

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

Abstract

Despite advances in Big Data Analytics, its utilitarian discourse is yet to move beyond early capture to focus on its post adoption impacts on firms' financial and non-financial performance, especially in Nigeria's. This study advances BDA beyond organizational readiness for change by empirically and analytically focusing on the reality of 261 Nigerian professionals by drawing on business-to-business marketing, dynamic capabilities, and Technology-Organization-Environment theoretical frameworks to contribute a conceptual model (Figure 1) on factors which really impact on organizations' readiness to adopt BDA. Consequently, our study's findings were used to develop Figure 2, showing the direct and moderating nature of interactions between BDA and TOE variables on BDA adoption. However, whereas hypotheses three and four confirm top management's support and overall organizational readiness, paradoxically, this study's hypotheses five and seven contribute to existing BDA discourse by highlight that environmental, competitive pressure, including regulation do not support the adoption of BDA. Additionally, while external support (H6) was found conducive for BDA adoption, interestingly, hypotheses eight, nine and 10a were also found supportive of not only financial but also non-financial performance. However, contrary to current theorisation, hypotheses 10b was not supportive of non-financial performance. Our results contribute to BDA's business competitiveness and regulation.

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

Introduction

While big data analytics (BDA) is witnessing an academic spike [14], and the technological, organizational and environmental (TOE) framework appears to be favourite when most organizations' managers decide whether to adopt BDA or not [57; 58; 59; 60; 61; 135; 28; 1], its extension beyond the dominant utilitarian value [i.e., the impacts of management decision on BDA adoption] has lagged particularly in the way it facilitates organizations' readiness for BD adoption and the post-decision making impacts on firms' financial and non-financial performance. While this lacuna highlights the significant need for more in-depth investigations into organizations' BDA adoption to understand how impacts not only on management decision making capabilities but also on organizations' financial and

non-financial performance opportunities [88], studying how digitalized business operations have revolutionized the volume, variety, and velocity of structured and unstructured information mechanisms through what is now known as "Big Data" [15] cannot be timelier for businesses and their partners [39;115], particularly in non western contexts. Therefore, the discourse of adopting these new western-based BDA techniques and capabilities and the reality of organizations' managers' readiness in revolutionizing business strategies, product and service development, human resources (HR), operations, and other essential processes [22] to meet the BDA of financial and non-financial performance from a non-western context are yet to be empirically studied and contributed to.

BDA is defined as the examination of extensive data, via modern technology to help reveal important information and facilitate more informed and better business decision-making [85]. Despite these benefits/successes, it is also opined that most businesses are yet to capitalize on what the utilitarian benefits-discourse of BDA [88]. While such a lapse may be attributable to organizations' general lack of the full understanding of the anticipated benefits of a range of information technology (IT) types and the analytical capabilities required to address a range of threats to BDA adoption [45], the scholarship also evinces [87] the lack of organizations' management and leadership's understanding of the factors driving BDA adoption [87]. This additional lacuna provides further justification to focus on the fundamental drivers why organizations' management adopting BDA and the practical impacts of their decisions on Nigerian firms' readiness to adopt BD and to perform.

Previous studies on BDA [29;42] have focused on individual-level adoption behaviours while organizational level BD adoption and its impacts on organizations' readiness to perform financially and non-financially outside western contexts remains relatively scarce [112;139;27]. The very few studies focusing on the organizational-level BDA adoption mainly align with the BDA readiness discourse [115;114] at the expense of how post adoption impacts on management and staff's behaviours (i.e., usage and benefits) [144;23] and significantly how the BDA drivers inform management's decision-making capabilities and the post decision making impacts on organizations' readiness and constraints to perform financially and non-financially. Previous studies have demonstrated how BDA's application have popularized its utilitarian value discourse in organizational operations - including business intelligence, customer relationship management, and marketing [74] while the

required management capabilities in BD's adoption for the required firm-level financial and non-financial performance in developing economies is sorely missing. To address the afore gaps, this paper focuses on the following research question:

'What are the TOE characteristics driving Nigerian management's BDA adoption and the real post-decision making impacts on organizational level financial and non-financial performance?'

The authors analyze survey data from 261 management respondents from Nigeria's manufacturing and service sectors to address the key research question and nine testable hypotheses. By drawing from business-to-business (B2B) marketing to examine how western-based BD logics impact on firm-level performance outcomes [115], the authors examined a range of technological, organizational and environmental factors, information flows and management learning capability and BDA adoption propensity [56;129]. By combining capabilities with the TOE framework, we seek to develop understanding on the western discourse on the benefits of BDA adoption and the practical impacts of managements' post-decision making on organizational-level performance [56;129]. Secondly, by drawing from Dynamic Capabilities theory [35], the authors examine the extent to which BDA applications in B2B marketing situations not only provide substantial dynamic information and management's decision-processing power in resource configurations and reconfigurations [116;119] to help explore what its real impacts on an organization readiness to perform financially and non-financially. By drawing on the Technology-Organization-Environment framework (TOE – [124], the authors examine the multidimensional range of factors that the western discourse on BD suggests could lead to and its practical and theoretical impact in a Nigerian manufacturing and service industry setting [8].

