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ENTREPRENEURIAL DECISIONS IN THE DIGITAL AGE: THE ROLE OF BIG DATA ANALYTICS IN MAKING ENTREPRENEURIAL DECISION IN EMERGING ECONOMY

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Abstract
The specific objectives of this study are to examine the effect of Big Data Analytic Method (BDAM) and Big Data Analytic Tools (BDAT) on entrepreneurial decision and investigate how Data-driven Insight (DDI) mediates the relationship between BDAM, BDAT and entrepreneurial decision. A Survey questionnaire was used to collect 320 useable responses from the IT owner/managers of SMEs in Lagos. PLS-SEM was employed in the data analysis. The results of the study show that significant relationship was found to exist between BDAM and entrepreneurial decision and BDAT has significant effect on entrepreneurial decision. These results suggest that BDAM and BDAT have emerged as the most important factors for generating meaningful insights for entrepreneurial decision-making. The study recommends among others that the advantage of the wide range of artificial intelligence (AI) applications BDAM, BDAT and data-driven insight must be taken by Industry leaders and entrepreneurs in order to enhance their decision-making process for the benefit of the firm and the society.

Keywords: Data, analytic, tool, Entrepreneurship, decision.

1. Introduction

The contemporary business environment is experiencing an intensive wave of digitalization that influences entrepreneurial functions and transforms all business sector (Wirtz & Zeithaml 2018). As technology becomes better and more convenient, entrepreneurs seek ways to utilize it to achieve a competitive advantage (Amoako et al., 2021). To give spark to economic activities an entrepreneur acts as a trigger head by his industrial decisions (Dhaliwal, 2016**)**. With the right environment and technological tools entrepreneurs change the economic situation of emerging economy, utilize the appropriate technology tools to detect business trends and offer valuable insights, which are required for business decisions (Akinyemi & Adejumo 2018; Amoako et al., 2021).

Entrepreneurial organizations have long used Artificial Intelligence-based solutions to automate routine tasks in operations and logistics. Recent advances in computational power, the exponential increase in data, and new machine-learning techniques now allow organizations to also use AI-based solutions for managerial decision making (Brynjolfsson & McAfee, 2017). AI enables new entrepreneurial decisions such as the creation of new ventures as well as the design of corporate spin-outs. These enhanced venturing processes—driven by two fundamental properties of digital technologies, specificity and rationality (von Briel et al. 2018)—open new innovation opportunities and broaden the possibilities for value creation and value capture (Dong et al., 2021). Moreover, under certain conditions, digital technologies may make predicting the evolution of markets, technologies and industries more precise, thus enhancing internationalization in regions where the organization has no past experience, or venturing into new technological domains and areas. Organizations implementing AI applications are expected to attain gains in terms of added business value, such as increased revenue, cost reduction, and improved business efficiency (AlSheibani et al., 2020). A recent study by MIT Sloan Management Review found that more than 80%

of organizations see AI as a strategic opportunity, and almost 85% see AI as a way to achieve competitive advantage (Ransbotham et al., 2017). In the search for competitive advantage, many organizations are thus investing in AI technologies.

In other words, accurate data are not obtained solely for the creation of practical insight, but also for their implementation in strategic entrepreneurial decision-making. Therefore, this is expected of entrepreneurs due to the significance of making precise decisions under unpredictable conditions, in order to discover business opportunities (Shane & Venkataraman 2000). Entrepreneurs take high-risk decisions (Baron 2004) under highly unpredictable, ambiguous, time-constrained, and emotionally strained contexts. The efficient exploitation of data has accompanied the growth of information technology architecture, thereby influencing decisions concerning the desirability and viability of entrepreneurial ideas, making entrepreneurial decision-making primarily knowledge based (Wiklund & Shepherd 2008). Therefore, knowledge-based information systems are valuable tools for entrepreneurs, enabling evidence-based decision-making in complex business situations. Moreover, artificial intelligence (AI) based applications are developing in a wide range of knowledge-based domains (Agrawal et al. 2019).

