MODELLING THE ADOPTION OF BIG DATA ANALYTICS AMONG ACCOUNTING PRACTITIONERS IN NIGERIA

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ABSTRACT

The competitive terrains in many organisations have changed as a result of rapid development in information technology. Accounting practitioners are not exempted from this because of the unprecedented level of unstructured and semi-structured large volume of data the firms are to manage to gain competitive advantage innovatively. This study is built on the technology acceptance model to investigate and model the adoption of big data analytics among accountants using constructs such as perceived benefits, technology complexity, data quality, and IT infrastructure. The study also examined the mediating role of top management support in adopting big data analytics. Cross-sectional research design was employed by designing and distributing questionnaire electronically to accounting practitioners working in selected organisations in Nigeria. Data obtained from 264 responses were analysed descriptively and the research model estimated using regression analysis to establish the links among the variables. The results showed that perceived benefits, technology complexity, and data quality positively and significantly impact BDA adoption. IT infrastructure has a positive but non-significant impact on BDA adoption. It is recommended that organisations harness the power of big data analytics to achieve increased data value and derive valuable insights from complex datasets to make informed business decisions.

Keywords: Accountants, Big data analytics, Data quality, Technology, Top management support.

INTRODUCTION

Rapid advancements in information technology have transformed the competitive landscape globally and across various industries. One of these technological advancements is big data analytics (BDA), which plays a pivotal role in analysing and deriving meaningful insights from large and complex datasets (Omitogun & Al-Adeem, 2019). Historically, BDA could be traced back to the late 20th Century, characterized by the exponential growth of the Internet and digital technologies (Batistic & Laken, 2019). Internet and digital technologies resulted in an unprecedented volume and variety of data sources from various transaction records, social media interactions, and engagement. The emergence of BDA was driven by several factors, such as the explosion of data volume, diverse data types, increased data volume, growing data complexity, advancement in technology, cost-effective storage solutions, and demand for data-driven decision making among others (Dahiya *et al*., 2022; Morales-Serazzi *et al*., 2023). As the field of BDA developed, the emphasis shifted from mere gathering or storing voluminous data to sophisticated analytics tools and machine learning algorithms to help organizations extract useful insights from complex datasets. The transformative impact of BDA makes it highly relevant to businesses in making informed decisions, gaining a competitive edge, enhancing customer understanding, promoting operational efficiency, and playing a crucial role in identifying and mitigating risks (Dahiya *et al*., 2022).

There is a noticeable trend in the adoption of Big Data Analytics (BDA) in the field of accounting and finance. This is demonstrated in the more efficient ways of collecting, processing, analysing and utilising financial data. Before the advent of BDA and other modern technologies, the field of accounting and finance relied more on traditional methods of analysing financial data, which were often time-consuming and limited in their ability to handle large volumes of data (Thakker & Japee, 2023). However, there has been a significant shift in the approach to financial data with the advent of BDA technologies such as Apache Hadoop, Apache Spark, Tableau, Python and R Programming language, Alteryx, Palantir, and so on, which have further increased the competition terrains by enabling businesses to leverage real-time insights, optimise decision-making, enhance customer experiences, and gain strategic advantages through data-driven innovations.

Accounting firms are not exempted from the increased competition orchestrated by technological adoption and advancements such as BDA, regulatory compliance and risk management, client relationship management, talent development and so on. This is because they need to manage large quantities of data to gain competitive advantage innovatively.

However, empirical investigations into BDA adoption among accounting firms and experts in Nigeria are scanty (Falana *et al*., 2023; Igbekoyi *et al*., 2023; Mendy *et al*., 2023; Oyewo *et al*., 2021) despite its growing significance in transforming organisational processes and decision-making (Dahiya *et al*., 2022). For instance, Oyewo *et al* (2021), in their study on the diffusion of big data analytics among consulting firms in Nigeria, acknowledged the evolving nature of BDA and suggested the incorporation of variables such as relative advantage (perceived benefits), complexity, managerial intervention (top management support) and other factors to deepen the understanding of the dynamics involved in the adoption and spread of BDA technologies. Aside from this, Nigeria's unique socio-economic, technological, and regulatory environment, as well as the distinctive characteristics of the accounting field, calls for empirical examination of the factors that could influence the adoption of BDA. In filling these research gaps, this study investigated the adoption of big data analytics among accountants using constructs such as perceived benefits (the advantages and positive outcomes that accounting professionals and organisations anticipate when adopting BDA technologies to manage and analyse large volumes of financial data), technology complexity (the intricate nature of the technological components and processes involved in implementing and managing BDA systems), data quality (the accuracy, reliability, consistency, and relevancy of financial data), and IT infrastructure (underlying technological framework necessary for the storage, processing, and analysis of large volumes of financial data).