The remainder of this paper is structured as follows: the following section will explore the process and drivers of BD adoption, followed by the study's theoretical framework and its methodology. Findings on management's decision to adopt BDA and practical impacts on firm financial and non-financial performance are highlighted and the study's contributions to BDA are discussed. Finally, the implications and future research are presented.

Understanding Big Data (BD)

There is no universally agreed definition of BD, However, for this study, the authors opted to draw on the generally adopted working definition from the IT adoption literature, which defines BD as high-volume (big scale), high-velocity (moving/ streaming), and high-

variety (e.g., numerical, text, video, etc.) information assets that enhance cost-effective, creative information processing for improved insight and decision-making [41]. BD has been shown to significantly impact on outcomes particularly when sophisticated analytical approaches (e.g., BDA) is applied to vast data sets [23] to help 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]. While firms may wonder if BD and the accompanying analyses are merely repackaged versions of old business intelligence and data mining, the extent to which they enhance new management decision-making capabilities and whether these practically make firms effectively performing entities is not only limited [23] but poignantly underdeveloped in Nigeria.

To address this issue, there are distinctions between BDA and traditional business intelligence technologies. According to a June 2011 International Data Corporation (IDC) research, the amount of globally available data has increased more than 50% each year since 2005, and it was predicted to approach 8,000 exabytes by 2015. Unstructured data, such as online material, news feeds, social media postings, video clips, and other data that cannot be easily categorized into repeating fields, have been driving such developments. BD is, therefore, an umbrella phrase for the collection of data sets that are so large and complicated that they are challenging to gather, analyze, and manage through available data management tools and standard data processing programmes [109]. While BDA has been used in a range of scientific disciplines including e-commerce, market intelligence, e-government, health care, and security [22] and its contextual applications vary [23;114; 74], it is often seen as a dramatic departure from typical business intelligence gathering tools [41] as its utilitarian impact on management decision-making and organizational-level performance readiness dominates current BD and BDA discourse [23]. To ascertain the nature and impact of the anticipated utilitarian value of BDA adoption, the authors examine how such a crucial resource capacity is utilized by businesses to help resolve the organizational need for readiness to perform financially and non-financially in Nigeria [43]. This warrants the examination of Dynamic Capabilities theory [62].

Dynamic capabilities

One of the most important management theories of the last decade is "dynamic capabilities" [105], which explains how a company can maintain competitive advantage in ever-changing environments [94;119;62]. Inspired by "Schumpeterian's gale of creative destruction," [119, 1997, p. 12], dynamic capabilities was perceived to 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 can build the internal capacities to enhance operational procedures [81;82;91;133]. However, combining such a resource-focused and adaptability theory to enhance management's BDA adoption and firm-level organizational financial and non-financial performance in a non-western context is missing.

BDA Adoption as a Resource Dynamic Capability

Researchers have used "dynamic capabilities" to highlight how businesses adapt to unpredictable situations and competencies needed to do so [35;116;119]. Competences range from integrating, reconfiguring, acquiring, and releasing resources, as a combined set of distinctive internal initiatives [119;62]. These are expected to enhance an organization's strategic resource capability especially when markets form, collide, divide, change or even expire [23]. Based on these western-dominated logics, we define the application of BDA inside organizations as the development of nimble capacities to help businesses establish and analyze routines and capacities [35;62] to generate and utilize knowledge in highly dynamic markets [116]. BDA is also sometimes perceived as an internal, organizational information processing capability [36], which decreases external and internal uncertainty by increasing the generation of new insights and management's organizational knowledge and strategic decision making [116;119]. Although there have emerged "best-practice" recommendations on how to generically apply BDA [22;23], a uniform usage of BDA tools across businesses and contexts is missing [23], partly because enterprise-level technology [116] and management's use of marketing information (such as social media marketing, e-commerce, customer relationship management, innovation, customer services) varies from one context/market to another [23;119]. Consequently, while perceiving and examining management's BDA adoption, via BDA, as a dynamic capability makes sense in western logic/discourse on the effective utilization of resources, knowledge on how management's capability development

and decision-making practically facilitate organizations' financial value creation in non-western contexts, especially Nigeria, is lagging.