Recently, Big Data Analytics Method (BDAM) and Big Data Analytic Tool (BDAT) have emerged as one of the most important factors for generating meaningful insights for decision-making (Dubey et al., 2019). The power of BDAM and BDAT in the pursuit of more regenerative and restorative business operations has led to emerging literature on closing loops in production and consumption and increasing resource utilization (Murray et al., 2017). Due to the important role of BDAM and BDAT in organizations, scholarly attention has focused on exploring the links between BDA and decision-making performance in emerging market firms (Shamim et al., 2020). Despite BDAM and BDAT potential, however, there is relatively limited research that has empirically explored the antecedents of data-driven insights for enhancing decision-making quality (Rialti et al., 2019). BDAM and BDAT capabilities are increasingly becoming important for broader entrepreneurial decision-making in the gaining significant attention from academicians and practitioners (Gupta et al., 2019)

Extant literature on BDAM and BDAT have paid limited attention to understanding the enabling role of Data-Driven Insights (DDI) for supporting decision-making. Many companies struggle to realize value from BDAM and BDAT (Fountaine et al., 2019). Some studies adduced that the expected benefits of BDAM and BDAT may be absent even though companies invest time, effort, and resources into the adoption process (Makarius et al., 2020), Several studies fails to highlight the potential value that BDA can deliver, or helps entrepreneurs evaluate, discover, and exploit opportunities and solutions under business uncertainties (Agrawal et al. 2019). The existing literature on the role of BDAM and BDAT in facilitating and making informed decisions has largely focused on organizational performance (Ghasemaghaei & Calic, 2019; Gunasekaran et al., 2017; Wamba et al., 2017) and innovation competency (Ghasemaghaei & Calic, 2019). While some scholars found significant application of BDA results in improved decision making and better business performance (Agrawal et al., 2018). The majority of these studies do not adopt a theoretical lens that can explain how entrepreneurial firms need to be set up in order to utilize these novel BDAM and BDAT toward entrepreneurial decision. In addition, the academic literature that exists to date primarily focuses on the technical elements pertaining to BDA, often disregarding the challenges associated with deploying such solutions and aligning them with entrepreneurial objectives. This has led to several commentaries and research studies arguing that it is important to understand the necessary resources that organizations should foster in order to be ready to deploy BDAM and BDAT technologies to support their core activities (Ågerfalk, 2020).

Despite the prediction that Worldwide revenue for "big data" and business analytics solutions was forecasted to reach $274.3 billion by 2022 (IDC 2019), these investments have yet to yield productivity gains in the aggregate (Syverson 2017; Brynjolfsson *et al.* 2021). At the firm level, managers struggle to close the gap between the promise of predictive analytics and its performance (Ransbotham *et al*.2015, 2017; Wu *et al.* 2019). Therefore, the objectives of this paper are: To examine the effect of BDAM on entrepreneurial decision and to examine the effect of *BDAT* on entrepreneurial decision.

Moreover, it is widely recognized that Nigerian firms have a weak technological capacity to upgrade by absorbing existing advanced technologies. Entrepreneurial firms experience limitations when adopting the latest technology as it is adopted by the big organizations. The number of studies concerning the drivers and outcomes of business digitalization for entrepreneur remains rather limited and primarily focused on large firms. These technical problems bedeviling entrepreneurial performance in Nigeria are related to the data management, data extraction and functional structure of the organization that supports the new technology implementation might show a different outcome for BDAM and BDAT in Nigeria. Hence this study hypothesizes null hypothesis that:

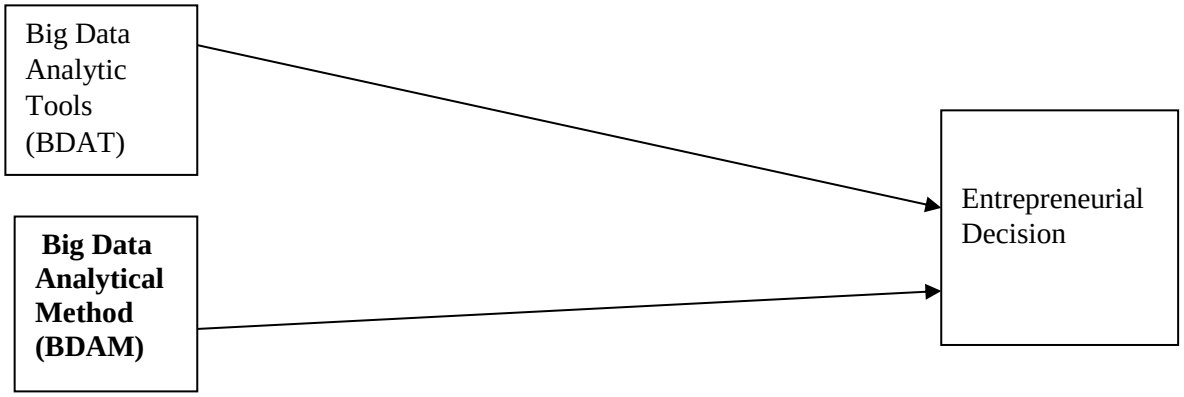
H01*: BDAM might not lead to superior entrepreneurial decision of producing more timely, relevant and actionable information and not creating an incentive for entrepreneur to act upon that information for superior entrepreneurial decision by means of automation of decisions and business processes in Nigeria.*

