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Determinants of the adoption of big data analytics in business consulting service: a survey of multinational and indigenous consulting firms*

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ABSTRACT
This study investigates the factors affecting the adoption of big data analytics (BDA) by business consulting firms. With the aid of a structured questionnaire, survey data was obtained from one hundred and eighteen (118) business and management consultants working in multinational and indigenous consulting firms in Nigeria. Discriminant analysis and multinomial logistic regression were applied to assess the determinants of BDA adoption, while structural equation modelling (path analysis) was used to assess the complexity of the interrelationship among the determinants. Robustness check using least square regression, correlation, covariance (Cov) and sum of squares and cross-products (SSCPs) analysis confirms that results are valid. Whilst the desire to enhance competitive position will cause incremental improvement in BDA adoption, consulting firms are likely to intensify BDA usage because of the need to increase market share. The determinants of BDA adoption are interrelated, implying that the advantages of BDA are systemic and could yield synergistic benefits.

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1. Introduction

Recent developments in the business world, such as changing customers' tastes, intense competition and environmental uncertainty, among other issues, are imposing pressure on organisations to seek strategies to remain competitive (Agyapong, 2021; Du, Yang, & Dang, 2020). It has been suggested that since data has strategic ramifications (e.g. Dunk, 2004; Maelah, Auzair, Amir, & Ahmad, 2017), the analysis of data can offer competitive advantage. Insights from the analysis of data can shape the formulation and implementation of competitive strategies (Kushwaha, 2011). With the advent of technological innovation, it is now possible for organisations to process myriads of structured, semi-structured and unstructured data (i.e. 'big data') at the shortest time possible (Singh, 2019). The concept of big data is characterised by: volume (amount of data generated per time); variety (the various types of structured and unstructured data that can nowadays be used), velocity (the speed at which new data are constantly created and processed to meet the demands of accurate information), veracity (the reliability of data), value and complexity (Mohammadpoor & Torabi, 2019). Owing to these attributes, big data cannot be analysed using traditional data processing techniques, thereby necessitating the application of big data analytics (BDA). BDA involves the extensive analysis of voluminous and varied data sets (i.e. big data) for the purpose of detecting useful insights that enhance decision-making (Navickas & Gružauskas, 2016; Rowe, 2005; Sharma, Mithas, & Kankanhalli, 2014). With the avalanche of data generated on a daily basis in the ordinary course of business, the problem confronting organisations has shifted from the paucity of data to deriving useful insight from data. This development presents business opportunities to consulting firms to leverage their expertise in assisting clients convert data to actionable intelligence (Tras, 2015; CB Insights, 2018). Against this backdrop, the need for business consulting firms to apply big data and analytics to improve the quality of their services and their overall competitiveness has never been more pressing.

The discourse on big data in the field of business and management science is growing (e.g. Appelbaum, Kogan, & Vasarhelyi, 2018; Dilla, Janvrin, & Raschke, 2010; Jans, Alles, & Vasarhelyi, 2014; Li, Dai, Gershberg, & Vasarhelyi, 2016; Vasarhelyi, Kogan, & Tuttle, 2015). This notwithstanding, studies on BDA in business and management consulting services are lacking. Whereas literature acknowledges the rising importance of big data in

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business consulting (CB Insights, 2018; Schneider, Dai, Janvrin, Ajayi, & Raschke, 2015; Warren, Donald, Moffitt, & Byrnes, 2015), surprisingly, little research attention has been focused on the application of BDA in the business consulting context. As business and management consulting practice primarily operate by analysing data on existing organisational problems with a view to developing plans for improvement, the use of big data and BDA by such entities is too important to be ignored, thus meriting research attention. Furthermore, it is worthwhile to gain an understanding of the determinants of BDA adoption among consulting firms, as the subject is yet to be rigorously researched. Such knowledge will assist in promoting the uptake of big data and analytics among consulting firms, because how well consultants are able to apply BDA in improving the quality of their services may impact the operational success and performance of their clients. With these thoughts in mind, this paper seeks to address the following research questions: (i) What are the factors affecting the adoption of BDA as an innovation by consulting firms? (ii) What factors would cause consulting firms to intensify BDA usage? (iii) To what extent is there a relationship among the determinants of BDA adoption.

Analysis of survey data from one hundred and eighteen (118) consultants reveals that the underlying considerations driving BDA adoption by consulting firms are the need to: maintain a robust database, better satisfy clients, enhance decision quality, improve internal business processes, increase market share, improve meeting deadlines and improve competitive position (research objective one). Whilst the desire to enhance competitive position will cause incremental improvement in BDA adoption, consulting firms are likely to intensify BDA usage because of the need to increase market share (research objective two). The determinants of BDA adoption are interrelated, implying that the advantages of BDA are systemic and could yield synergistic benefits (research objective three). Considering the complexity of interrelationship among the determinants, firms are encouraged to step-up the implementation level of BDA in order to enjoy its synergistic benefits. The study contributes to knowledge by exposing the relevance of BDA to business and management consulting using empirical evidence from both Multinational and Indigenous Consulting Firms. Meanwhile, the consulting sector in Nigeria is dominated by multinational consulting firms with transnational presence in developed and developing countries. The cosmopolitan nature of the consulting sector in Nigeria – which provides a level-playing field to both indigenous and multinational consulting firms – presents a rich context to investigate determinants of the adoption of BDA in business consulting service. Thus, this study is relevant to international/transnational audience. The consideration that majority of the respondents emanate from multinational consulting firms (101, 85.6%) bolsters the claim that this study has international/transnational relevance. To the researchers' knowledge, this is one of the earliest studies to investigate the application of big data and analytics by business consulting firms in the Nigerian context. The study presents empirical evidence that the deployment of BDA can be a source of competitive advantage for consulting firms. Further, the study adds to literature on management accounting in the digital economy and the application of big data to business and management consulting.

The remainder of this paper is organised into five Sections 2–6. Section 2 focuses on literature review; Section 3 covers methodology, followed by results and discussion of findings in Sections 4 and 5, respectively. The paper is concluded in Section 6.

2. Literature review

2.1. Theoretical framework

Big data, BDA and business analytics are relatively new concepts in the Information Technology field (Frizzo-Barker, Chow-White, Mozafari, & Ha, 2016; McAfee & Brynjolfsson, 2012), and BDA is gaining momentum (Koseleva & Ropaite, 2017; Mohammadpoor & Torabi, 2019), especially the analysis of semi-structured and unstructured data (Russom, 2011). BDA has, therefore, been conceived and researched as an innovation (e.g. Davenport, 2014; Koseleva & Ropaite, 2017). According to Koseleva and Ropaite (2017), the first science research on the topic of big data was done in 1974. However, the extent of research in the area has been rapidly increasing during the last 10 years (Koseleva & Ropaite, 2017). Advanced data analytics software is replacing traditional decision-making processes and disrupting tried and trusted traditional data analysis methodologies, with big data being one of the main forces of disruption (Vulpen, 2018).

By conceiving BDA as an innovation, this study invokes Rogers' (2003) diffusion of innovation theory as the theoretical framework. Prior studies have applied the diffusion of innovation theory to explain the factors affecting the adoption of technological innovation (e.g. Ax & Greve, 2017; Love & Cebon, 2007; Sahin, 2006). Rogers

(2003, p. 12) conceives an innovation as 'an idea, practice, or project that is perceived as new by an individual or other unit of adoption'. Although an innovation may have been invented a long time ago, if individuals in a location, place or organisation perceive it as new, then it may be construed as an innovation for them. Whereas the analysis of data to improve organisational effectiveness has been a long-standing phenomenon (Thong, 1999), the analysis of large volume of data, particularly semi-structured and unstructured data, is increasingly gaining momentum (Ang & Seng, 2016; Navickas & Gružauskas, 2016) and could be regarded as an innovation. Recently, big data, business analytics and BDA have been subjects of research in various disciplines (e.g. Koseleva & Ropaite, 2017; Mathew et al., 2015; Oyewo & Tran, 2021).