Theoretical Framework and Hypotheses Development

This study combines Dynamic Capabilities (DC) [9] to examine how specific businesses' unique pasts [119] create competitiveness [116] and the TOE framework [135; 28; 1; 57; 58; 59; 60; 61] to ascertain the extent to which technological, organizational and environmental factors influence management decision to adopt BDA and its impacts. In terms of DC, the literature highlights route dependence as one of the factors shaping an organization's capacities and management's decision making capabilities [35]. Although these aspects vary from context to context [119] and technical issues and an organization's external fitness are also variant [48], the authors have used the TOE framework [126;1] from the IT management discourse to identify specific factors why management are more likely to adopt BDA in a manufacturing and service industry in Nigeria. As a framework, TOE proposes technical, organizational, and environmental aspects, as fundamental determinants for management's BD adoption [8], both of which were combined to develop the study's conceptual model [1] (see Fig. 1). Measurable hypotheses, were initially developed using the extant literature on Dynamic Capabilities and TOE, and the extent to which the western based organizational readiness discourse on BD adoption agrees or disagrees with the reality of the impact of management's decision to adopt BDA and their financial and non-financial performance implications on businesses were assessed. From the extant, seminal research, the authors examined a range of 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 utilitarian business value/benefits of BDA adoption especially in marketing contexts. The development and justifications of the 9 selected hypotheses are provided below.

Technological factors

Anticipated value: The existing BDA literature focus on anticipated value, which indicates the anticipated operational and strategic advantages when companies adopt new

technology similar to BDA [128]. Additionally, while such BDA discourse highlights direct advantages such as lower organizational operating costs, improved internal, resource efficiency and lower mistake rates [79] on novel products and services[18] owing to the utilitarian value of BDA, there are some additional indirect advantages for such adoption [14] such as enhanced customer service, process reengineering [24;122], increased collaboration and inter-organizational information exchange[128]. However, such utilitarian value constructs (see Figure 1) have not been tested outside of traditional, western BDA discourse settings, particularly in Nigeria.

Insert Figure 1 about here

Consequently, based on the BDA adoption discourse focusing on utilitarianism, and management having a high opinion of such utilitarian value, organizations are logically expected to adopt full usage of BDA to meet crucial financial requirements [23]. Hence, it is hypothesized that:

Hypothesis 1: The anticipated organizational, utilitarian value of BDA adoption positively influences management's decision making capability and propensity to adopt BDA.

Technological competence: According to BDA discourse [124], using contemporary technologies effectively enhances innovation capability because “the degree to which the innovation is perceived as consistent with the existing [organizational] values, past experiences [path dependence], and needs of the potential adopter” [97, 1983, p. 223;35;119]. It would be logical to evince that applying BDA discourse, as a definitional and utilitarian construct, will facilitate organizations' desire to adopt BDA. To this end, the existing literature evince that “compatibility of an innovation may refer to its congruence with (1) the value systems (e.g., organizational culture), and (2) the business's [BD] practices” [23, p. 17]. It has also been outlined by [119], and validated in recent studies [52], that cognitive and operational compatibility are facilitated if organizations adopt BDA. However, applying such logics in all situations could be contextually problematic [128], particularly in contexts where they were not originally designed for, even in instances where BDA techniques are evinced to be consistently, utilitarianly aligned with company values, standard operating procedures and marketisation mechanisms. Thus, it is hypothesized that:

Hypothesis 2: Technological compatibility with an organization's values and standard operating practices (SOPs) positively influence management's decision to adopt BDA.

Organizational factors

Top management support: As part of the organizational factors, existing literature evince that top management support is crucial for organizations to adopt modern IT-based systems (e.g., BDA). The current literature further recognizes variable capabilities and data creation potential as key success indicators [103]. While such western influenced, utilitarian discourse on BDA adoption also highlights that when senior managers have optimistic expectations of IT system's potential benefits, they are more likely to adopt BDA [67] and to propel as a driver for changes in organizational norms, values, and cultures, the adoption of new technologies [53;55;69] and the development of network-based benefits [6;20;67], such utilitarian assertions have not been tested in the Nigerian manufacturing and service industry contexts. Thus, it is hypothesized that:

Hypothesis 3: As part of critical organizational factors, top management-level support enhances change in organizational culture thereby positively leading to management's propensity to adopt BDA.

Organizational readiness: Existing BDA literature highlight organizational readiness as a significant factor for firm-level capacity and propensity to embrace technological change [37]. It is a measure of the company's technical IT capacity and experience, showing its propensity to invest and manage new technology [118;138]. BDA scholarship contends that an organization's readiness is key for BD adoption and implementation [37;98]. According to [7] and [40], as an instance within the Marketing discipline, organizational readiness is key for such organizational level adoption. Thus, it is hypothesized that:

Hypothesis 4: Organizational readiness positively influences a firm's propensity to adopt technological changes positively leading to management's BDA adoption.

Environmental factors

Competitive pressures: While the afore technological and organizational (TO) factors seem to highlight the positivity of such aspects in influencing firm level BDA adoption, "competitive pressure" focuses on the environmental threat posed by a company's rivals in the

same market [83]. Such a challenge may force firms to embrace new technology as a way to gain advantage [86], although according to [86], rival firms can use more sophisticated BD tactics to win over customers from other firms, by incorporating cutting-edge, not-easily-affordable technological advancements [144]. Such competitive pressures may force smaller firms to mimic market leaders' practices particularly during volatility [69]. Others opine [2] that the fear of being seen as unique within the same sector may be a motivating factor in adopting newer technologies, although doing so may come at a financial cost. This not only acts as a driving force [86;97] but may slow down new business starts and the spread of innovative technologies in the same industry. Thus, it is hypothesized that:

Hypothesis 5. Competitive pressure, including the adoption of cutting edge technologies, amongst businesses operating in the same sector could either positively or negatively influence management's BDA adoption.