H02*: BDAT might not lead to superior entrepreneurial decision of producing more timely, relevant and actionable information and not creating an incentive for entrepreneur to act upon that information for superior entrepreneurial decision by means of automation of decisions and business processes in Nigeria.*

2. Literature Review

This paper carries out literature review on Big Data Analytic Method & Big Data Analytic Tools and their relationship with entrepreneurial decision

Conceptual Frame work



2.1 Big Data Analytics Method (BDAM), Big Data Analytic Tool (BDAT) and Entrepreneurial Decision

Analytics is the science of analysis". It is the process of developing actionable decisions or recommendation for actions based upon insights generated from historical data (Turban et al. 2008). Analytics can be descriptive, predictive, and prescriptive in nature (Chen et al. 2012; Davenport 2014). Data analytics involves multiple disciplines, in particular, mathematics and statistics, but also data mining, business intelligence (BI), machine learning, pattern recognition, and data visualization. Advanced Analytics prepares big data for making intelligent decisions by the users (Russom, 2011). Big Data Analytical Tools (BDAT) refers to software applications that analytic professionals use in data analytics. These range from basic spreadsheets to

business intelligence (BI) tools, statistical packages, data mining suites, data visualization tools, and high performance computing tools. BDAM refer to quantitative methods that analytic professionals use in data analytics. These comprise statistical methods, machine learning, data mining, artificial intelligence, operations research, optimization models, and path modelling (Dhar, 2013). Meanwhile, entrepreneurs take high-risk decisions (Baron 2004) under highly unpredictable, ambiguous, time-constrained, and emotionally strained contexts. Entrepreneurial decisions are strategic, tactical, and operational (Nowduri 2011). Strategic decisions include how an entrepreneur initiates new products, services, or market channels, which major suppliers it selects, etc. Operational decisions involve day-to-day decisions in various business functions, e.g. marketing, operations, and procurement (Thiraton et al., 2017).

BDAM and BDAT provide solutions for better entrepreneurial decision-making, enabling the achievement of good returns on investments (Ohlhorst 2013). BDAM is the comprehensive method of gathering, capturing, and analyzing enormous and diverse datasets in order to find concealed patterns, unidentified correlations, market trends, and consumer preferences that can assist firms in making informed and better business decisions (Obschonka & Audretsch 2020). As a framework enhanced for obtaining, shaping, and stacking unstructured data into databases, BDAM and BDAT can recognize growth opportunities in new and existing businesses, predict customers' behavior, and assist businesses in making better and more strategic business decisions (Obschonka & Audretsch 2020). BDAM and BDAT can transform data into value, process, and evaluate how the data that can improve decision-making for the benefit of businesses are handled. BDAM and BDAT have an enormous potential for creating value for firms, particularly when properly aligned with business cycles and knowledge needs. It can substantially enhance performance and the nature of entrepreneurs' decisions (Obschonka & Audretsch 2020). BDAM and BDAT offer valuable insights that could improve entrepreneurial decision making, particularly in recognizing growth patterns and creating growth opportunities for entrepreneurs (Obschonka &Audretsch 2020). BDAM and BDAT prepare entrepreneurs to capture, evaluate, store, and manage vast volumes of existing data. Business owners utilize BDAM and BDAT to discover weaknesses in their services and products, suppliers, and customers, as well as consumer intentions and preferences, to design new and improved products (Obschonka & Audretsch 2020).