Against this backdrop, this study built on the technology acceptance model to investigate and model the adoption of big data analytics among accountants using constructs such as perceived benefits, technology complexity, data quality, and IT infrastructure. The study also examined the mediating role of top management support in adopting big data analytics among accountants in Nigeria.

LITERATURE REVIEW

The adoption of BDA is considered a technological innovation and a strategic resource capable of conferring competitive advantages on an organization (Horani *et al*., 2023). Several theories have been propounded to explain why users, both at individual and corporate levels, respond to innovation differently. Some of these theories include the: "Diffusion of Innovation Theory" (Rogers, 2003), the “Technology Acceptance Model” [TAM] (Davis, 1986) and the "Unified Theory of Acceptance and Use of Technology" (Venkatesh *et al.,* 2003). Researchers commonly use TAM to explain adoption behaviour. TAM could be traced to the pioneering work of Fred Davis in 1986 on information systems and technology. Davis developed the model to explain and predict users' acceptance of new information technologies within organisational contexts. TAM posits that the intention to accept and use a technology is determined by perceived usefulness (benefit) and perceived ease of use. Perceived usefulness is the user's belief that the technology will enhance their job performance, while perceived ease of use relates to the user's perception of the effort required to deploy the technology.

According to the original TAM, users' decision to adopt or not to adopt an innovation is based on the ease of use, perceived benefit or usefulness or relative advantage. Venkatesh and Davis (1996) proposed TAM 2 by adding "social influence" and "cognitive factor" as additional dimensions that determine the pace of innovation adoption. TAM 3 emanated from the combinations of TAM 1 and 2 dimensions to explain adoption behaviour (Venkatesh & Bala, 2008). Additional factors identified for explaining adoption behaviour include performance expectancy, voluntariness of use, effort expectancy, compatibility, demography, among others. TAM is a relevant theoretical framework for studying Big Data Analytics (BDA) adoption. This is because the model identified the determining factors influencing individuals or corporate decisions to adopt modern and innovative technologies.

Review of extant studies has shown that several factors influence BDA adoption. For instance, Lai, Sun and Ren (2018) broadly categorised the factors into technology context, organisational context, and environmental context. This study focused on the technology context or factors which include perceived benefits, technology complexity and data quality as discussed by Lai *et al*. (2018). Two additional factors namely IT infrastructure and top management support are incorporated to provide a more robust understanding of the subject matter. The rationale for focusing on the technology factors is that the technological landscape which is made up of the characteristics, compatibility, and complexity of BDA tools and systems have a considerable influence on perceptions of users as well as the acceptance of the technology.

Perceived Benefit: This is also known as relative advantage or perceived usefulness. It is defined as "the degree to which a person believes that using a specific system will increase his or her job performance" (Davis, 1986: 985). Foroughi *et al*. (2019) described it as an individual perception of improving the quality of service received due to using a specific technology. Lai *et al*. (2018) described it as the degree to which organisations perceived BDA technology as beneficial to their operations. BDA is a potent tool for mitigating the effects of asymmetric information within firms (Lutfi *et al*., 2022). It helps organisations robustly analyse industry changes and trends using available internal and external data. Other benefits of BDA adoption include accurate financial forecasting and planning, fraud detection and risk management, operational efficiency, cost optimisation, and trends and patterns identification in financial data to guide decision-makers in making valuable insights into market dynamics, consumer preferences, and industry trends (Dahiya *et al*., 2022; İdil & Akbulut, 2018). Lai *et al*. (2018) found that perceived benefit positively and significantly influences the intention to adopt BDA. It, therefore, implies that the greater the perceived benefit of BDA, the greater the likelihood of its adoption. Thus, it is hypothesised that the perceived benefits of BDA will positively and significantly impact BDA adoption.