External support: The extant literature define external support as extended support from a vendor or third party to encourage enterprises to technologically innovate and implement a new strategy [12;37]. It is a critical driver of technological innovation adoption and successful resource utilization [40;101]. Access to vendor support is crucial for management's technological, innovative capacity and BDA adoption since it enables learning from suppliers and open-source platforms [37]. As [23] noted, outsourcing to external parties and suppliers may work effectively for an organization, especially in new start-ups without sufficient BDA expertise. Thus, on the basis of existing literature, it is hypothesized that:

Hypothesis 6: External support enhances technological innovation adoption through successful resource utilization thereby positively influencing management's BDA adoption.

Regulatory environment: Existing BDA literature highlight the significance of a favourable regulatory environment, whereby a government promotes entrepreneurial utilization of BD technologies. The literature evinces a suitable infrastructure, legal framework, regulatory directives, and assistance to do so [144]. For instance, with government support, legal steps can be taken to address people's worries about information leakage and illegal data trading as a way to address BD adoption constraints [58;135]. Thus, following the literature, it is hypothesized that:

Hypothesis 7: A favorable regulatory environment, including adequate infrastructure, legal framework, regulatory directives, and assistance, provides the legal infrastructure leading to management's BDA adoption

BDA adoption and financial and non-financial performance

Western-dominated empirical research suggests that the benefits of management's BDA adoption also has substantial impacts on firm-level 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 BD adoption has a positive relationship with a firm's financial performance even when high levels of market turbulence and environmental changes abound and threaten.

Although investing in BDA may come at a financial price, existing research suggests that it increases business productivity [80]. [84], [83], and [65] and beneficially impacts on innovative capabilities through a financial performance boost [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 use on essential determinants of financial performance, including market performance, organizational performance and operational performance [10;51]. [137] went further to state that BDA improves a firm's financial performance rather its market share.. Thus, on the basis of existing BDA literature, it is hypothesized that:

Hypothesis 8a: Management's adoption of BDA positively influences organizational level financial performance, increases business profitability and productivity despite market turbulence and environmental changes.

Hypothesis 8b: Management's adoption of BDA positively influences an organization's non-financial performance even when markets and external environments are turbulent and changing.

The Moderating Role of Environmental Dynamism

This study went beyond a critical appraisal of the TOE framework in the context of BDA, by examining environmental dynamism to ascertain whether other (external) factors could influence management's decision to adopt BDA. This is critical because existing BDA

studies limit themselves only to the TOE framework despite current studies highlighting that an examination of environmental dynamism to reveal how its unpredictability/external environmental changes could impact on BDA adoption is fundamental [142;35]. It is also a critical situational component in Dynamic Capabilities theory, in studying the variance of competitive advantage (e.g., financial sustainability) on an organization's/management's capability in interacting with and addressing environmental dynamism threats. Earlier studies argued that the effects of dynamic capabilities in a volatile market are uncertain and threatening [77;79]. In a moderately dynamic market, according to [35], organizations often thread linear and predictable paths given the stable industry structures and defined market boundaries that characterize such markets, 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 such developments threaten traditional, organizational path dependences [76].

However, while existing western-dominated scholarship expresses concerns about the unexpected and disruptive nature of environmental dynamism, particularly on organizational outcomes (e.g., positive results from BDA adoption) [3;79], it could also be argued that such types of environments present opportunities for organizations if management make good use of BDA techniques. [3] study uncovered that a volatile external environment may either boost management's valuable BDA skills but could also degrade them particularly in high-velocity markets, see [77;46]. Additionally, although existing research supports the logic that information sharing may lead to increased variation in financial performance results, especially in dynamic circumstances [72], environmental dynamism also pressurizes organizations to use additional management knowledge to drive BDA actions [31;54;113]. This is partly because key organizational decision-makers (management) are increasingly required to analyze events and information quickly and act effectively [17]. Despite the propounded benefits of such utilitarian discourse, market volatility could increase management stress and cognitive demands, potentially hindering their ability to make sense of events and execute critical BDA ideas to ward off the environmental threats to BDA adoption and their firms' financial viability [17]. This undermines management confidence and their strategic decision-making capability [19]. Thus, when faced with such a volatile environment, the necessity for BDA becomes critical

for corporate decision-makers (management) as the required dynamic capabilities depend less on existing information rather than on swift innovation and situation-specific new knowledge [35;119].