BDAM and BDAT can influence improvements in the efficiency of business operations by helping organizations in predicting unpredictable situations and improving their performance process through cost reduction, best operation plan, smaller inventory sizes, productive labor force, and removal of wastage (Hiba et al. 2017). BDAM and BDAT are fundamental in business decision-making and can help businesses achieve a competitive advantage (Hiba et al. 2017). Additionally, BDAM and BDAT can affect the operation process effectiveness and organizational performance (Ghasemaghaei et al. 2015). Utilizing BDAM and BDAT, entrepreneurs can predict customer behavior and design, as well as enhance marketing strategies and sales planning. BDAT can promote innovation and growth that enable the informed decision-making in companies and can aid in offering new and existing companies unparalleled insight (Obschonka et al. 2020). Utilizing BDAT makes entrepreneurs more knowledgeable and puts them in a position to make better decisions and invest wisely (Obschonka & Audretsch 2020). BDA records are extracted from various applications and platforms and can alter development, as well as fast-track social and economic advancement. Table 1 depicts BDA Application and Entrepreneurial Decision,

Table 1: BDAM and BDAT Application and Entrepreneurial Decision

BDAM and BDAT **Application**	**Business Question**	**Entrepreneurial Decision**
Customer Segmentation	What market segments do my customers fall into, and what are their characteristics?	Personalize customer relationships for higher satisfaction and retention
Propensity to buy	which customers are most likely to respond to my promotion	Target customer based on their need to increase their loyalty to your product line. Also increase campaign profitability by focusing on the most likely to buy
Customer profitability	What is the lifetime profitability of my customer	Make individual business interaction decision based on the overall profitability of customers
Fraud detection	How can I tell which transactions are likely to be fraudulent?	Quickly determine fraud and take immediate action to minimize cost
Customer attrition	Which customer at risk leaving	Prevent loss of high-value customers and let go of lower value customer
Channel optimization	What is the best channel to reach my customer in each segment	Interact with customer based on preference and you need to manage cost

Source: Ziama and Kisher (2004) Data Mining Primer for the Warehousing professional, Teradata

Supply chain analytics enhances capability of decision makers by getting an integrated view of the data within supply chain. We can extract, transform, analyze data from data sources within supply chain system and run analytics to derive intelligence. Supply chain analytics provide several advanced capabilities such as dashboards, pattern and trend analysis, drill down views, forecasts, knowledge base, scenario and what-if analysis, simulations and optimization capabilities. These enhance decision making capabilities and interpretations of situations which is very crucial for firms in competitive business environments (Nair, 2016).

Predicting Future Outcomes, there are several opportunities of using datasets for predicting future outcomes. Analytics frameworks can be developed to analyze different datasets and make predictions as a) Based on historical transactional data; using forecasting models such as regression predict future sales for the product or services for a firm. b) Based on correlations found in historical purchases, identify products purchased together by customers. Referring to these correlations and purchase history of a customer, predict which products a customer is most likely to buy and make online recommendations (Artun & Levin, 2015). BDA can provide managers with information for real-time planning and continuous forecasting (McAfee and Brynjolfsson 2012, Moffitt & Vasarhelyi 2013, Barské-Erdogan 2014). BDAM and BDAT techniques are capable of analysing larger amounts and types of data with increasingly advanced algorithms, which allow more prescriptive analytics. With such 'easy to use' information, entrepreneurs are expected to act more on analytics and improve decision efficiency and effectiveness (Brown-Liburd et al. 2015).

However, it has been found that there is a very few percentage of the population who are aware of the terms like predictive analytics, advance analytics and big data analytics (BDAM and BDAT). RDBMS, data warehousing, data mining, clustering, association, OLAP, BPM,

ETL, regression, classification, analysis, genetic algorithm, multivariate statistical analysis and heuristic research are the tools for BDAM and BDAT (Russom, 2011). In spite of the benefits there are few barriers in the use of big data analytics for making decisions. These barriers generally include inadequacy of staff for handling the advanced analytics for decision making, lack of business support and the problems that frequently arises with the database software. Despite the growing interest BDAM and BDAT, many companies struggle to realize value from BDAM and BDAT (Fountaine et al., 2019). Some studies adduced that the expected benefits of BDAM and BDAT may be absent even though companies invest time, effort, and resources into the adoption process (Makarius et al., 2020).