Technological complexity: This describes the difficulty associated with understanding and effectively deploying BDA technology within an organisational setting (Akter *et al*., 2016). Big Data requires practical actions such as training or acquiring BDA talent or skills, allocating financial resources for BDA operations, and fostering the dissemination of BDA across inter-organisational functions to extract valuable insights. The presence of technological complexity, such as incompatibility with existing Information Technology (IT) systems, the adaptability of IT infrastructure, data processing capabilities, substantial investment and maintenance costs associated with establishing BDA and related Information Systems (IS) (Akter *et al*., 2016; Fosso-Wamba *et al*., 2016) pose a severe barrier to firms considering the adoption of new technological innovations. Hence, it is hypothesised that technological complexity of BDA will negatively and significantly impact BDA adoption.

Data quality: This dimension describes the extent to which the data essential for analytical processes are characterised by accessibility, consistency, and completeness (Mabotja, 2022). The need to create diverse capabilities by organisations is imperative for successful adoption of BDA. Such capabilities include data governance and management, data architecture, data integration, data profiling and cleaning, data protection and privacy, data mining, text mining, data processing, visualization, and aggregation. Wook *et al*. (2021) investigated the impact of big data traits and dimensions of data quality on applying BDA. They categorised data quality into intrinsic quality (accuracy, objectivity, believability, reputation and value-added), contextual quality (relevancy, timeliness, completeness, appropriate amount of data and interpretability) and representational quality (understandability, concise representation, consistent representation, accessibility and ease of operations). Using questionnaire for data collection and analysed by partial least squares structural equation modelling technique, Wook *et al* (2021) found that big data traits significantly influence all the dimensions of data quality. It can be deduced that increased data quality will instil greater confidence in organisations to utilize BDA in day-to-day operational activities. Hence, it is hypothesized that data quality of BDA will positively and significantly impact BDA adoption.

IT Infrastructure: Maximising the potential inherent in big data by an organisation require establishing systems that necessitate expansive networked hardware architecture that relies on cloud-based storage and computing as well as high-speed Internet connections (Donta *et al*., 2023). Effective governance of BDA infrastructure is imperative in this context, as it should enable team agility in the development of requisite applications, facilitate the creation of impactful information, establish channels for data-sharing across business units, and institute systems that fortify functional integration (Akter *et al*., 2016; Mikalef *et al*., 2020). Hardware components of big data IT infrastructure include servers, storage systems, and processing units. They provide the foundational support necessary for handling voluminous and complex datasets and facilitate the storage, processing, and analysis required for effective BDA adoption. The availability and compatibility of advanced analytics software are essential components of IT infrastructure that influence BDA adoption. The software infrastructure determines the organisation's ability to extract valuable insights from data. Important also is the networking infrastructure. A well-established networking infrastructure with high bandwidth and reliability is crucial for seamless data flow within and outside the organisation. It have been empirically proven that a positive relationship exists between IT innovation adoption and IT infrastructure and capabilities (Lai *et al*., 2018; Maduku, 2021). Hence, it is hypothesized that IT infrastructure for BDA will positively and significantly impact BDA adoption.

Top management support: This refers to the endorsement, commitment, and active involvement of senior executives and leaders within an organisation in the integration and utilisation of BDA capabilities (Lai *et al*., 2018). Top management support for BDA can be demonstrated through commitment to priotising and investing in BDA initiatives, allocation of financial and non-financial resources, alignment of BDA initiatives with organisational strategy, and continuous monitoring and evaluation of BDA initiatives. Thong *et al*. (1996) found that increased top management support correlates positively with increased overall Information System (IS) effectiveness. This finding is supported by the understanding that substantial backing from top management significantly contributes to fostering an enabling environment and allocating sufficient resources to expedite the adoption of IT innovations (Srisathan *et al*., 2023). Therefore, the extent of support accorded by TM to BDA technology determines its adoption and success in an organisation. Hence, increased top management support is hypothesized to positively and significantly mediate the relationship between BDA adoption and its determining factors (perceived benefits, technology complexity, data quality, and IT infrastructure).

METHODOLOGY

This study used a cross-sectional research survey. It provides a snapshot of a population at a specific time, enabling researchers to collect data from a diverse range of individuals or entities within the population. The population of the study was the total number of ICAN members of 46,000 Chartered Accountants in Nigeria (ICAN, 2023). The sample size of the study of 400 was determined using the Taro Yamane method (where sample size [$n = N/(1 + N(e)^2$] and N signifies the population under study e signifies the margin error being 0.05). The sample was purposively determined and limited to only Abuja and Ikeja District Societies and questionnaire link (https://forms.gle/AA2wcqcj2Q9RZE399) sent them. The response rate was 66% as 264 responses was received from ICAN District Societies in Abuja and Lagos.