Rogers (1983, 2003) postulates that innovation attributes, such as relative advantage, compatibility, complexity, trialability and observability explain the adoption of an innovation. According to Rogers (2003, p. 229), Relative advantage is 'the degree to which an innovation is perceived as being better than the idea it supersedes'. An innovation is adopted if it is considered more advantageous than an existing practice. Relative advantage is often expressed in terms of economic, profitability, social prestige or other similar benefits (Vagnani & Volpe, 2017). Compatibility is the degree to which an innovation is perceived by potential adopters as being consistent with the existing values and past experiences. An idea that is not compatible with the values of an individual, organisation or social system will face a low adoption level in comparison to a practice that is compatible (Gupta, Seetharaman, & Raj, 2013). Complexity is the degree to which an innovation is perceived as difficult to understand and use. The more complex the innovation, the less likely it is to be quickly adopted (Rogers, 2003; Thong, 1999). Trialability is the degree to which an innovation may be subjected to limited experimentation. An innovation that can be partially implemented or tried on a limited basis has greater propensity to be adopted (Ramdani, Chevers, & Williams, 2013). Observability is the degree to which the benefits from the adoption of an innovation are visible to others (Rogers, 1983). The more the results are visible to others, the more likely the innovation is to be adopted (Hashem & Tann, 2007).

The contextualisation of Rogers' (2003) diffusion of innovation theory to this study implies that the BDA adoption by consulting firms is informed by its relative advantage in enhancing organisational competitiveness (Duan & Xiong, 2015; Lycett, 2013). BDA will be preferred over traditional data analysis techniques because the analysis of voluminous structured, semi-structured and unstructured data provides in-depth knowledge of issues affecting organisations (Warren et al., 2015; Rouhani, Rotbei & Shamizanjani, 2017). The more the benefits accruing to BDA adopters (in terms of enhanced competitiveness) become visible, the greater the tendency to adopt BDA by non-adopters. Furthermore, adopters are likely to upscale BDA usage as benefits of adoption become more observable (observability). Empirical evidence supporting the proposition that innovation attributes affect adoption rate abounds (e.g. Premkumar, 2003; Sahin, 2006; Vagnani & Volpe, 2017).

2.2. Benefits of big data analytics in business consulting service

The application of BDA in various aspects of business consulting can deliver tremendous benefits. In the area of brand building and product positioning, insights from BDA can be useful in developing products that appeal to customers in terms of cost, functionality and quality (Saleem & Rashid, 2011; Spenner & Freeman, 2012). Data could help relate revenues and costs to customers or to groups of customers to assess the relative profitability of providing goods or rendering services to customers (BPP, 2008; Cadez & Guilding, 2008; Salehan & Kim, 2016). Customer profitability analysis could benefit from the existence of a database of customers (data-warehousing). The existence of such database makes data-mining possible. Database marketing, which thrives on the analysis and use of customer database to aid the direct marketing of products, could offer benefits to a business in the areas of identifying the best customers, tailoring messages based on customer usage, electronic commerce, digital marketing (application of information system and internet techniques to achieve marketing objectives), cross-selling of related and complementary products, and developing new customers (BPP, 2009; Kitchens, Dobolyi, Li, & Abbasi, 2018; Saldanha, Mithas, & Krishnan, 2013). With respect to innovation and strategy consulting, insights from BDA could shape competitive strategies (Cinquini & Tenucci, 2010; Frezatti, Bido, Cruz, & Machado, 2015). The deployment of BDA in auditing and internal control could assist in the collection of robust audit evidence with minimal cost (Appelbaum et al., 2018; Li et al., 2016). In relation to financial advisory service, consulting firms could apply BDA in advising clients on investment decisions (Cuzdriorean, 2017). In market research diagnostics, consultants can use data mining techniques to advise clients concerning products that are in joint demand and the marketing strategies to drive sales (Khade, 2016; Verma, Malhotra, & Singh, 2020). In risk consulting, BDA becomes instrumental for analysing risk patterns and profiling customers for risks – such knowledge is useful to banks and insurance companies in product pricing (Baesens, Dejaeger, Lemahieu, & Moges, 2013; Miller, 1992).

A consulting firm that is able to extensively apply BDA in the various areas of business and management consulting may be strategically positioned to gain competitive edge over others using traditional data processing techniques. This is because consulting firms with capabilities in BDA would analyse data more thoroughly and have deeper knowledge of the issues confronting clients (Khanra, Dhir, & Mäntymäki, 2020). Such insights from BDA could influence the quality of service rendered, as well as the extent to which consulting service adds value to clients (Rialti, Marzi, Ciappei, & Busso, 2019). Thus, the need to better satisfy customers, improve the quality of decision, develop new consultancy service/improve existing ones, grow consultancy income; increase market share and improve overall competitiveness may prompt a consulting firm to adopt BDA. Studies show that the benefits of BDA adoption are diverse (Gillon, Aral, Lin, Mithas, & Zozulia, 2014; Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013), interrelated (Gangadharan & Swami, 2004; Sharma et al., 2014; Sharma & Shanks, 2011) and synergistic (Habjan, Andriopoulos, & Gotsi, 2014; Huang, Pan, & Ouyang, 2014; Sun, Sun, & Strang, 2018). Processing large data will cause an organisation to maintain robust database (Raguseo, 2018), which also promotes corporate culture on data management (Rouhani, Rotbei, & Shamizanjani, 2017). The acquisition of big data technology makes it easy and cost-effective to amass and process large volumes of data (Sheng, Amankwah-Amoah, & Wang, 2019). Quick processing of data enables a firm to improve turnaround time, whilst meeting deadlines for assignments (Ivanov, Dolgui, & Sokolov, 2019). The existence of a robust database, on account of accumulating voluminous and varied data using big data technology, could contribute to the competence of a consulting firm in developing new services and/or improving existing ones (Kohli, 2007; Rowe, 2005; Sharma & Shanks, 2011). With BDA, quick turnaround time is achieved, which results in improved customer satisfaction, higher customer patronage and increased market share (Ballings & Van Den Poel, 2012). Higher customer patronage and increased market share ultimately determine the overall competitiveness of a consulting firm (Duan & Xiong, 2015; Murthy, Kalsie, & Shankar, 2021). Conceptual model on the relationship between determinants and BDA adoption by business consulting firms is presented in Figure 1.