3. Methodology

A questionnaire survey was carried out among a population of registered SMEs in Lagos, Nigeria. The study collected data from key frontline employees and managers involved in big data–related activities. Sekaran, (2003) provides a sample size decision table for population 3,390, the appropriate sample size according to sample size decision table is 300. In addition to this, the sample size of 300 was increased by 40% to further minimize low response rate from those respondents that might not cooperate (Salkind, 1997). The sum of this percentage (120) with 300 gave rise to total sample size of 420 In total 420 questionnaires survey was used to distribute questionnaire to the respondents, 330 were received. The questionnaires were completed by the IT managers of SMEs. However, only 320 respondents were considered as usable for the purpose of data analysis. The remaining 10 sets of questionnaires were excluded from data analysis because they were incomplete or totally blank.

3.1 Measures

In this study, the measure of BDA was adopted from Thirathon et al. (2017). It was operational ized along two dimensions; (a) analytic tools (BDAT) and (b) analytic methods (BDAM) (Acito & Khatri 2014). In this study BDAT refer to software applications that analytic professionals use in data analytics. These range from basic spreadsheets to business intelligence (BI) tools, statistical packages, data mining suites, data visualization tools, and high performance computing tools. BDAM comprises statistical methods, machine learning, data mining, artificial intelligence, operations research, optimization models, and path modelling (Dhar, 2013). IT managers of SMEs were asked to rate their analytics expert/team in terms of various analytic tools and methods (skills) on a seven-point Likert scale in terms of frequency of use of each analytic tool or method, with 1 = never and 7 = very frequently. Similarly, Entrepreneurial decision's measure is adopted from Thiraton et al. (2017) based on strategic, tactical, and operational (Nowduri 2011). Strategic decisions include how an entrepreneur initiates new products, services, or market channels, which major suppliers it selects, etc. Operational decisions involve day-to-day decisions in various business functions, e.g. marketing, operations, and procurement. IT managers of SMEs were asked to rate the level of their entrepreneurial strategic and operational decisions relying on insights derived from data analysis/analytics on a seven-point Likert scale.

4. Data Analysis

Henseler, Ringle and Sinkovics (2009)'s Two - step processes are employed to calculate and report the result of PLS-SEM. This entails (1) the assessment of measurement model and (2) the assessment of a structural model.

4.1 Assessment of Measurement Model

There was examination of the outer loading of each construct's measure in order to have assessment of individual items reliability (Hair et al., 2013). The indicators with outer loadings between 0.40 are retained, while some items below the threshold of 0.40 are deleted (Hair et al., 2013).

Composite reliability's threshold; values between 0.70 and 0.90 are considered satisfactory, value above 0.95 is regarded unsuitable and value below 0.60 indicate lack of internal consistency validity (Bernstein & Nunnally, 1994). Hence, this study employed composite reliability to ascertain the internal consistency of the measures adapted. Table 4.1 depicts the Composite Reliability (CR), items loading and Average Variance Extracted (AVE) for the measurement model.

Table 4.1: Items, loading, CR and AVE of the Latent Variables

Constructs	Items	Loadings	CR	AVE
BDAM	BDAM2	0.832	0.884	0.717
	BDAM3	0.849		
	BDAM4	0.859		
BDAT	BDAT1	0.815	0.844	0.576
	BDAT2	0.773		
	BDAT3	0.742		
	BDAT5	0.700		
Entrepreneurial Decision	EBD1	0.844	0.810	0.588
	EBD3	0.728		
	EBD5	0.723		

Table 4.1 depicts the composite reliability coefficient of the latent construct. The composite reliability of each construct ranged from .810 to .903. This connotes internal consistency of the scale. The composite reliability of all constructs is above the threshold of .70. Table 4.2 further shows construct reliability and validity of the indicators.