264 responses received served as the sample size and were used for data analyses. The questionnaire was divided into two parts. The first part contains the respondents' demographic profile such as gender, age, educational and professional qualifications, and working experience. The variables in the second part are perceived benefits, technology complexity, data quality, IT infrastructure and top management support. The items were structured in a 5-point Likert scale format ranging from "Strongly Agree" to "Strongly Disagree". The items were adapted from previous studies conducted by Lai *et al*. (2018), and Agrawal (2015). Data collected were descriptively and inferentially analysed. Descriptive statistics such as mean and standard deviation were used to describe the items used in measuring the different constructs. Normality test was conducted using skewness and kurtosis. Correlation and regression analyses were used to estimate the relationship between BDA adoption and its determining factors. Sobel test was used to estimate the mediating role of top management support on the relationship between BDA adoption and its determining factors. All analyses were performed using SPSS version 24 and hypotheses tested at a 5% significance level.

RESULTS AND DISCUSSIONS

The profiles of the respondents are presented in Table 1 below:

Table 1: Respondents' demographic bio-data

Demographics	Category	Frequency	Percent
Gender	Female	128	48.5
	Male	136	51.5
	Total	264	100
Age (Years)	Below 30	96	36.4
	30 - 39	116	43.9
	40 - 49	42	15.9
	50 years & above	10	3.8
	Total	264	100
Educational Qualification	HND/B.Sc or Equivalent	132	50.0
	Masters	118	44.7
	PhD	14	5.3
	Total	264	100
*Professional Qualification	ACCA	30	11.4
	ANAN	8	3.0
	CITN	18	6.8
	ICAN	264	100
	Others	108	40.9
Working Experience	Below 1 year	18	6.8
	1 - 5years	124	47.0
	6 - 10years	74	28.0
	11 - 15years	38	14.4
	16years & above	10	3.8
	Total	264	100
Sector	Private	196	74.2
	Public	68	25.8
	Total	264	100

*Note: * connotes that respondents can select more than one option*

Table 1 shows that 128 (48.5%) and 136 (51.5%) of the respondents were female and male respectively. It shows that more male completed the questionnaire than female. 96 (36.4%) of the respondents were below 30 years while majority of them (43.9%) were between 30 and 39 years old. 42 (15.9%) of the respondents were between 40 and 49years. Only 10 (3.8%) were 50 years and above. The highest qualification of the respondents shows that 132 (50%) have HND/B.Sc or Equivalent, 118 (44.7%) have Masters while 14 (5.3%) have PhD. The professional qualification of the respondents shows that all the respondents (100%) are chartered by ICAN. In addition, 30 (11.4%), 18 (6.8%) and 8 (3%) were also chartered by ACCA, CITN and ANAN respectively. 108 (40.9%) of the respondents were chartered by other accounting. The working experience of the respondents shows that majority of them have worked between one to five years. 46.2% of them have worked for six years and above. Table 1 also shows that 196 (74.2%) and 68 (25.8%) of the respondents worked with private and public organisations respectively.

Table 2: Description of BDA constructs

Variables	Mean ($\bar{X}$)	Std. Deviation (SD)	Skewness		Kurtosis	
			Statistic	SE	Statistic	SE
Perceived benefits (PRB)	4.375	0.633	-1.590	0.150	4.502	0.299
Technology Complexity (THC)	3.754	0.789	-0.109	0.150	-0.460	0.299
Data Quality (DTQ)	3.705	0.820	-0.371	0.150	-0.260	0.299
IT Infrastructure (ITF)	3.701	0.777	-0.340	0.150	-0.019	0.299
Top Management Support (TMS)	3.996	0.799	-0.779	0.150	0.314	0.299
BDA Adoption (BDAADP)	3.763	0.943	-0.677	0.150	-0.041	0.299

Table 2 shows the descriptive statistics of the different constructs used for the study. The mean and standard deviation scores of the variables are perceived benefits ($\bar{X}$ = 4.375; SD = 0.633); technology complexity ($\bar{X}$ = 3.754; SD = 0.789), data quality ($\bar{X}$ = 3.705; SD = 0.820), IT infrastructure ($\bar{X}$ = 3.701; SD = 0.777); top management support ($\bar{X}$ = 3.996; SD = 0.799) and BDA adoption ($\bar{X}$ = 3.763; SD = 0.943). The reported absolute values of the skewness and kurtosis statistics for all the constructs are less than 3.0 and 8.0 respectively. This is in line with Kline's (2011) benchmark. The outcome implies that the dataset is normally distributed.