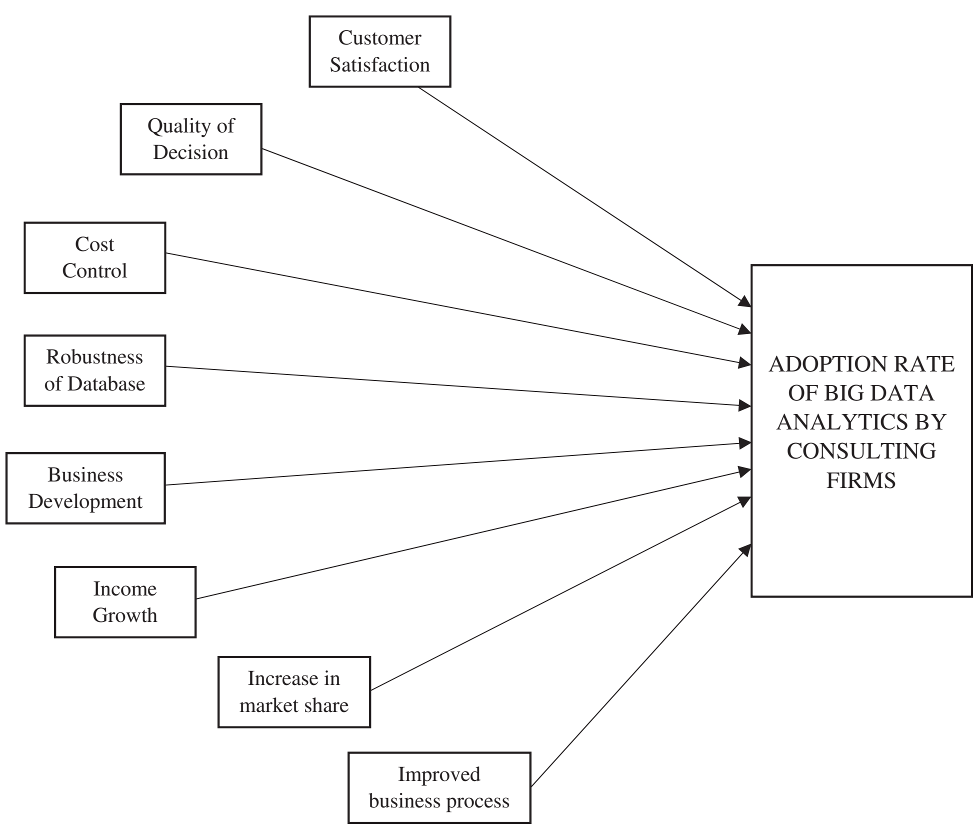

Figure 1. Determinants of the adoption of big data analytics by business consulting firms. Source: Researchers' conceptualisation.

3. Methodology

3.1. Research design

The population of the study comprises all business and management consulting firms in Nigeria, but the study focuses on top-ranking firms providing diverse consulting services. After scrutinising the directory of registered consulting firms from five different online sources [viz: (i) https://www.businesslist.com.ng; (ii) http://www.jarushub.com/ranking-worlds-top-consulting-firms-by-categories-2016/; (iii) https://www.consultingcase101.com/list-of-consulting-firms-in-lagos-nigeria;(iv) https://www.nairaland.com/2481274/list-top-management-consulting-companies; and (v) https://www.nigerianinfopedia.com/best-consulting-firms-nigeria-top-10], top twenty (20) firms that consistently appear across the lists were selected, including the big 4 and sixteen (16) non-big 4 firms. This technique was used to select top-consulting firms as there is no comprehensive list of business and management consulting firms in Nigeria. Some studies have used a similar approach for sample selection (e.g. Oyewo, 2017; Soobaroyen & Poorundersing, 2008). The 20 firms, which include both multinational and indigenous consulting firms, represent approximately 45% of the mainstream business consulting firms in Nigeria. Data collection was by a structured questionnaire distributed through the consulting firms to individual consultants working in those firms. Fifteen (15) copies were distributed in each of the big 4 considering their size, while seven (7) copies were distributed to each of the sixteen (16) non-big 4 firms, making a total of one hundred and seventy-two (172) copies distributed. Respondents were requested to complete the questionnaire based on the experience of their firms on BDA adoption. Data collection lasted almost four months (September–December 2019).

3.2. Measurement of variables

3.2.1. Adoption rate of BDA

Adoption rate of big data analytics (ARBDA) in the context of this study refers to the degree to which a consulting firm is implementing BDA as a new idea. This was measured by requesting respondents to indicate on a scale of 1 ('not applied') to 5 ('very extensive') the extent to which analysis of big data is applied by their firms in ten critical areas of consulting services covering (Ernst & Young, 2014; Vulpen, 2018): (i) Human Resource Consulting; (ii) Risk consulting; (iii) Financial Advisory Services; (iv) Innovation & Strategy consulting; (v) Brand building & Product Positioning; (vi) Market Research/Diagnostic Studies; (vii) Scenario-Based Planning/Business Simulation; (viii) Information Technology consulting; (ix) Internal Control/Internal audit consulting; (x) Taxation and Tax Management consulting. Thereafter, hierarchical cluster analysis (*between-groups linkage* cluster method using *Squared Euclidean distance* interval measure) was applied to regroup firms into three adopter categories of [using Rogers'(2003) nomenclature]: *laggards* (firms with low adoption rate) labelled as Group 1; *early majority* (firms characterised by generally moderate adoption rate) labelled as Group 2; and *innovators* (firms with relatively high adoption rate across the different areas)labelled Group 3. Studies on diffusion of innovation have used a similar methodology to group adopters of innovations (e.g. Elliott, 1968; Holloway, 1977; Ostlund, 1974; Oyewo, Ajibola, & Ajape, 2020).

3.2.2. Determinants of the adoption of big data analytics

In the context of this study, the relative benefits of BDA are conceptualised as the determinants of BDA adoption based on Rogers' diffusion of innovation theory. Determinants of BDA adoption were measured by asking respondents to rate on a scale of 1 (not at all) to 5 (very great extent) the extent to which the following considerations influenced the decision of their firms to apply BDA: (i) the need to consolidate competitive position (*position*); (ii) improvement in quality of decision (*decision*); (iii) client satisfaction (*satisfaction*); (iv) reduction in cost of service provision (*cost*); (v) development of corporate culture on big data (*culture*); (vi) the need to maintain robust database (*database*); (vii) meeting deadlines on assurance engagements (*deadline*); (viii) development of new consulting services/improvement in existing services (*service*); (ix) growth in consultancy income (*income*); (x) improvement of market share (*market*); and (xi) efficiency of internal business process (*process*). These 11 aspects were selected based on their enumeration in literature as critical areas of organisational excellence (Hoque & James, 2000; Cadez & Guilding, 2012; Chartered Global Management Accountants & CGMA, 2015; Ajibolade & Oyewo, 2017).

3.3. Model specification

To assess the factors affecting BDA adoption, Model 1 is specified:

$$\begin{aligned} \text{ARBDA} = {} & \alpha_0 + \alpha_1 \text{ position} + \alpha_2 \text{ decision} + \alpha_3 \text{ satisfaction} + \alpha_4 \text{ cost} + \alpha_5 \text{ culture} + \alpha_6 \text{ database} + \alpha_7 \text{ deadline} \\ & + \alpha_8 \text{ service} + \alpha_9 \text{ income} + \alpha_{10} \text{ market} + \alpha_{11} \text{ process } + \text{et} \end{aligned} \tag{1}$$

where ARBDA is adoption rate of BDA based on the three groups of *innovators, early majority* and *laggards;* α_0 *is the constant; position* is competitive position; *decision* is quality of decision; *satisfaction* is level of client satisfaction; *cost* is cost of service provision; *culture* is corporate culture on big data; *database* is the robustness of database; *deadline* is meeting deadlines on assurance engagements; *service* is business development in consulting service; *income* is growth in consultancy income; *market* is market share; *process* is efficiency of internal business process; *α1–11* are discriminant coefficients or weights of predictor variables; *et is stochastic error term*.

Model 1 is underpinned by Rogers' (2003) diffusion of innovation theory which advocates that the relative advantage of BDA over traditional data processing technique promotes its diffusion rate. Prior studies have investigated the adoption rate of innovation in a similar context (e.g. Vagnani & Volpe, 2017; Van Helden & Tillema, 2005).