4.1.1 Convergent validity

Convergent validity is the extent to which a measure correlates positively with alternative measure of the same construct (Hair et al., 2013). The assessment of convergent validity is usually based on the Average Variance Extracted (AVE) of each construct and outer loadings the indicators (Fornell and Larker, 1981). Average variance extracted is grand mean value of the squared loadings of the indicators related with the construct. All outer loading of the indicators above .40 are retained and AVE above .50 is threshold of convergent validity (Fornell and Larker, 1981). The AVE for this study ranged between 0.588 and 0.701. This shows that the constructs of the study satisfied the condition of convergent validity. It also indicates that all the constructs explains 50 percent or more of the variance of the items that make up the construct. While outer loading of all the constructs ranged between 0.700 to 0.859. Table 4.2 also shows construct reliability and validity

Table 4.2: Construct Reliability and Validity of the indicators

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Entrepreneurial Decision	0.652	0.678	0.810	0.588
ABDM	0.805	0.818	0.884	0.717
BDAT	0.754	0.765	0.844	0.576

Source: Survey data analyzed using Smart PLS, 2023

4.1.2 Discriminant Validity

Discriminant validity threshold is that the square root of the average variance extracted is all greater than the correlation among latent constructs, signifying sufficient discriminant validity (Fornell & Larcker). In Table 4.3, the squared root of the AVE, (0.767, 0.847 & 0.759) is all greater than the correlation among the latent constructs which shows discriminant validity.

Table 4.3: Square Root of AVE and Correlation of Latent Variable

Latent Variables	**Entrepreneurial Decision**	**BDAM**	**BDAT**
Entrepreneurial Decision	**0.767**		
BDAM	0.500	**0.847**	
BDAT	0.582	0.412	**0.759**

Sources: Survey data analyzed using Smart PLS, 2023

Note: Diagonal elements (figures in bold) are the square root of the variance shared between the constructs and their measures. Off diagonal elements are the correlations among constructs. Discriminant validity was also ascertained by comparing the indicator loading with cross loading. Researchers have suggested that the entire indicators should be greater than the cross loading (Hair et al., 2013).

Table 4.4 compares the indicator loading with other reflective indicators. All the available indicators BDAM; 0.832, 0.849and 0.859 are greater than other reflective loading. Similarly, BDAT indicators loading; 0.815, 0.773, 0.742 and 0.700 are greater than reflective indicators. The indicators loading of Entrepreneurial Decision; 0.844, 0.728 and 0.723 are also greater than the entire reflective indicator. This means that the requirement of discriminant validity has been established.

Table 4.4; Cross Loading Factor Analysis

Variables	**Entrepreneurial Decision**	**BDAM**	**BDAT**
EBD1	**0.844**	0.457	0.514
EBD3	**0.728**	0.359	0.401
EBD5	**0.723**	0.319	0.412
BDAM2	0.351	**0.832**	0.323
BDAM3	0.427	**0.849**	0.321
ABDM4	0.475	**0.859**	0.395
BDAT1	0.515	0.375	**0.815**
BDAT2	0.449	0.283	**0.773**
BDAT3	0.385	0.226	**0.742**
BDAT5	0.402	0.356	**0.700**

Source: Survey data analyzed using SMART PLS, 2021

4.2 Structural Model

Having confirmed that the construct measures are reliable and valid, standard bootstrapping procedure was used with a number of 5000 bootstrap samples to assess the significance of the paths (Henseler *et al.,* 2009; Hair *et al.,* 2013). Table 4.5 summarizes the results of reflective measured constructs, BDAM, BDAT and entrepreneurial decision by showing the original outer weights estimates, the t values and the corresponding significance levels marked in asterisks as well as the p values

Table 4.5: The Result of the Structural Model and Mediator

Hypotheses	**Beta**	**T Statistics**	**P Values**	**Decision**
Ho1: BDA T -> Entrepreneurial decision	0.371	5.968***	0.000	Not Supported
Ho2: BDA M -> Entrepreneurial Decision	0.244	4.652***	0.000	Not Supported

Note: *** (P<0.01), ** (P<0.05), *(P<0.1)

Result

Table 4.5 summarizes the result of reflective measured constructs (BDAM, BDAT and Entrepreneurial Decision) by showing the original outer weight estimates, the t values and the corresponding significance level as well as the p values with the result of the mediating effects.

Ho1: BDAT not enable the development of new entrepreneurial decision in Lagos.

The result from the Table 4.5 shows that BDAT enables the development of new entrepreneurial decision in Lagos, with β=0.371, t=5.968, P=0.000. Thus Ho1 is not supported and therefore rejected at 5% level of significance, since there is enough statistical evidence to reject the null hypothesis, the study accept the alternative hypothesis that BDAT enables the development of new entrepreneurial decision in Lagos.