Following the western argument that BDA's enhancement of an organization's new knowledge and insight in highly dynamic contexts [22], such claims are especially pertinent not only in marketing, as enormous volumes of data are routinely gathered from many departments and locations across an organization's infrastructure (e.g., advertising, social media marketing, content marketing etc. – [35] but increasingly in other disciplines such as Human Resource Management. The need for management to holistically process, integrate, analyze and understand tonnes of data enhances managers' propensity to make effective strategic decisions [72] and deal with the psychological challenges of uncertainty [46] by swiftly recognizing and responding to the changing nature of threatening situations is therefore real [72]. Thus, it is hypothesized that:

Hypothesis 9a: Environmental dynamism, including the unpredictability and changing nature of the external environment positively moderates the impact of management's BDA adoption to enhance on organizations' financial performance.

Hypothesis 9b: Environmental dynamism including the unpredictability and changing nature of the external environment positively moderates the impact of management's BDA adoption to enhance on organizations' non-financial performance.

Methodology

Our research investigates the factors that influence the adoption of BDA by management and the subsequent effects on financial and non-financial performance. We employed a quantitative approach to explore the relationships between the different components of our theoretically derived conceptual model and empirically validate our hypotheses. A survey was designed as the quantitative method to assess and verify the model's ensuing hypotheses.

Instrument Development

To create the survey items, we initiated the process by conducting a thorough review of the relevant BDA and TOE literatures. We crafted the construct items using pre-existing items from previous studies, aiming to maximize the reliability and validity of our survey items. We measured the construct items using a seven-point Likert scale with anchors ranging from 1 (strongly disagree) to 7 (strongly agree) except for financial and non-financial performance. Moreover, the two performance constructs were measured using a seven-point

Likert scale ranging from 1 ('worse than major competitors') to 7 ('much worse than major competitors'). The respondents were also asked to provide demographic data about themselves and their organizations.

Before (survey) the data collection phase, the survey questions were pilot tested (across Nigeria's manufacturing and service sectors) with ten management experts in August 2021. This was done because existing literature purport that pilot studies enhance survey quality by offering input from various viewpoints to prevent problems that may develop during the actual data-gathering process [104]. According to [104] 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).

Data collection: Inclusion/exclusion criteria and sampling procedures

To be eligible for inclusion, participants must have at least 7 years of experience working with big data systems and at least 11 months of employment within their current organization. We excluded participants that did not meet these criteria. We reduced the minimum requirement for years of experience with the current employer to 11 months because some participants joined the organization within a year of us conducting the study but had acquired ample experience in big data systems elsewhere. These characteristics were considered by the research team as invaluable in the context of Nigeria, where such experiences are rare. The selected participants include those who have worked with their current employer between less than a year to 4 years. Such participants had between 7 and 10 years of big data system experience, having worked with a range of other employers (see Table 1).

After the inclusion-exclusion process, we randomly sent out approximately 870 survey questionnaires to professionals from various organizations in Nigeria between September and November of 2021. This respondent sample was selected as the most knowledgeable about big data systems in the firms, given that not all organizations employ big data analytics specialists. The survey was sent in both 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 decent 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, a sufficient sample size of more than 200 was chosen, and the final sample size was an impressive 261 usable management responses.

Of the 261 respondents, 55.1% were male, and 44.8% were female. The participants belonged to different age groups, with the most significant percentage being (34-41 years) age group (see the respondents' profile in Table 1). The different education levels, sector types,

number of employees, company positions and working experience (including the number of years the respondent had worked in their previous big data organization and the current) are also provided in Table 1.

Insert Table 1 about here...

Analysis

Given the model's complexity, consisting of 11 constructs, including a second-order factor (BDA) with 4 dimensions, we employed Covariance-Based Structural Equation Modelling (CB-SEM) in IBM AMOS version 22 as the statistical tool for analyzing the measurement and structural models. Following the approach outlined by [47], we conducted a two-step assessment of the model: first, evaluating the measurement model and then examining the structural model for reliability and validity.

5.1. Measurement model

Our study examined the convergent and discriminant validity of the measurement items and constructs. Table 2 presents the results of the reliability and convergent validity tests. To assess reliability, we utilized composite reliability, with values above 0.7 considered satisfactory, according to [47]. Convergent validity evaluates the extent to which the items align with the theoretical conceptualization of the construct and can be assessed by analyzing the item loadings and average variance extracted (AVE) for each construct, as [47] suggested. In our analysis, all item loadings exceeded 0.7, and AVE values exceeded 0.5 for all constructs, indicating satisfactory convergent validity of the measurement model. Additionally, for the second-order factor BDA, consisting of 4 lower-order dimensions, all 4 dimensions successfully passed the convergent validity test.

Insert Table 2 about here...

Discriminant validity was evaluated using the heterotrait-monotrait (HTMT) ratio of correlations method, as suggested by [48]. The detailed methodology and results can be found in Table 3. According to [48], HTMT values exceeding 0.85 indicate potential issues with discriminant validity, while smaller values indicate good discriminant validity. In our analysis, all HTMT values, as presented in Table 3, were below 0.85 [130] confirming good discriminant validity. Both assessments relating to convergent and discriminant validity, provided robust evidence supporting the validity and reliability of the study's measured items. Consequently, these items can be utilized to test the formulated hypotheses reliably and validly.