3.4. Method of data analysis

Discriminant analysis was used to evaluate the factors affecting BDA adoption, while multinomial logistic regression was applied to assess the factors responsible for intensifying BDA usage. Structural equation modelling (path analysis) was used to assess the complexity of the interrelationship among the determinants. Least square regression, correlation, covariance (Cov) and sum of squares and cross-products (SSCPs) analysis were applied to evaluate the robustness of results.

3.5. Respondents' attrition and response rate

From the one hundred and seventy-two (172) copies of the questionnaire administered, one hundred and twenty-three (123) copies were retrieved, representing a response rate of 71.5%; five (5) copies were found unsuitable for use because of incomplete response, thereby reducing the number of usable copies to one hundred and eighteen (118). This diminished the effective response rate to 68.6%. The one hundred and eighteen (118) valid responses were processed for analysis. Non-response bias was assessed by comparing the first 20% of responses obtained with the last 20% of responses using global presence (big 4/non-big 4 dichotomies) as a basis for comparison of early response with late response. Independent sample *t*-test result shows no significant difference at 5% ($p = .355 > .05$), confirming the absence of non-response bias (Oyewo, 2021; Saunders, Lewis & Thornhill, 2007). The profile of respondents and attributes of the consulting firms where they work is presented in Table 1.

The responses obtained from the survey span across various consulting firms in terms of size, affiliation and global presence (Table 1). Consultants from both multinational (101, 85.6%) and indigenous (17, 14.4%) firms participated in the study. While 49 (41.5%) respondents have 3–6 years of experience, more than half (69, 58.5%) have over 6 years of consulting experience, suggesting that the informers should be sufficiently familiar with

Table 1. Respondents' profile and consulting firms' attributes.

Variable	Category	Freq.	%	Total
Length of experience as a consultant (years)	3–6	49	41.5	
	7–10	37	31.4	
	11–15	27	22.9	
	Over 15	4	4.2	118
Number of partner(s) in firm (firm size)	2–4 Partners	17	14.4	
	5–9 Partners	50	42.4	
	10 and above partners	51	43.2	118
Affiliation to International Firm	Affiliated/multinational	101	85.6	
	Not-affiliated/indigenous	17	14.4	118
Scope of operation	Big 4	56	47.5	
	Non-Big 4	62	52.5	118

issues affecting BDA adoption in their firms. Altogether, the diversity in the background of respondents presents an important context for investigating the subject matter of the study. The consideration that majority of the respondents emanate from multinational consulting firms (101, 85.6%) bolsters the claim that this study has international/transnational relevance.

4. Results

4.1. Determinants of the adoption of big data analytics

Results from multi-discriminant analysis assessing the dimension(s) of organisational competitiveness responsible for the adoption rate of BDA are reported in Tables 2 and 3 and Appendix 1.

The multi-discriminant analysis generated two Functions (1 and 2) with 76.1% variance explained by Function 1, while Function 2 explains 23.9% of the variation (Table 2). The Eigenvalue (1.033) and canonical correlation (0.713) of Function 1 contrast sharply with that of Function 2 at 0.325 and 0.495, respectively. The Wilks' Lambda (λ) of Function 1 through 2 (0.371) is lower than the one for Function 2 (0.755) (Table 2). Both Functions 1 and 2 are statistically significant at 1% (Model 1: $p = .000 < .01$; Model 2: $p = .001 < .01$), meaning that discriminant Functions 1 and 2 were able to significantly discriminate the adoption rate of BDA based on the determinants (Table 2). As these statistics suggest that Function 1 is more sophisticated than Function 2, discriminant analysis yielded by Function 1 was utilised for analysis. The hit ratio of the discriminant analysis at 77.1% (i.e. addition of figures on the principal diagonal: $54 + 22 + 15 = 91/118$) (classification Table in Appendix 1c) suggests that the discriminant function was fairly accurate in predicting the considerations driving BDA adoption.

Result in Table 3 indicates the discriminating power of the determinants. Reckoning with the absolute value of the coefficients to gauge the magnitude of contribution of each predictor to the function (see Malhotra & Birks, 2007), dimensions of organisational competitiveness markedly explaining the adoption rate of BDA, at a threshold of 0.10, are: robustness of database [*database*] (0.911), better satisfaction of clients [*satisfaction*] (0.697), improvement in quality of decision [*decision*] (0.588), enhancement of internal business processes/automation of activities [*process*] (0.498), improved market share of firms [*market*] (0.448), growth in consultancy income [income] (0.261), improvement in meeting deadline of assurance engagements [*deadline*] (0.159) and improvement in competitive position [*position*] (0.155). Other considerations (with coefficients less than 0.10) such as development of new consultancy services/improvement of existing services [*service*] (0.099), reduced cost of providing consultancy services [*cost*] (0.029), and improved corporate culture on big data management [*culture*] (0.009) appear not to strongly drive BDA adoption. Based on these results, it is concluded that the considerations underlying BDA adoption by consulting firms are the need to: maintain a robust database, better satisfy clients, enhance decision quality,

Table 2. Goodness of fit for discriminant function.

Function	Eigenvalue	% of Variance	Cumulative %	Canonical correlation	Wilks' Lambda	Chi-square	Sig.
1	1.033[a]	76.1	76.1	0.713	0.371	109.042	0.000
2	0.325[a]	23.9	100.0	0.495	0.755	30.984	0.001

[a]First 2 canonical discriminant functions were used in the analysis.

Table 3. Standardised canonical discriminant function coefficients.

		Function	
S/N	Determinants	1	2
1	Position	−0.155	1.437
2	Decision	0.588	−0.742
3	Satisfaction	−0.697	0.340
4	Cost	0.029	−0.377
5	Culture	−0.009	−0.478
6	Database	0.911	−0.113
7	Deadline	−0.159	0.831
8	Service	0.099	−0.181
9	Income	0.261	−0.396
10	Market	−0.448	0.228
11	Process	0.498	−0.071

improve internal business processes, increase market share, improve meeting deadlines and improve competitive position (research objective one).

4.2. Factors driving the usage intensity of big data analytics

The discriminant analysis provides a general view of the considerations driving the application of BDA but does not reveal the factors responsible for intensifying BDA usage. To address this concern, multinomial logistic regression was applied. By selecting Group 1 (the *laggards*) as the reference group, comparison was made between Group 1 (*laggards*) and Group 2 (*early majority*), as well as Group 1 (*laggards*) and Group 3 (*innovators*). Result of the analysis is presented in Table 4.

From the result in Table 4, considerations that will cause firms to slightly upscale BDA usage from *laggards* to *early majority* (i.e. factors with significant odds ratio responsible for movement from Groups 1 to 2) are: the need to improve competitive position [*position*], the need to improve the quality of decision (*decision*), the desire for a robust database (*database*), the need to meet deadlines (*deadline*), the need to grow consultancy income (*income*) and the desire to improve market share (*market*). However, the need to improve competitive position (*position*) is the strongest determinant, with odds ratio of 66.721 ($p < .01$), implying that consulting firms are 66.7 times more likely to incrementally apply BDA because of the desire to enhance competitive position.

Similarly, considerations that will cause organisations to substantially upscale BDA usage from *laggards* to *innovators* (i.e. factors with significant odds ratio explaining movement from Groups 1 to 3) are: the need to improve competitive position (*position*), the need to maintain a robust database (*database*), the need to grow income (*income*), the need to improve market share (market) and the need to enhance efficiency of internal business process (*process*). However, the need to improve market share (*market*) is the strongest determinant, with the highest odds ratio of 70.457 ($p < .01$), implying that organisations are 70.5 times more likely to extensively apply BDA for the purpose of increasing their market share in the consulting business. The model fitting information in Table 5

Table 4. Multinomial logistic regression result on determinants of BDA usage intensity.