Table 3: Pearson's correlation coefficient

Variables	BDAADP	PRB	THC	DTQ	ITF	TMS
BDA Adoption (BDAADP)	1					
Perceived benefits (PRB)	0.154*	1				
Technology Complexity (THC)	0.214**	0.129*	1			
Data Quality (DTQ)	0.598**	0.211**	0.280**	1		
IT Infrastructure (ITF)	0.593**	0.381**	0.257**	0.608**	1	
Top Management Support (TMS)	0.778**	0.320**	0.135*	0.649**	0.736**	1

** & ** connote correlations are significant at the 0.01 & 0.05 levels (2-tailed) respectively*

The correlation coefficients using Pearson's approach are presented Table 3. The results showed that a positive and statistically significant relationship exist between BDA Adoption (BDAADP) and Perceived benefits (PRB) [$r = 0.154$, $p < 0.05$], Technology Complexity (THC) [$r = 0.214$, $p < 0.05$], Data Quality (DTQ) [$r = 0.598$, $p < 0.05$], IT Infrastructure (ITF) [$r = 0.593$, $p < 0.05$] and Top Management Support (TMS) [$r = 0.778$, $p < 0.05$]. All the correlation coefficients for the constructs are below 0.80. This adheres to Bryman and Cramer's (1997) benchmark that suggests a threshold not exceeding 0.80.

Table 4: Estimated model on BDA adoption

Independent Variables	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
(Constant)	0.1460	0.2984		0.4895	0.6249
PRB → BDAADP	0.1741	0.0606	0.1168	2.8743	0.0044
THC → BDAADP	0.1123	0.0475	0.0940	2.3634	0.0189
DTQ → BDAADP	0.1461	0.0599	0.1270	2.4386	0.0154
ITF → BDAADP	0.0164	0.0722	0.0135	0.2271	0.8205
TMS→ BDAADP	0.8395	0.0715	0.7107	11.7471	0.0000

$R^2 = 0.639$; Adj $R^2 = 0.632$; F-Statistic = 91.424; F-Statistic (Prob) = 0.000; N = 264

Table 4 shows that BDA adoption (BDAADP) is positively and significantly related to Perceived Benefits (PRB) [$\beta = 0.1741$, $p = 0.0044$], Technology Complexity (THC) [$\beta = 0.1123$, $p = 0.0189$], Data Quality (DTQ) [$\beta = 0.1461$, $p = 0.0154$], and Top Management Support (TMS) [$\beta = 0.8395$, $p = 0.0000$]. However, the relationship between BDA adoption (BDAADP) and IT Infrastructure (ITF) [$\beta = 0.0164$, $p = 0.8205$] is not statistically significant. The coefficient of determination (R^2) of 0.639 shows that the independent variables account for 63.9% of the variations in the dependent variable. The Adjusted R^2 of 0.632 indicates that the independent variables jointly explained 63.2% of the variation in the dependent variable. The F-statistic of 91.424 is significant at $p = 0.000$ implying that the overall regression model explains a considerable percentage of the variability in the dependent variable.

Table 5: Test for mediation using Sobel approach

Relationships	Coefficient (Indirect Effect)	Std. Error	t-Stat	p-value	Conclusion
PRB → TMS →BDAADP	0.1461	0.0524	2.7906	0.0053	Significant
THC → TMS →BDAADP	0.0943	0.0407	2.3177	0.0205	Significant
DTQ → TMS →BDAADP	0.1226	0.0514	2.3881	0.0169	Significant
ITF → TMS →BDAADP	0.0138	0.0606	0.2271	0.8203	Not Significant

Table 5 revealed a positive and significant indirect effect of top management support (TMS) [$\beta = 0.1461$, $p = 0.0053$] on the relationship between PRB and BDAADAP. The results also show a positive and significant indirect effect of top management support (TMS) [$\beta = 0.0943$, $p = 0.0205$] on the relationship between THC and BDAADAP. Similarly, the results further show a positive and significant indirect effect of top management support (TMS) [$\beta = 0.1226$, $p = 0.0169$] on the relationship between DTQ and BDAADP. However, top management support (TMS) [$\beta = 0.0138$, $p = 0.8203$] does not significantly affect the relationship between ITF and BDAADAP.

