *Journal of Management Information Systems*, 24(3), 227–268. <https://doi.org/10.2753/mis0742-1222240308>
117. Tallon, P. P. (2007b). A Process-Oriented Perspective on the Alignment of Information Technology and Business Strategy. *Journal of Management Information Systems*, 24(3), 227–268. <https://doi.org/10.2753/mis0742-1222240308>

118. Taxman, F. S., Henderson, C., Young, D., & Farrell, J. (2012). The Impact of Training Interventions on Organizational Readiness to Support Innovations in Juvenile Justice Offices. *Administration and Policy in Mental Health and Mental Health Services Research*, 41(2), 177–188. <https://doi.org/10.1007/s10488-012-0445-5>
119. Teece, D. J., Pisano, G. P., & Shuen, A. (1997a). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(sici\)1097-0266\(199708\)18:7](https://doi.org/10.1002/(sici)1097-0266(199708)18:7)
120. Teece, D. J., Pisano, G. P., & Shuen, A. (1997b). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(sici\)1097-0266\(199708\)18:7](https://doi.org/10.1002/(sici)1097-0266(199708)18:7)
121. Teece, D. J., Pisano, G. P., & Shuen, A. (1997c). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(sici\)1097-0266\(199708\)18:7](https://doi.org/10.1002/(sici)1097-0266(199708)18:7)
122. Thong, J. Y. (1999). An Integrated Model of Information Systems Adoption in Small Businesses. *Journal of Management Information Systems*, 15(4), 187–214. <https://doi.org/10.1080/07421222.1999.11518227>
123. To, M. L., & Ngai, E. (2006). Predicting the organisational adoption of B2C e-commerce: an empirical study. *Industrial Management & Data Systems*, 106(8), 1133–1147. <https://doi.org/10.1108/02635570610710791>
124. Tornatzky, L. G., & Klein, K. J. (1982a). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management*, EM-29(1), 28–45. <https://doi.org/10.1109/tem.1982.6447463>

125. Tornatzky, L. G., & Klein, K. J. (1982b). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management, EM-29*(1), 28–45. <https://doi.org/10.1109/tem.1982.6447463>
126. Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27*(3), 425. <https://doi.org/10.2307/30036540>
127. Venkatesh, V., & Bala, H. (2012a). Adoption and Impacts of Interorganizational Business Process Standards: Role of Partnering Synergy. *Information Systems Research, 23*(4), 1131–1157. <https://doi.org/10.1287/isre.1110.0404>
128. Venkatesh, V., & Bala, H. (2012b). Adoption and Impacts of Interorganizational Business Process Standards: Role of Partnering Synergy. *Information Systems Research, 23*(4), 1131–1157. <https://doi.org/10.1287/isre.1110.0404>
129. Waller, M. A., & Fawcett, S. E. (2013a). Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. *Journal of Business Logistics, 34*(2), 77–84. <https://doi.org/10.1111/jbl.12010>
130. Waller, M. A., & Fawcett, S. E. (2013b). Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. *Journal of Business Logistics, 34*(2), 77–84. <https://doi.org/10.1111/jbl.12010>
131. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>

132. Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, 176, 98–110.
<https://doi.org/10.1016/j.ijpe.2016.03.014>
133. Wang, N., Liang, H., Zhong, W., Xue, Y., & Xiao, J. (2012). Resource Structuring or Capability Building? An Empirical Study of the Business Value of Information Technology. *Journal of Management Information Systems*, 29(2), 325–367. <https://doi.org/10.2753/mis0742-1222290211>
134. Wang, Y., Kung, L., Wang, W. Y. C., & Cegielski, C. G. (2018). An integrated big data analytics-enabled transformation model: Application to health care. *Information & Management*, 55(1), 64–79. <https://doi.org/10.1016/j.im.2017.04.001>
135. Wen, K. W., & Chen, Y. (2010). E-business value creation in Small and Medium Enterprises: a US study using the TOE framework. *International Journal of Electronic Business*, 8(1), 80. <https://doi.org/10.1504/ijeb.2010.030717>
136. Yang, Y., See-To, E. W., & Papagiannidis, S. (2020). You have not been archiving emails for no reason! Using big data analytics to cluster B2B interest in products and services and link clusters to financial performance. *Industrial Marketing Management*, 86, 16–29.
<https://doi.org/10.1016/j.indmarman.2019.01.016>
137. Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach. *Journal of Business Research*, 114, 1–15. <https://doi.org/10.1016/j.jbusres.2020.03.028>