							95% Confidence interval for OR	
Group[a]	Variables	B	Std. error	Wald	Sig.	OR	Lower bound	Upper bound
Group 2 (*early majority*)	Intercept	1.577	2.050	0.591	.442			
	Position	4.201	1.294	10.533	.001	66.721***	5.279	843.235
	Decision	−2.717	1.280	4.503	.034	.066**	0.005	0.813
	Satisfaction	1.321	1.124	1.382	.240	3.747	0.414	33.904
	Cost	−0.049	0.532	0.008	.927	0.952	0.336	2.703
	Culture	−1.046	0.687	2.315	.128	0.351	0.091	1.352
	Database	−2.206	1.060	4.334	.037	.110**	0.014	0.879
	Deadline	1.538	0.473	10.583	.001	4.654***	1.843	11.755
	Service	−0.551	0.704	0.613	.434	0.576	0.145	2.289
	Income	−1.190	0.712	2.793	.095	.304*	0.075	1.228
	Market	1.258	0.743	2.865	.091	3.519*	0.820	15.108
	Process	−1.111	0.722	2.371	.124	0.329	0.080	1.354
Group 3 (*innovators*)	Intercept	14.071	5.047	7.772	.005			
	Position	2.447	1.453	2.837	.092	11.553*	0.670	199.186
	Decision	−3.163	2.944	1.155	.283	0.042	0.000	13.555
	Satisfaction	1.835	2.783	0.435	.510	6.268	0.027	1465.204
	Cost	0.605	1.025	0.349	.555	1.832	0.246	13.659
	Culture	−1.354	1.261	1.153	.283	0.258	0.022	3.058
	Database	−5.517	1.570	12.350	.000	.004***	0.000	0.087
	Deadline	0.466	0.842	0.306	.580	1.594	0.306	8.299
	Service	2.190	1.579	1.924	.165	8.935	0.405	197.257
	Income	−2.735	1.540	3.152	.076	.065*	0.003	1.329
	Market	4.255	1.690	6.340	.012	70.457**	2.568	1933.412
	Process	−3.922	1.474	7.081	.008	.020***	0.001	0.356

[a]Reference category is Group 1 (laggards).
***Significant at 1%; **significant at 5%; *significant at 10%.

Table 5. Model fitting information for multinomial logistic regression.

Model 1	Model fitting criteria −2 Log likelihood	Likelihood ratio tests Chi-square	df	Sig.	Pseudo R^2
Intercept only	204.150				Cox and Snell = 0.614
Final	91.933	112.217	22	.000	Nagelkerke = 0.714
					McFadden = 0.486

shows that the Model is statistically significant ($p < .01$), and the determinants jointly determine 48.6–71.4% (i.e. the pseudo-R^2) of the variation in BDA adoption.

The result of the discriminant analysis is consistent with that of the multinomial logistic regression as to the factors driving BDA adoption. Whereas items having discriminant coefficients above 0.10 in Table 3 have significant odds ratio in Table 4 (i.e. *position*, *decision*, *database*, *deadline*, *income*, *market*, and *process*), items with coefficients below 0.10 in Table 3 also have insignificant odds ratio in Table 4 (i.e. *cost*, *culture* and *service).* Further, *position*, *database*, *income* and *market* retained statistical significance in both categories of comparison (i.e. Groups 1 *versus* 2 and Groups 1 *versus* 3), thereby reiterating their relevance as strong determinants of BDA adoption. To recap, whilst the desire to enhance competitive position will cause incremental improvement in BDA adoption, consulting firms are likely to intensify BDA usage because of the need to increase market share (research objective two).

4.3. Interrelationship among the determinants of big data analytics adoption

Result from the analysis of the interrelationship among the determinants of BDA adoption is presented in Table 6 and Figure 2.

From the result in Table 6, the existence of a robust database of big data enhances the quality of decision ($b = 0.3604153$, $p < .01$). Client satisfaction is affected by the quality of decision-making by the consultant ($b = 0.6176606$, $p < .01$), the development of new consultancy services/improvement of existing services ($b = 0.141292$, $p < .05$), reduction in the cost of providing consultancy services ($b = .1045253$, $p < .10$) and the maintenance of a robust database ($b = 0.3400828$, $p < .01$). The competitive position of a consulting firm is enhanced by the quality of decision-making ($b = 0.4495603$, $p < .01$), client satisfaction ($b = 0.7278435$, $p < .01$), development of new consultancy services/improvement of existing services ($b = 0.2472617$, $p < .01$), reduction in cost of consultancy services ($b = 0.0760781$, $p < .10$), and the maintenance of robust database ($b = 0.3675987$, $p < .01$). Growth in consultancy income/revenue is dependent on the quality of decision-making ($b = 0.1280594$, $p < .05$), client satisfaction ($b = 0.2073297$, $p < .05$), development of new consultancy services/improvement of existing services ($b = 0.7318503$, $p < .01$) and maintenance of a robust database ($b = 0.6546059$, $p < .01$).

Improvement in market share of a firm in the consulting sector is dependent on the quality of decision ($b = 0.3214771$, $p < .01$), client satisfaction ($b = 0.5204752$, $p < .01$), development of new consultancy services/improvement of existing services ($b = 0.073539$, $p < .05$), reduction in cost of consultancy services ($b = 0.1981689$, $p < .10$) and existence of a robust database ($b = 0.1770047$, $p < .01$). The automation of processes as a result of BDA adoption helps a firm improve its turnaround time by meeting deadlines ($b = 0.7479135$, $p < .01$), while the existence of a database for big data enhances the ability of a consulting firm to introduce new services and/or reinvigorate existing ones ($b = 0.8313877$, $p < .01$). Overall, the result shows that the determinants of BDA adoption are interrelated. Their interrelatedness suggests that the advantages of BDA are systemic and could yield synergistic benefits (research objective three).

4.4. Robustness check

To check the robustness of results, least square regression, correlation and Cov analysis were carried out. The result of the analysis is presented in this section.

4.4.1. Determinants and usage intensity of big data analytics

Robustness of result on the determinants and usage intensity of BDA was verified using ordinary least square regression analysis. BDA adoption index was computed by obtaining the composite Mean of all the eleven areas measuring BDA adoption (yielded a Cronbach coefficient = .885; Kaiser–Meyer–Olkin coefficient = 0.765, $p < .01$). This was regressed against the determinants as independent variables. The result of the analysis is presented in Table 7.

In Table 7, five variables (*position*, *decision*, *satisfaction*, *database* and *deadline*) evince statistical significance. Meanwhile, these five items are among the seven determinants notably determining BDA adoption (Table 3), except *market* and *process*. Further, three items with negligible contribution to BDA adoption, such as *cost*, *culture* and *service* also have no statistically significant coefficients. This confirms that the need to: develop new

Table 6. Path analysis (total effects) result of the interrelationship among determinants of BDA adoption.