Structural model

Our analysis commenced with an evaluation of the goodness-of-fit of the structural model. The R^2 value for BDA adoption was determined to be 0.787, indicating a substantial proportion of the variance explained by the model. However, the model chi-square test

yielded a statistically significant result ($\chi^2(511) = 989.673, p < .001$), leading us to reject the hypothesis of an exact fit. On the other hand, the χ^2/df value of 2.079 suggests a good fit for the model. This ratio signifies that the discrepancy between the observed and expected covariance matrices is relatively small, further supporting the overall adequacy of the model fit. However, as this test is susceptible [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 VIFs exceeds 5, indicating that multicollinearity is not an issue in our study.

Insert Table 3 about here...

Hypotheses testing (direct effects)

The first two hypotheses state that the elements of technology factors, 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 and 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 is 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 management's BDA adoption positively influenced financial performance ($\beta = 0.096, p < .031$) and non-financial performance ($\beta = 0.095, \beta < 0.018$).

Insert Figure 2 about here...

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 interaction model, the interaction terms are significant with the addition of each interaction variable. 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 uses BDA, it substantially influences the organization's financial performance, especially in a dynamic environment. See Table 3 for a summary of the moderation test results.

Discussion

In the discussion, the authors address the extent to which the organizational readiness discourse in western-based Dynamic Capabilities and TOE frameworks varies from and/or is corroborated by the reality of management's decision to adopt BDA. To do so we start with the study's research question which states: *'What are the TOE characteristics driving Nigerian management's BDA adoption and the real post-decision making impacts on organizational level financial and non-financial performance?'* First, while the TOE framework's technological (anticipated value and technological competence), organizational (top management support and organizational readiness), and most of the environmental aspects (competitive pressure, external support, and regulatory environment) were found to have a significant positive influence on BDA adoption, the impacts of one environmental aspect, namely external support, were not supported by this study's findings. Therefore, external support is taken not to have any significant impact on firm performance, despite existing studies' affirmation. Additionally, by going a step further to examine whether an organization's BDA adoption impacts on financial performance, as enunciated in the extant Dynamic Capabilities and TOE frameworks, these relationships were supported as shown in testing the moderating effect of environmental dynamism on BDA adoption. Additionally, the results also found support for the moderating impact of environmental dynamism on financial performance. However, the moderating impact of environmental dynamism (ED) on non-financial performance of organizations and their propensity to adopt BDA was not supported. These findings are discussed further to evince additional contributions made by this study on the dominant TOE framework, particularly regarding organizational readiness for BDA adoption and its impacts.

Technological factors

In line with the TOE framework, the analysis of this study's results show that technological components in our model (anticipated value and technological compatibility) directly influence management's propensity for BDA adoption. Additionally, what these results demonstrate is a new insight into how BDA's implementation could ultimately pay dividends not only for organizations' benefits, as evinced in the BDA utilitarian perspective, but also the need to enhance management's capability for BDA adoption and implementation. Particularly, since it was found that it is not the technical components in themselves but rather in how the actual use of the technologies of BDA bore significant impacts on an organization's performance, it is therefore logical to evince that the ultimate impact of big data on organizational outcomes is therefore mediated by BDA adoption and management capability to use it. As such, while the results highlight the importance of the TOE variables, as significant antecedents in the promotion of management's propensity to adopt BDA, contributing to enhancing a business's ability to perform financially should also be simultaneously complemented with enhancing management's technical capacity.

Organizational factors

Both organizational factors (top management support and organizational readiness) were shown to have an impact on management's BDA adoption of various forms of technology, such as ICT, cloud computing, e-commerce, CRM, and ERP [5;7;28;40]. Top management vision impacts the extent of support received at organizational level for BDA implementation by fostering a favourable environment for enterprises' propensity to embrace new technology (7;106). This is partly owing to top-level management being perceived as key drivers for organizational transformation by conveying and fostering a clear and coherent set of values and a clear organizational vision for BDA adoption [28]. While top-level management assistance may help by speeding up learning in facilitating the spread of technology across organizations [7], as opined in previous and existing BDA discourse [37;28;58;64], it is also worthy to note that without enough technical, financial, and qualified human resources, organizations' and management's propensity to implement BDA meaningfully (i.e., to impact on organizational level performance outcomes) doing so becomes problematic. An organization is unlikely to implement BDA if it does not have the

necessary technological and human resources and competencies. While previous and existing BDA scholarship note that outsourcing BDA could address an organization's financial and technology resource constraints, and thereby forestall threats from environmental dynamism, these aspects should be dealt with at both the internal and external organizational levels respectively for BDA adoption to meaningfully happen [37].