Discussion of Findings

Firstly, it was found that perceived benefits positively and significantly impact BDA adoption. The finding is supported by the work of Lai *et al*. (2018), which found a positive and significant relationship between perceived benefits and the intention to adopt BDA in logistics and supply chain management. This outcome empirically strengthens the argument that the greater the perceived benefits of BDA, the higher the likelihood of adoption. It also reinforces the usefulness of BDA to organisations in analyzing industry changes and trends, facilitates accurate financial forecasting and planning, fraud detection and risk management, operational efficiency, cost optimatisation, and trends and patterns identification in financial data to guide decision makers in making valuable insights into market dynamics, consumer preferences, and industry trends.

Secondly, it was found that technology complexity positively and significantly impacts BDA adoption. This contradicts finding of related study by Akter *et al*. (2016) that found that presence of technological complexity such as incompatibility with existing IT systems could pose a severe barrier to firms considering the adoption of new technological innovations. To mitigate technology complexity in BDA adoption, there is need for a thorough assessment of the technological ecosystem which includes a meticulous examination of the compatibility of available infrastructure with the BDA solutions, and identification of potential integration challenges.

Thirdly, it was found that data quality has a positive and significant impact BDA adoption. This outcome aligns with Wook *et al* (2021) that investigated the impact of big data traits and dimensions of data quality on the application of BDA and found that big data traits significantly influence all the dimensions of data quality. The finding is also supported by the Lai *et al* (2018) argument that organisations that possess high-quality data are more likely to adopt Big Data Analytics (BDA). This further shows the importance of data quality in making accurate decisions, enhancing operational efficiency, effective risk management and supporting strategic planning and fostering innovation within organisations that leverage on BDA.

Moreover, the study revealed a positive but non-significant relationship between IT infrastructure and BDA adoption. This outcome aligns with the finding of Lai *et al*. (2018) reported a non-significant relationship between IT capabilities and the intention to adopt BDA in logistics and supply chain management. The non-significant relationship between IT infrastructure and BDA adoption may be due to incompatibility of existing IT systems, insufficient allocation of skilled personnel and financial resources, absence of strategic alignment between organisational goals and IT infrastructure, widespread resistance among employees or management to embrace new IT infrastructure required for BDA adoption among other.

Finally, top management support significantly mediates the relationship between BDA adoption and its determining factors except IT infrastructure. This outcome aligns with established evidence by previous studies Maduku (2021) and Hsu *et al*. (2019) that revealed a significant impact of managerial support on the adoption of Information Technology (IT) within organizations. Moreover, the observed outcome could be linked to an increased level of familiarity among certain firms with the utilisation of BD. As posited by Maduku *et al*. (2016), organisations that are familiar with contemporary information technology and dynamic IT trends are likely to possess extensive knowledge concerning the operationalisation and effective leveraging of this emerging data-driven IT technology. Consequently, such organisations would easily identify and mobilise the requisite tangible and intangible resources for the adoption and utilisation of BDA.

CONCLUSION AND RECOMMENDATIONS

The competitive settings of organisations have undergone changes as a result of continuous advancement in information technology. Accounting firms, in particular, are not immune to these changes, given the unprecedented volumes of unstructured and semi-structured data they must proficiently manage to attain a competitive edge. This study therefore modelled big data analytics among accountants by identifying factors that could influence its adoption in organisation. Factors such as perceived benefits, technology complexity, data quality, IT infrastructure and top management support were selected and empirically investigated by designing and distributing questionnaire electronically to accounting professionals working in selected organisations in Nigeria. Finding from the study showed that perceived benefits, technology complexity, and data quality have a positive and significant impact on BDA adoption. IT infrastructure has positive but non-significant impact on BDA adoption while top management support played a significant role in mediating the relationship between BDA adoption and its determining factors. The study concludes that organisations are more inclined to adopt BDA when they perceive tangible advantages, navigate technology complexities effectively, and maintain high data quality standards.

Based on the findings, the study recommends that:

- Accounting and financial firms should harness the power of big data analytics to achieve increased data value and derive useful insights from complex datasets to make informed business decisions.
- the perceived benefits of BDA adoption should be continuously communicated to stakeholders, such as employees and others involved in its implementation, to improve decision-making and operational efficiency and promote a conducive environment for its deployment.
- cross-functional collaboration should be encouraged among departments or units such as IT, accounting, finance, and management to align strategies, share insights, and collectively contribute to the successful adoption and integration of BDA.
- mechanisms for continuous monitoring and evaluation of BDA initiatives should be established to maintain organizational agility and capacity to respond to evolving challenges and opportunities.

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