	Coef.	Std. Err.	z	$p > \|z\|$	[95% Conf. interval]	
−+−						
Decision <-						
Culture	0.1314565	0.1156966	1.14	.256	−0.0953047	0.3582178
Database	.3604153***	0.1081544	3.33	.001	0.1484366	0.572394
−+−						
Satisfaction <-						
Decision	.6176606***	0.0576928	10.71	.000	0.5045848	0.7307364
Deadline	−0.0663439	0.0517776	−1.28	.200	−0.1678261	0.0351383
Service	.141292**	0.0607804	2.32	.020	0.0221646	0.2604194
Culture	0.0811955	0.0718626	1.13	.259	−0.0596525	0.2220436
Process	0.0607637	0.0621095	0.98	.328	−0.0609687	0.1824961
Cost	.1045253*	0.0555791	1.88	.060	−0.0044078	0.2134584
Database	.3400828***	0.0855251	3.98	.000	0.1724568	0.5077088
−+−						
Position <-						
Decision	.4495603***	0.0720294	6.24	.000	0.3083852	0.5907353
Satisfaction	.7278435***	0.0947497	7.68	.000	0.5421374	0.9135495
Deadline	−0.048288	0.0382066	−1.26	.206	−0.1231716	0.0265957
Service	.2472617***	0.0864564	2.86	.004	0.0778102	0.4167132
Culture	0.0590976	0.0528675	1.12	.264	−0.0445207	0.1627159
Process	0.0442265	0.0455711	0.97	.332	−0.0450913	0.1335443
Cost	.0760781*	0.0416476	1.83	.068	−0.0055497	0.1577059
Database	.3675987***	0.0851685	4.32	.000	0.2006715	0.534526
−+−						
Income <-						
Decision	.1280594**	0.0606246	2.11	.035	0.0092373	0.2468815
Satisfaction	.2073297**	0.0962226	2.15	.031	0.0187369	0.3959224
Deadline	−0.0137551	0.0124897	−1.10	.271	−0.0382345	0.0107244
Service	.7318503***	0.0706741	10.36	.000	0.5933317	0.870369
Culture	0.0168342	0.0168234	1.00	.317	−0.0161391	0.0498076
Process	0.0125981	0.0141424	0.89	.373	−0.0151204	0.0403166
Cost	0.0582679	0.0772614	0.75	.451	−0.0931616	0.2096974
Database	.6546059***	0.0725097	9.03	.000	0.5124896	0.7967223
−+−						
Market <-						
Decision	.3214771***	0.07909	4.06	.000	0.1664635	0.4764906
Satisfaction	.5204752***	0.11846	4.39	.000	0.2882979	0.7526526
Deadline	−0.0345303	0.0280715	−1.23	.219	−0.0895495	0.0204889
Service	.073539**	0.0357896	2.05	.040	0.0033926	0.1436853
Culture	0.0422603	0.0386196	1.09	.274	−0.0334328	0.1179533
Process	0.031626	0.0331182	0.95	.340	−0.0332844	0.0965364
Cost	.1981689*	0.1015616	1.95	.051	−0.0008882	0.397226
Database	.1770047***	0.060037	2.95	.003	0.0593342	0.2946751
−+−						
Deadline <-						
Process	.7479135***	.0804764	9.29	.000	0.5901826	0.9056444
−+−						
Service <-						
Database	.8313877***	.0546633	15.21	.000	0.7242495	0.9385258
−+−						
p close probability RMSEA $<=$ .05						

***p Value significant at 1%; **p value significant at 5%; *p value significant at 10%.

consultancy services/improvement of existing services [*service*], reduce cost of providing consultancy services [*cost*] and improve corporate culture on big data management [*culture*] do not strongly drive BDA adoption as earlier concluded from the result of Table 3. While the F ratio of 8.629 ($p < .01$) establishes Model fitness, the coefficient of determination ($R^2 = 0.472$) confirms that the proposed determinants jointly explain 47.2% of the variation in BDA adoption. This is also consistent with the result in Table 5 in which the determinants explain 48.6–71.4% (i.e. the pseudo-R^2) of the usage intensity of BDA.

4.4.2. Interrelationship among determinants of BDA adoption

To examine the interrelationship among the determinants, correlation and Cov analysis were carried out. The correlation coefficients (R), SSCP and Cov coefficients are reported in Table 8.

The correlation and Cov coefficients show that there are significant positive relationships among the determinants, confirming that the advantages of BDA adoption are interrelated (supports result of Table 6 and Figure 2)

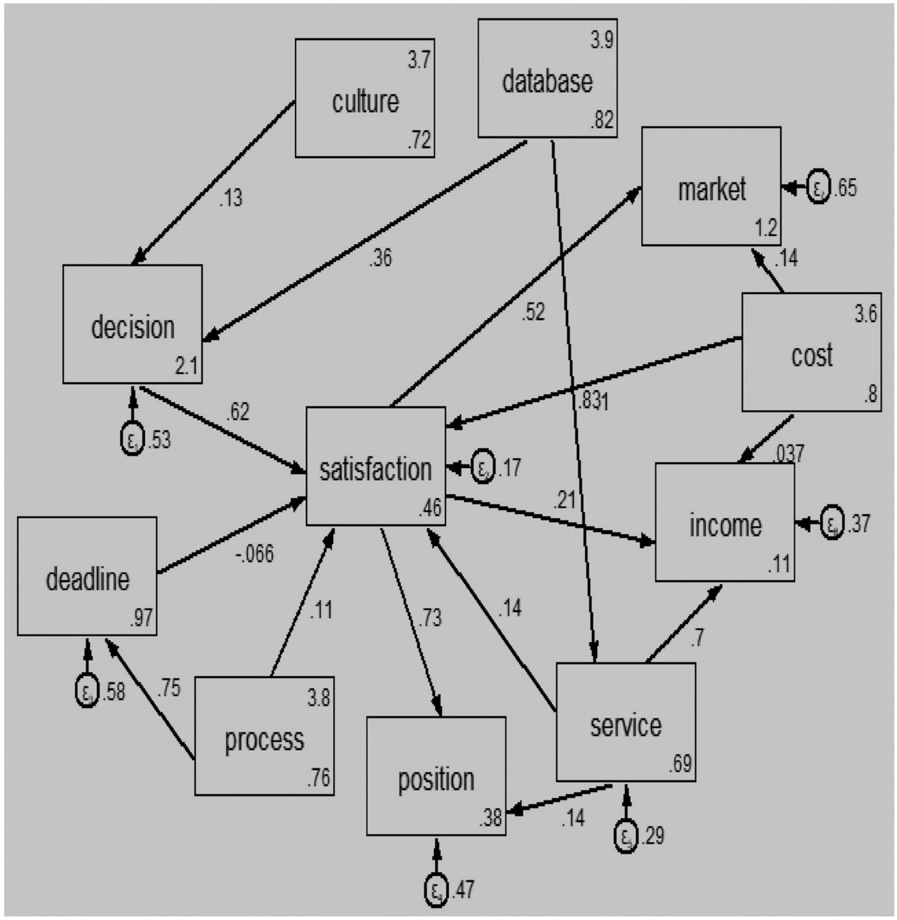

Figure 2. Interrelationship among the determinants of big data analytics adoption.

Table 7. Least square regression result on the determinants of BDA adoption.

	Unstandardised coefficients		Standardised coefficients		
Variables	B	Std. error	Beta	t	Sig.
(Constant)	1.521	0.287		5.305	.000
Position	0.249	0.101	.347**	2.456	.016
Decision	0.424	0.145	.524***	2.917	.004
Satisfaction	0.270	0.126	.313**	2.139	.035
Cost	0.063	0.074	0.083	0.849	.398
Culture	0.151	0.106	0.188	1.427	.156
Database	0.315	0.116	.420***	2.720	.008
Deadline	0.175	0.070	.258**	2.518	.013
Service	0.083	0.104	0.114	0.799	.426
Income	0.102	0.107	0.147	0.947	.346
Market	0.045	0.101	0.063	0.449	.654
Process	0.139	0.107	0.178	1.301	.196
$R = 0.687$ $R^2 = 0.472$ F ratio $= 8.629$ ($p < .01$)					

***p Value significant at 1%; **p value significant at 5%.

and could yield synergistic benefits. However, the strength of the relationship in most cases is moderate (i.e. $R < 0.70$), suggesting that the tendency for multicollinearity among the independent variables is minimal. This buttresses the results of the various regression analyses, as multicollinearity among the independent variables appears not to be a problem (Tabachnick & Fidell, 2001). The SSCPs coefficients confirm that the interactions between determinants produce notable effects, further corroborating the synergistic nature of BDA adoption benefits. Further, the Cov coefficients indicating the direction of the relationship between the variables are all positive, connoting that the determinants reinforce each other. In sum, the result in Table 8 validates the suggestion that the application of BDA could yield synergistic benefits.