Environmental factors

Among the three environmental factors (competitive pressure, external support, and government regulation), while only external support was found to have played any substantial role in BDA adoption, the insignificant impact of competitive pressure contradicts earlier and existing results [40]. This disconnect between western-centric discourse on organizational readiness and local competitors' pressures to meaningfully affect an environmental impact in Nigeria's manufacturing and service industries' BDA adoption is interesting on a number of levels. First, our finding demonstrates that Nigerian institutions are less impacted by globalization in comparison to their counterparts in western countries. This is partly explicable in the sense that successive years of sanctions have prevented major investments by international corporations in the Nigerian manufacturing and service markets, thereby minimizing organizational readiness to engage in competitive behavior emanating from a highly presurized BDA market environment. Third, as competitive pressure is reduced, local businesses are slower to embrace BDA, thereby accounting for the apparent negligibility of business owners and managers to decide to implement BDA [23]. Fourth, the study's results highlight a significant relationship between external support and organizational BDA adoption in line with the current BDA discourse to technically train management toward a utilitarian logic of BDA discourse [40;37], the resultant organizational-level shortage of knowledge not only drives management to rely heavily on external assistance for decision-making but it also questions the extent to which management and organizations may be ready for BD adoption and implementation readiness. Fifth, our results highlight a distinct contrast with existing studies' results [64;40], by showing that government regulations do not influence organization's and management's readiness for BDA adoption. Such an unusual but interesting insignificance of this correlation is that Nigerian organizations see BDA adoption as a substantial investment and that government

incentives are inadequate to justify expenditure and uptake. Additionally, rapid changes in government regulations in Nigeria negatively impact the degree to which managers' actions become dependent on government regulations, thereby limiting organizations' decision making capacity to invest in BDA adoption. This is at variance with current BDA organizational readiness and utilitarian discourse.

While our study's results align with Dynamic Capabilities and the organizational readiness discourse within the TOE framework, [77;82;97] that BDA adoption is financially beneficial for enterprises as it BDA favours enterprises' marketing success [83], helps in goods and services' creation, thereby enhancing higher value, customer retention and profitability against rivals [101; 97], these purported competitive advantages and reputation enhancements [91] are threatened when organizations lack the necessary competence to do so. By going a step further to examine the moderating effects of environmental dynamism on the relationship between management's BDA adoption and financial and non-financial performance, it was additionally interesting to note that the existing literature's affirmation of management's information processing skill as critically impactful on organizational level financial and non-financial performance. Although these results partially support the existing literature [132;18] on information processing as a dynamic competence for an organization's readiness for BDA adoption and competitiveness [35], this study's addition of the moderating effects of environmental dynamism to examine the interaction between management's decision to adopt BDA and its impacts on both financial and non-financial performance has not been previously conducted in the Sub-Saharan, African context and the TOE framework.

Contributions, Implications, limitations, and future research direction

This research is filled with unique contributions. First, based on existing BDA literature, the authors have used a large-scale field questionnaire and its results to produce an integrated conceptual model on the factors influencing and leading to management's decision to adopt BDA. It is the first of its kind to examine the disconnect between the organizational readiness discourse as evinced in western-centric Dynamic Capabilities and TOE frameworks and the real impacts/post-decision making effects of BDA adoption and implementation within manufacturing and service environments in Nigeria. The findings extend the Dynamic Capabilities framework by highlighting the need for environmental dynamism to take into

account a range of externally changing competitive pressures on businesses' readiness to adopt BDA, including the propensity to invest additional resources on BDA. Secondly, the findings extend the TOE framework by highlighting that the fluctuating and unreliable nature of government's propensity to initiate, monitor and evaluate the effectiveness of regulatory mechanisms is a major determinant and has impactful bearing on organizations' and management's propensity to adopt BDA in Nigeria.

Third, while previous and existing TOE studies highlight technological, organizational and environmental aspects that could either facilitate or hinder BDA adoption, their limited focus on which types of managerial/organizational level competences need to be developed to dynamically match a range of threatening environmental aspects (from regulatory changes, financial to competitive pressures) has been surfaced through this study's tested hypotheses (see Table 3) and additionally by showing the impact of the direct and moderating effects of the theory and empirically based variable on the study's results (see Figure 2). Such double-edge contributions highlight the practical usefulness of developing management's capability via a more dynamic and multi-level management - organizational information processing system than what the current financial utilization model that the TOE framework has developed thus far [119].

Fourth, this study also extends the TOE framework [8;1] by adding a range of other types of anticipated value (other than financial aspects) to the original triple-helix factorial dimension whose focus was mainly on building organizational readiness for BDA adoption and financial gain. This study added technological competence, top management's internal and external support to show how the reality of adopting as well as implementing BDA should be complemented with the understanding of the western-centric underpinnings of the organizational readiness discourse if management and organizations are to directly and indirectly impact on BDA adoption choice and application. Future research should investigate the impact of firm-level use of BDA (or other knowledge systems) on other dimensions of organizational performance.