Ho2: BDAM does not aid firm to develop entrepreneurial decision

The result from the Table 4.5 shows that BDAM aids firm to develop entrepreneurial decision with β=0.244, t=4.652, p= 0.000. Thus Ho2 is not supported and therefore rejected at 5% level of significance, since there is enough statistical evidence to reject the null hypothesis, the study accept the alternative hypothesis that BDAM aids firm to develop entrepreneurial decision in Lagos.

5. Discussions and Conclusion

The objectives of this paper are to provide answer to the following exemplary research questions:

Does AI enable the development of new entrepreneurial decisions? How do firms develop new entrepreneurial decisions with various analytics? Which new entrepreneurial decisions are shaped on and because of digital platforms, and how? The result of the data gathered from IT managers of SMEs in Lagos Nigerian and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) Shows that BDAM; Statistical Methods, Machine Learning, Data Mining, AI, OR, Optimisation Methods and Path Modelling. BDAT; Spreadsheets, BI Planning/Reporting Suites, Data ETL/Management Solutions, Statistical Suites – Basic Use Statistical Suites – Advanced Use, Specialized Data Mining Suites, Data Visualisation Tools and BD/High Performance Computing Tools have significant impact on entrepreneurial decision (strategic, tactical, and operational decision. Strategic decisions include how an entrepreneur initiates new products, services, or market channels, which major suppliers it selects, etc. Operational decisions involve day-to-day decisions in various business functions, e.g. marketing, operations, and procurement) This denotes that AI enables to develop entrepreneurial decision. The finding is consistent with Shamim et al. (2020), Thirathon et al. (2017) on Impact of BDAT and BDAM on decision making

Similarly, AI Analytics helps to develop actionable decisions or recommendation for actions based upon insights generated from historical data. BDAM and BDAT drills down into past or current data to discover trends or patterns to support entrepreneurial managerial decisions. BDAM and BDAT support entrepreneurial decisions and strategies by gathering historical data, forecasting, and simulating to anticipate possible future situations. Prescriptive analytics refers to descriptive and predictive analysis of data that suggests a set of potential actions to managers considering rules, constraints, thresholds, risks, and uncertainty. Prescriptive analytics provides the most concrete decision support, and considering that the trend in analytics is moving from historical analysis to forward-looking predictive and prescriptive analytics (Hagel 2015).

Moreover, the findings of this study also show BDAM and BDAT as established influencer of entrepreneurial decision (Germann et al., 2014). BDAM helps entrepreneurial firms to evaluate the strategies through the lens of data (Amankwah-Amoah, 2016). Particularly in the context of this study BDAM and BDAT are becoming extremely crucial component of decision-making process and enabling entrepreneurial firms for data driven decision-making (Hagel, 2015; Janssen et al., 2017). Literature acknowledges BDA as dynamic capability (Shamim et al., 2019a), as DCs are actually based on knowledge-based resources (Zheng et al., 2011). Therefore, BDAM and BDAT are essential for entrepreneurial decision-making (Janssen et al., 2017). Janssen et al. (2017) also suggested that BDA capabilities could lead to better entrepreneurial decision-making performance.

In conclusion, this paper revealed that currently businesses are dynamic and basically digital. Consequently, entrepreneurs profit from this revolution. A modern-day business is established on data, since people are affected by the ability of businesses to collect, analyze, manage, and use data. A number of online platforms are endowed with avenues for data collection. Besides, the capacity to transform the collected data into value-for-economic gain is innovative, which is expected of the contemporary entrepreneur. The actual data lies in the capability of entrepreneurs to develop actionable insight and apply it in strategic and better decision making. To the best of this study's knowledge, no research has so far confirmed that higher BDAT and BDAT creates an incentive for entrepreneur to use it as base for their decisions making in emerging economies.

This study recommends that the advantage of the wide range of artificial intelligence (AI) applications BDAM, BDAT and data-driven insight must be taken by Industry leaders and entrepreneurs in order to enhance their decision-making process for the benefit of the firm and the society. Entrepreneurial friendly legislations and regulations should be made by national policy-maker to provide incentives to aspiring and existing entrepreneurs to expand the scope of their businesses. Moreover, government should enact policy towards overcoming barriers of lack of digital infrastructure, problem of access to finances and other constraints of entrepreneurial development.

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