138. Yoon, T. E., & George, J. F. (2013). Why aren't organizations adopting virtual worlds? *Computers in Human Behavior*, 29(3), 772–790.
<https://doi.org/10.1016/j.chb.2012.12.003>
139. Yu, C. S., & Tao, Y. H. (2009a). Understanding business-level innovation technology adoption. *Technovation*, 29(2), 92–109.
<https://doi.org/10.1016/j.technovation.2008.07.007>
140. Yu, C. S., & Tao, Y. H. (2009b). Understanding business-level innovation technology adoption. *Technovation*, 29(2), 92–109.
<https://doi.org/10.1016/j.technovation.2008.07.007>
141. Yu, C. S., & Tao, Y. H. (2009c). Understanding business-level innovation technology adoption. *Technovation*, 29(2), 92–109.
<https://doi.org/10.1016/j.technovation.2008.07.007>
142. Yu, S. (2016). Big Privacy: Challenges and Opportunities of Privacy Study in the Age of Big Data. *IEEE Access*, 4, 2751–2763.
<https://doi.org/10.1109/access.2016.2577036>
143. Zailani, S., Govindan, K., Iranmanesh, M., Shaharudin, M. R., & Sia Chong, Y. (2015). Green innovation adoption in automotive supply chain: the Malaysian case. *Journal of Cleaner Production*, 108, 1115–1122. <https://doi.org/10.1016/j.jclepro.2015.06.039>
144. Zhu, K., & Kraemer, K. L. (2005a). Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry. *Information Systems Research*, 16(1), 61–84. <https://doi.org/10.1287/isre.1050.0045>

145. Zhu, K., & Kraemer, K. L. (2005b). Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry. *Information Systems Research*, 16(1), 61–84. <https://doi.org/10.1287/isre.1050.0045>
146. Zhu, K., Kraemer, K. L., & Xu, S. (2006a). The Process of Innovation Assimilation by Firms in Different Countries: A Technology Diffusion Perspective on E-Business. *Management Science*, 52(10), 1557–1576. <https://doi.org/10.1287/mnsc.1050.0487>
147. Zhu, K., Kraemer, K. L., & Xu, S. (2006b). The Process of Innovation Assimilation by Firms in Different Countries: A Technology Diffusion Perspective on E-Business. *Management Science*, 52(10), 1557–1576. <https://doi.org/10.1287/mnsc.1050.0487>.

Appendix A
Construct Scales and Items

<p>First-order constructs</p> <hr/> <p>Anticipated value Chen et al., 2015; Ghobakhloo, Arias-Aranda et al., 2011; Premkumar & Roberts, 1999)</p> <ol style="list-style-type: none"> 1. Data Analytics improves the quality of work 2. Big Data Analytics makes work more efficient 3. Big Data Analytics lowers costs 4. Big Data Analytics improves customer service 5. Big Data Analytics attracts new sales to new customers or new markets 6. Big Data Analytics adoption identifies new product/service opportunities <p>Technological competence Chen et al., 2015; Ghobakhloo, Arias-Aranda et al., 2011; Thong, 1999; Tornatzky & Klein, 1982)</p> <ol style="list-style-type: none"> 1. Using Big Data Analytics is consistent with our business practices 2. Using Big Data Analytics fits our organizational culture 3. Overall, it is easy to incorporate Big Data Analytics into our organization <hr/> <p>Top management support (Chen et al., 2015; Lai et al., 2018; Priyadarshinee et al., 2017)</p> <ol style="list-style-type: none"> 1. Our top management promotes the use of Big Data Analytics in the organization 2. Our top management creates support for Big Data Analytics initiatives within the organization 3. Our top management promotes Big Data Analytics as a strategic priority within the organization 4. Our top Management is interested in the news about using Big Data Analytics adoption <hr/> <p>Organisational readiness (Chen et al., 2015)</p> <ol style="list-style-type: none"> 1. lacking capital/financial resources has prevented my company from fully exploit Big Data Analytics 2. lacking needed IT infrastructure has prevented my company from exploiting Big Data Analytics 3. lacking analytics capability prevent the business fully exploit Big Data Analytics 4. lacking skilled resources prevent the business fully exploit Big Data Analytics <hr/> <p>Competitive pressure (Lai et al., 2018)</p> <ol style="list-style-type: none"> 1. Our choice to adopt Big Data Analytics would be strongly influenced by what competitors in the industry are doing 2. Our firm is under pressure from competitors to adopt Big Data Analytics <hr/>
--

3. Our firm would adopt Big Data Analytics in response to what competitors are doing

External Support (Ghobakhloo, Arias-Aranda et al., 2011, 2011b; Li, 2008)

1. Community agencies/vendors can provide required training for Big Data Analytics adoption
 2. Community agencies/vendors can provide effective technical support for Big Data Analytics adoption
 3. Vendors actively market Big Data Analytics adoption
-

Government Regulation (Agrawal, 2015; Gupta and Barua, 2016; Lai et al., 2018; Li, 2008)

1. The governmental policies encourage us to adopt new information technology (e.g., big data analytics)
 2. The government provides incentives for using big data analytics in government procurements and contracts such as offering technical support, training, and funding for big data analytics
 3. There are some business laws to deal with the security and privacy concerns over the Big Data Analytics technology
-

Big Data Analytics Adoption (Raguseo & Vitari, 2018)

In terms of Strategic Benefits

1. My company has used Big Data Analytics to.....
Respond more quickly to change
Create competitive advantage. Improve customer relations.