Table 8. Correlation and covariance matrix for determinants of BDA adoption.

	Position	Decision	Satisfaction	Cost	Culture	Database	Deadline	Service	Income	Market	Process
Position											
R	1										
SSCP	105.568										
Cov	0.902										
Decision											
R	.827**	1									
SSCP	77.331	82.924									
Cov	0.661	0.709									
Satisfaction											
R	.679**	.822**	1								
SSCP	59.551	63.873	72.788								
Cov	0.509	0.546	0.622								
Cost											
R	.422**	.602**	.604**	1							
SSCP	42.042	53.144	49.907	93.839							
Cov	0.359	0.454	0.427	0.802							
Culture											
R	.484**	.416**	.463**	.332**	1						
SSCP	45.695	34.763	36.271	29.559	84.373						
Cov	0.391	0.297	0.310	0.253	0.721						
Database											
R	.536**	.485**	.605**	.457**	.728**	1					
SSCP	54.127	43.432	50.720	43.517	65.678	96.551					
Cov	0.463	0.371	0.434	0.372	0.561	0.825					
Deadline											
R	.252**	.310**	.346**	.399**	.554**	.601**	1				
SSCP	28.136	30.661	32.102	42.085	55.390	64.254	118.271				
Cov	0.240	0.262	0.274	0.360	0.473	0.549	1.011				
Service											
R	.462**	.419**	.531**	.457**	.618**	.814**	.599**	1			
SSCP	47.678	38.305	45.508	44.424	56.949	80.271	65.356	100.780			
Cov	0.408	0.327	0.389	0.380	0.487	0.686	0.559	0.861			
Income											
R	.345**	.367**	.538**	.436**	.621**	.727**	.582**	.766**	1		
SSCP	37.686	35.534	48.890	44.992	60.661	75.975	67.373	81.864	113.263		
Cov	0.322	0.304	0.418	0.385	0.518	0.649	0.576	0.700	0.968		
Market											
R	.390**	.391**	.514**	.396**	.674**	.618**	.541**	.663**	.818**	1	
SSCP	41.246	36.636	45.059	39.466	63.644	62.398	60.492	68.458	89.551	105.703	
Cov	0.353	0.313	0.385	0.337	0.544	0.533	0.517	0.585	0.765	0.903	
Process											
R	.421**	.392**	.486**	.375**	.782**	.710**	.650**	.697**	.646**	.700**	1
SSCP	40.915	33.712	39.186	34.322	67.881	65.966	66.831	66.153	65.017	68.068	89.356
Cov	0.350	0.288	0.335	0.293	0.580	0.564	0.571	0.565	0.556	0.582	0.764

*******R* is significant at the .01 level (2-tailed).

5. Discussion

Result shows that consulting firms are likely to intensify BDA usage because of the desire to increase market share (Table 4). As shown in shown in Table 6, client satisfaction is the strongest determinant of increase in market share. This implies that organisations that will increase market share must excel in customer satisfaction (Holm, Kumar, & Plenborg, 2016), and BDA adoption can assist in this regard – business intelligence derived from BDA can improve the quality of service to customers and overall customer satisfaction (He & Xu, 2015; Li et al., 2017; Sun et al., 2018). Meanwhile, client-satisfaction also emerged as a top-ranking determinant of BDA adoption (Table 3). The influence of customer satisfaction on the decision to adopt an innovation has been a subject of extensive research in management literature (e.g. Brown & Gulycz, 2002; Guilding & McManus, 2002; Simester, Hauser, Wemerfelt, & Rust, 2000). Customer satisfaction has been debated to be a critical success factor for business survival (Perrera, Harrison & Poole, 1997; Kennedy, Goolsby, & Arnould, 2003; Chartered Institute of Management Accountants [CIMA], 2013), and the importance of technological innovation in engendering customer satisfaction has been well documented in literature (e.g. Premkumar, 2003; Salehan & Kim, 2016; Singh, 2019). The desire to satisfy customers (clients) should therefore propel organisations to extensively apply big data.

Customer (client) satisfaction is majorly affected by the quality of decision-making and the maintenance of a robust database (Table 6), while the quality of decision-making is significantly affected by the existence of a robust database (Table 6). Taken together, the quality of information available to consulting firms (through their database) determines the quality of service rendered to customers (i.e. quality of decision-making), which ultimately affects customer satisfaction. This result corroborates the contention that organisations with better information capabilities achieve improved performance in diverse ways (e.g. Mithas, Tafti, Bardhan, & Goh, 2012; Saldanha et al., 2013; Schryen, 2013). Not surprisingly, therefore, customer (client) satisfaction and availability of robust database emerged as the strongest determinants of BDA adoption (Table 3). The quality of information has been linked to the quality of decision-making (Gorla, Somers, & Wong, 2010; Oyewo & Tran, 2021), and literature shows that the need to improve decision-quality affects the adoption of an innovation (e.g. Griffin & Wright, 2015; Jung, 2004). Consulting firms will apply big data to improve the quality of decision (Fredriksson, 2018).

Further examination of the interrelationship among the determinants shows that the ability of a firm to increase its market share is dependent on other factors – aside client satisfaction – such as improvement in the quality of decision, development of new consultancy services/improvement of existing services, reduction in cost of consultancy services and existence of a robust database (Table 6). While the ability to improve the quality of decision is affected by the existence of a robust database, client satisfaction – in addition to quality of decision-making and the maintenance/existence of a robust database – is also determined by the development of new consultancy services/improvement of existing services and reduction in the cost of providing consultancy services (Table 6). The interrelationship among the determinants provides empirical evidence supporting the proposition that the benefits of BDA adoption are systemic and synergistic.

The need to improve market share (*market*) emerged as the strongest reason for intensifying BDA usage (Table 4). This connotes that BDA adoption could be an effective competitive strategy to increase market share. Forward-looking organisations are always seeking ways of improving their performance (Fredriksson, 2018). Consulting firms that would be at the cutting edge would deploy BDA to improve the quality of services offered to clients. As robust analysis of data underlines uncommon insight (Lehrer, Wieneke, Brocke, Jung, & Seidel, 2018), it may be expected that consulting firms deploying BDA to undertake in-depth analysis of the issues confronting their clients may be more competent and strategically positioned to render high-quality service, thus increasing customer (client) patronage. Result shows that the need to develop new consultancy services/improvement of existing services [*service*], reduce cost of providing consultancy services [*cost*] and improve corporate culture on big data management [*culture*] do not strongly drive BDA adoption (Tables 2 and 7). The boxplot of the benefits of BDA adoption confirms that these three items are low-ranking among the other determinants (Appendix 2). This may suggest that BDA adoption is still at the rudimentary stage, as consulting firms are yet to fully acknowledge the service-improvement and operational-efficiency capabilities of BDA.