Fifth, this study's results contribute to earlier TOE research that found competitive pressure and government regulation to be key drivers of management's BDA adoption [37;40;64]. This study's clearly shows that there were no significant testable associations between these concepts in Nigeria partly due to the volatility of the regulatory environment

in Nigeria. Despite earlier TOE studies' concerns, our research shows that management's choice to adopt BDA significantly impacts organizational level financial as well as non-financial performance [80] and that environmental dynamism is crucial. It is also shown how management's values-based choices in adopting BDA [131] are not only crucial in deepening understanding about the extent to which organizations are realistically ready to adopt BDA as paradoxically opposed the Dynamic Capabilities and TOE frameworks whose discourse evinces a natural progression towards BDA adoption. Therefore, this study has shown the disconnect between TOE's financialization, utilitarian discourse and the reality of non-significant impact of environmental dynamism on BDA adoption in Nigeria. Additionally, this study has added to Dynamic Capabilities theory by evincing the types of environmental aspects (technological and socio-cultural) that management need to develop capabilities on if they are to adopt BDA and meaningfully impact on their firms' financial and non-financial performance. Future research can include other complimentary theoretical viewpoints into our framework .

Sixth, the outcomes of this research also have significant management practice contributions and implications. The study has shown evidence of how management's BDA adoption has a direct practical 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 based on the organizational readiness discourse [62]. As many businesses are still hesitant to make such commitments, the study extends [119] potential returns on investment by deepening management and overall organizational level understanding of how to make informed judgements on where to and where not to invest for efficient BDA outcomes. 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 performance outcomes should be done by critically understanding their organization's setting and their resource availability and scale. 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 TOE factors could impact on management's choices regarding BDA adoption, this study additionally found that management decision to implement BDA in Nigeria is primarily organizational and environmental rather than simply technological as earlier attested to if success is to be maximized [28]. Therefore, governments in developing economies 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 manufacturing, service and marketing contexts to ascertain the extent to which management, organizational and interorganizational readiness for BDA adoption, implementation, evaluation and impact across continents is feasible. 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] and interorganizational and cross management value sets.

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 Badwagons: Using Mathematical Modelling 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. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. [doi:10.1007/s11747-014-0403-8](https://doi.org/10.1007/s11747-014-0403-8)

49. 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>
50. 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>
51. 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>
52. 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>
53. 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>
54. 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>
55. 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>

56. 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>
57. 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>
58. 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)
59. 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)
60. 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)
61. 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)
62. 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)

63. 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>
64. 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>
65. 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>
66. 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>
67. 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>
68. 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>
69. 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>

70. 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>
71. 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>
72. 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>
73. 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>
74. 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>
75. 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>
76. 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>

77. 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>
78. 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>
79. 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>
80. 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>
81. 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>
82. 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>
83. 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*.

84. 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>
85. 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>
86. 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>
87. 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>
88. 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>
89. 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>
90. 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>

91. 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>
92. 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>
93. Petter, Straub, & Rai. (2007). Specifying Formative Constructs in Information Systems Research. *MIS Quarterly*, 31(4), 623. <https://doi.org/10.2307/25148814>
94. 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>
95. 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>
96. 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>
97. 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>

98. 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>
99. 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>
100. 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>
101. 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>
102. 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>
103. Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2-An improved criterion for assessing discriminant validity in structural equation modelling. *Industrial Management & Data Systems*. [doi:10.1108/IMDS-02-2021-0082](https://doi.org/10.1108/IMDS-02-2021-0082)
104. 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>

105. 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>
106. 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>
107. 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>
108. 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>
109. 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>
110. 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>
111. 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.
112. So, are the geeks inheriting the earth? (2013). *Strategic Direction*, 29(9), 12–15. <https://doi.org/10.1108/sd-08-2013-0051>

113. 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>
114. 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>
115. 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>
116. 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>
117. 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>
118. 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>
119. 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>

120. 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)
121. 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)
122. 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)
123. 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>
124. 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>
125. 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>
126. 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>
127. 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>

128. 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>
129. 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>
130. Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science*, 44(1), 119–134. [doi:10.1007/s11747-015-0455-4](https://doi.org/10.1007/s11747-015-0455-4)
131. 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>
132. 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>
133. 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>
134. 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>
135. 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>
136. 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>
137. 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>
138. 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>
139. 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>
140. 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>
141. 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>
142. 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>

143. 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>
144. 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>
145. 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>
146. 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>
147. 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>
148. 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>
149. 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

First-order constructs

Anticipated value Chen et al., 2015; Ghobakhloo, Arias-Aranda et al., 2011; Premkumar & Roberts, 1999)

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

Technological competence Chen et al., 2015; Ghobakhloo, Arias-Aranda et al., 2011; Thong, 1999; Tornatzky & Klein, 1982)

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
-

Top management support (Chen et al., 2015; Lai et al., 2018; Priyadarshinee et al., 2017)

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
-

Organisational readiness (Chen et al., 2015)

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
-

Competitive pressure (Lai et al., 2018)

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
-

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.
-