In terms of Transactional Benefits

2. My company has used Big Data Analytics to.....
Enhance savings in supply chain management.
Reduce operating costs.
Reduce communication costs. Enhance employee productivity.

In terms of Transformational Benefits

3. My company has used Big Data Analytics to.....
Improve employees' skill level.
-

Develop new business opportunities.
 Expand capabilities. Improve organizational structure and processes.

In terms of Informational Benefits

- 4. My company has used Big Data Analytics to.....
 Enable faster access to data.
 Improve management data. Improve data accuracy.

Financial Performance (Ren et al., 2017; Raguseo & Vitari, 2018)

Compared with your major competitors, how do you rate your firm's performance in the following areas over the past 3 years

- 1. Improving customer retention
- 2. Improving sale growths
- 3. Improving profitability

Non-financial Performance (Ren et al., 2017; Raguseo & Vitari, 2018)

Compared with your major competitors, how do you rate your firm's performance in the following areas over the past 3 years.

- Entering new markets quickly.
- 1. Introducing new products or services to the market quickly.
 - 2. Success rate of new products or services.
 - 3. Market share.

Environmental Dynamism

- 1. The rate at which your customers' product/service needs change.
 - 2. The rate at which your suppliers' skills/capabilities change.
 - 3. The rate at which your competitors' products/services change.
 - 4. The rate at which your firm's products/services change.
-

Figure 1:

Conceptual Model

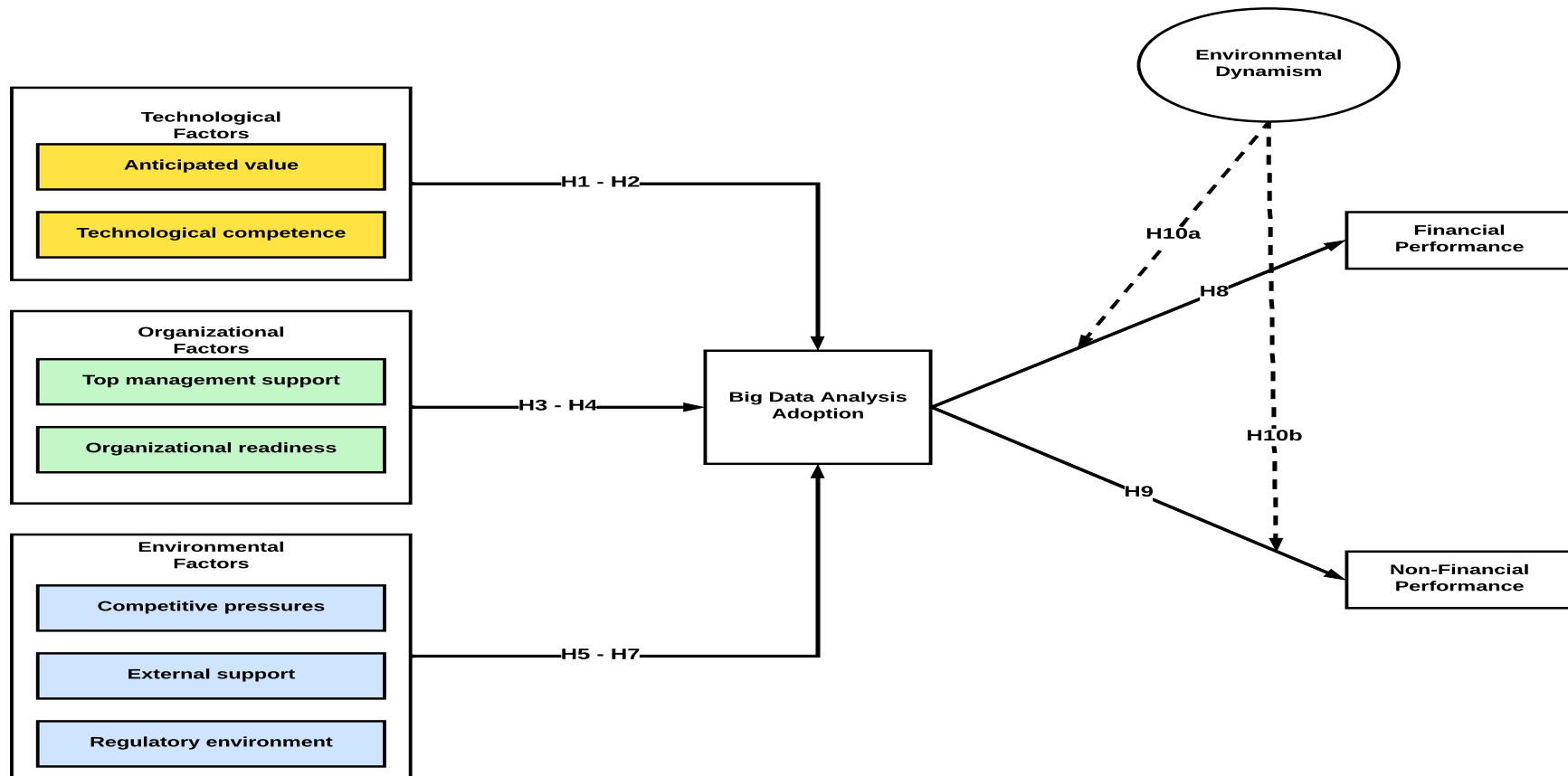


Table 1:
Demographic profile

Characteristic (n = 261)	Frequency	Percentage
Education		
Primary qualification	23	8.8
Secondary qualification	32	12.2
Diploma	68	26
Undergraduate degree	111	42.5
Postgraduate degree (Master/PhD)	27	10.3
Age		
18–25 years old	25	9.5
26–33 years old	67	25.6
34–41 years old	89	34
42–49 years old	46	17.6
50 years old or older	33	12,6
Gender		
Male	144	55.1
Female	117	44.8
Number of Employees		
1–10 employees	50	19.1
11–49 employees	122	46.7
50–99 employees	57	21.8
100–149 employees	31	11.8
Sector Type		
Food and Beverages	55	21
Online and offline retail	33	12.6
Internet service provider	45	17.2
Machinery & Equipment	55	21
Office Equipment	34	13

Radio, TV& Communication Tools	33	12.6
Position		
Executive/Senior manager	115	44
Chief executive manager/owner	146	55.9
Big Data Experience		
< 1 year	48	18.3
1–2 years	112	42.9
2–3 years	90	34.4
3–4 years	52	19.9
4+ years	39	14.9

Table 2:**Descriptive statistics, correlations, Cronbach's alpha, and square root of the AVE**

Constructs	Mean	SD	CR	AVE	AV	TC	TMS	OR	CP	ES	RE	BDA	FP	NFP	ED
AV	3.296	0.873	0.858	0.972	0.844										
TC	3.813	0.952	0.994	0.862	0.381	0.885									
TMS	4.002	0.743	0.872	0.953	0.401	0.487	0.896								
OR	4.312	0.913	0.773	0.868	0.266	0.333	0.378	0.795							
CP	4.164	0.971	0.983	0.793	0.345	0.431	0.493	0.308	0.853						
ES	3.801	0.833	0.905	0.829	0.421	0.490	0.580	0.332	0.466	0.835					
RE	4.298	0.989	0.961	0.807	0.406	0.486	0.613	0.361	0.528	0.546	0.875				
BDA	4.062	0.643	0.961	0.802	0.431	0.500	0.685	0.250	0.468	0.650	0.678	0.832			
FP	3.701	0.719	0.978	0.829	0.099	0.063	0.078	0.050	0.133	0.015	0.058	0.118	0.839		
NFP	4.092	0.791	0.811	0.88	0.248	0.427	0.444	0.338	0.442	0.400	0.358	0.364	0.254	0.918	
ED	3.763	0.889	0.978	0.829	0.016	0.055	0.062	0.119	0.066	0.030	0.017	0.182	0.474	0.246	0.869

Table 3:
Structural Model Path Analysis.

Hypotheses	Relationships	Path Coefficients	P Values	Decision
Direct effect				
H1	AV ->BDA	0.172	0.003***	Supported
H2	TC ->BDA	0.374	0.005**	Supported
H3	TMS ->BDA	0.406	0.000***	Supported
H4	OR ->BDA	0.342	0.005**	Supported
H5	ES ->BDA	0.271	0.002***	Supported
H6	CP ->BDA	0.172	0.213	Not Supported
H7	RE ->BDA	0.005	0.783	Not Supported
H8	BDA ->FP	0.096	0.031*	Supported
H9	BDA ->NFP	0.095	0.018	Supported
Moderation effect				
H10a	ED ->FP	0.312	0.003***	Supported
H10b	ED ->NFP	-0.122	0.415	Not Supported

Note: *p <0.05; **p <0.01; ***p < 0.001 (one-tail).

Anticipated value (AV); Technological competence (TC); Top management support (TMS); Organisational readiness (OR); Competitive pressure (CP); External Support (ES); Government Regulation (GR); Big Data Analytics Adoption (BDA); Financial Performance (FP); Non-financial Performance (NFP)