While consulting firms may seek to increase market share/customer patronage by developing capabilities in BDA, it is also important to explore other benefits BDA can offer, such as developing new consultancy services/improving existing services using insights from BDA. It becomes compelling to exploit these other benefits, given that the determinants of BDA adoption are interrelated, systemic and could yield synergistic benefits (Tables 6 and 8, and Figure 2). However, realising such benefits requires adeptness in BDA (Cetindamar, Shdifat, & Erfani, 2022). The need to develop new consultancy services/improve existing services may not have exerted much influence on BDA adoption probably because BDA is still at the infancy stage in the consulting sector (Oyewo et al., 2020). Furthermore, realising economies of scale and economies of scope in BDA adoption – which result in reduced cost of providing consultancy services – is also dependent on the extensive usage of BDA (Müller, Fay, & Brocke, 2018). Consequently, it may not be surprising that BDA adoption is not strongly underpinned by the need to reduce cost of providing consultancy services, as its deployment among consulting firms may be rudimentary. The nascent nature of BDA may also have been responsible for the inability of corporate culture on big data management to strongly exert on BDA adoption (Oyewo & Tran, 2021; Singh, 2019).

The result of the discriminant analysis, least square regression and multinomial logistic regression in which various dimensions of organisational competitiveness (modelled as determinants of BDA adoption) significantly determine the adoption rate of BDA provides empirical support for Rogers' (2003) diffusion of innovation theory that relative advantage is responsible for the spread of an innovation. The result also extends studies on relative advantage as an innovation attribute promoting the uptake of an innovation (e.g. Premkumar, 2003; Vagnani & Volpe, 2017; Van Helden & Tillema, 2005). The result that consulting firms will upgrade BDA usage due to relative benefits such as the need to: improve competitive position (*position*), maintain a robust database (*database*), grow income (*income*), improve market share (*market*) and the enhance efficiency of internal business process

(*process*) (Table 4) provides empirical support for observability as an innovation attribute affecting BDA adoption. In other words, as these benefits of BDA adoption become visible, consulting firms are likely to intensify BDA usage. This result also extends literature on observability as a determinant of innovation diffusion (e.g. Hashem & Tann, 2007; Vagnani & Volpe, 2017).

6. Conclusion

This study investigates the factors affecting the adoption of BDA by business consulting firms. The objectives of the study were to: (i) determine the factors responsible for the decision of consulting firms to adopt BDA; (ii) assess the factors that would cause consulting firms to intensify BDA usage; and (iii) evaluate the extent to which there a relationship among the factors affecting BDA adoption. Analysis of survey data from one hundred and eighteen (118) business and management consultants working in multinational and indigenous consulting firms reveals that the underlying considerations driving BDA adoption by consulting firms are the need to: maintain a robust database, better satisfy clients, enhance decision quality, improve internal business processes, increase market share, improve meeting deadlines and improve competitive position (research objective one). Whilst the desire to enhance competitive position will cause incremental improvement in BDA adoption, consulting firms are likely to intensify BDA usage because of the need to increase market share (research objective two). The determinants of BDA adoption are interrelated, implying that the advantages of BDA are systemic and could yield synergistic benefits (research objective three).

Considering the complexity of interrelationship among the BDA determinants, consulting firms are encouraged to step-up the implementation level of BDA in order to enjoy its synergistic benefits. To drive corporate culture on big data management and, by extension, intensify BDA usage, challenges surrounding the full deployment of BDA at the organisational-level, such as low level of investment in BDA technologies, low awareness level on BDA, shortage of skilled personnel in data analytics, ossification of organisational practice and reluctance to embrace change, amongst other issues, would have to be looked into. In addition, country-level environmental challenges – especially in developing countries – including the deplorable state of public infrastructure, poor internet connectivity and epileptic power supply, which all makes it almost impossible to amass externally oriented data or difficult to generate on-line real-time data, must be addressed by relevant stakeholders. If these issues are not tackled, the extensive implementation of BDA may not be achievable, which incidentally debar organisations from fully realising the synergic benefits of BDA adoption.

The study contributes to knowledge by exposing the relevance of BDA to business and management consulting using empirical evidence from both Multinational and Indigenous Consulting Firms. Meanwhile, the consulting sector in Nigeria is dominated by multinational consulting firms with transnational presence in developed and developing countries. The cosmopolitan nature of the consulting sector in Nigeria – which provides a level-playing field to both indigenous and multinational consulting firms – presents a rich context to investigate determinants of the adoption of BDA in business consulting service: Thus, this study is relevant to international/transnational audience. The consideration that majority of the respondents emanate from multinational consulting firms (101, 85.6%) bolsters the claim that this study has international/transnational relevance. To the researchers' knowledge, this is one of the earliest studies to investigate the application of big data and analytics by business consulting firms in the Nigerian context. The study presents empirical evidence that the deployment of BDA can be a source of competitive advantage for consulting firms. The study also adds to literature on management accounting in the digital economy. Although the study is based on a sample of multinational and indigenous consulting firms operating in Nigeria – for which consultants from multinational consulting firms constitute majority of the respondents ($n = 101$, 85.6%) – the result of the study may be generalisable to other countries where multinational consulting firms have presence. This suggestion is informed by the awareness that the management practice of multinational organisations is expected to be consistent across international boundaries. In other words, considerations influencing BDA adoption by multinational consulting firms is not expected to be significantly different from one country to another where they operate because of consistency in organisational policy. However, the veracity of this claim is a subject of empirical investigation – this provides a research gap for future studies to address. Investigations could also be conducted on the adoption rate of BDA by consulting firms.

This study is not without its limitations. Although there are various factors affecting the adoption rate of innovation as suggested by Rogers such as relative advantage, compatibility, complexity, trialability and observability, the study focused on the relative advantage and observability of BDA adoption in enhancing organisational competitiveness. Future studies may examine other factors affecting diffusion of BDA among consulting firms. The survey of consulting firms was limited to top 20 firms operating in Nigeria; future studies may expand the scope of coverage to other consulting firms to enhance generalisability of results. Considering the inherent limitations of survey – including trumped-up response and associated socially-desirable response bias among other issues – future studies may triangulate data-collection method to ensure well-validated results. These limitations in no way invalidate the results of this study, but provide motivation and research direction for future studies given the nascent but burgeoning nature of the big data discourse.

Disclosure statement

The authors have no conflict of interest to declare.

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Appendix 1.

Discriminant analysis results

1a. Structure matrix.

Dimensions of organisational competitiveness	Function 1	Function 2
Database	0.873[a]	0.108
Service	0.674[a]	0.049
Process	0.654[a]	0.091
Culture	0.589[a]	0.018
Income	0.528[a]	−0.086
Deadline	0.456[a]	0.285
Market	0.381[a]	0.044
Decision	0.335[a]	0.316
Satisfaction	0.322[a]	0.213
Cost	0.305[a]	−0.069
Position	0.379	0.620[a]

Pooled within-groups correlations between discriminating variables and standardised canonical discriminant functions.
Variables ordered by absolute size of correlation within function.
[a]Largest absolute correlation between each variable and any discriminant function.

1b. Functions at group centroids.

BDA adoption rate	Function 1	Function 2
Innovators	0.708	−0.345
Early majority	−0.167	0.812
Laggards	−2.251	−0.537

Unstandardised canonical discriminant functions evaluated at group means.

1c. Classification results[a].

			Predicted group membership			
		BDA adoption rate	Innovators	Early majority	Laggards	Total
Original	Count	Innovators	54	6	3	63
		Early majority	12	22	4	38
		Laggards	0	2	15	17
	%	Innovators	85.7	9.5	4.8	100.0
		Early majority	31.6	57.9	10.5	100.0
		Laggards	0.0	11.8	88.2	100.0

[a]77.1% of original grouped cases correctly classified.

Appendix 2.

Boxplot of BDA adoption benefits