Acta Universitatis Danubius
ŒCONOMICA

Business Analytics and Market Adaptation in the E-Commerce Industry in Nigeria

Ladi Daodu[1], Amiya Bhaumik[2], Akinola Morakinyo[3]

Abstract: The study examined the impact of business analytics on market adaptation in the eCommerce industry in Nigeria. Using purposive sampling and random sampling techniques, a sample of 40 respondents from various eCommerce organizations was taken. The data collected were analyzed using the quantitative approach. Precisely, both correlation and ordinal regression analyses were applied. The result from the study shows that the most important aspect of business analytics that can have a significant impact on market adaptation is the area of data analysis and application of the result to decision-making in the organization. The study recommends the application of business analytics to eCommerce businesses if they want to improve their market adaptation.

Keywords: Market adaptation; Business Analytics; Data Analysis, eCommerce

JEL Classification: D40

1. Introduction

Today's business environment is highly competitive and is rapidly changing due to the dynamics around the expectations of customers and many more (A. Singh & Pawale, 2020). One of the challenges created by today's business environment is the satisfaction of customers as their taste is changing rapidly. Consequently, businesses across the globe especially those in the eCommerce industry need to be abreast of changes in the environment to create adaptation in their marketing strategy that can enable them to meet the dynamic nature of customers' demands.

[1] Nigeria, Corresponding author: ladidaodu.phd@gmail.com.
[2] Lincoln University College, Malaysia, Address: No. 2, Jalan Stadium, SS 7/15, Kelana Jaya, 47301, Petaling Jaya, Selangor Darul Ehsan, Malaysia, E-mail: amiya@lincoln.edu.my.
[3] Kennesaw State University in Georgia, United States of America, Address: 1000 Chastain Rd NW, Kennesaw, GA 30144, United States of America, E-mail: amoraki2@kennesaw.edu.

However, the reality nowadays is that many organizations across the globe have been out of business due to a lack of competitive strength because they cannot embrace the required market adaptation (Levinthal, 1991). One of the most important ways identified in the literature as a means of coping with dynamic customers satisfaction is the constant analysis of the business environment this includes the collection and analysis of data on various variables such as customers' demands, customers satisfaction, sales, product, sources of finance, competitors strength and weaknesses among others. This process is referred to as business analytics (Vitari & Raguseo, 2020)

In addition, one of the challenges often witnessed by the eCommerce industry which is the focus of this study is that it remains one of the most vulnerable industries to business environment dynamics. Changes in technological development and applications remain an important factor confronting organizations in the eCommerce industry (Pappas et al., 2018). An innovation today might become obsolete tomorrow and the ability of the business to embrace business policies that are less rigid and that are easily amenable to changes is believed to remain sacrosanct in the development of an appropriate market adaptation strategy that can ensure sustainable and improved performance of businesses (Chaudhuri et al., 2021)

Consequently, this study hopes to explore the impact of business analytics on market adaptation in the eCommerce industry to provide more insight into ways by which e-commerce organizations can leverage business analytics to aid the adaptability of their marketing strategies in the ever-increasing dynamics existing in businesses in the world. This is done in this paper by providing answers to the following research question

Research question

What is the impact of business analytics on market adaptation?

The objective of the study

The main objective of the study is to investigate the effect of business analytics on market adaptation

Significance of the study

The increase in competition among business organizations today and the rise in the mortality rate of businesses especially new ones have called for research into why these businesses lack competing powers that have led to their exit from their various industries at early ages. However, literature has established that inability of many businesses to adapt their marketing strategies to suit the ever-dynamic business environment has contributed largely to this problem. Consequently, efforts have recently been geared toward research on how this menace can be tackled. This study provides an insight empirically on the relationship between business analytics and market adaptation to prove answers to the extent of influence business analytics can have on market adaptation. This will go a long way to provide solutions to the problem of business mortality due to a lack of market adaptation strategy that can sustain their businesses.

The other key sections of the paper include literature review, methodology, results, discussion, conclusion, and recommendations.

2. Literature Review

Business Analytics

Business Analytics is the leverage of technology in processing business data for generating insightful results for making strategic business decisions (Fosso Wamba et al., 2015; Gao, 2021; Yin & Fernandez, 2020) defines business analytics as deep utilisation of data and application of statistical methods that produces factual results for decision making. Business analytics presents a comprehensive method to managing, process, and analyzing data for actionable insights (Fosso Wamba et al., 2015) and to help organizations proactiveness towards changes based on market requirements (Işik et al., 2013; Rahmah et al., 2020). BA is known as a competitive differentiator (Jeble et al., 2018), and (Nalchigar & Yu, 2020) opined that the development of data analytics as a new type of information system has proven to be complicated and challenging. Yahya-Imam & Aranuwa, 2020 opined that trend in technology has evolved and data is the new path to generating insights. Deep knowledge of big data is key to help in concluding information (Sharma et al., 2019; Yahya-Imam & Aranuwa, 2020) Business analytics has shown potential for significant synergies and opportunities for business-wide application and to forge a data-driven business model (G. Hindle et al., 2020). Some studies have shown that there are benefits for businesses that adopt business analytics over those that do not (Bradberry et al., 2017; Jahan et al., 2021) while some researchers opined that many businesses are still trying to identify how to adapt and harness the benefits in business analytics. (Duan et al., 2020; Kiron et al., 2012; Tim et al., 2020). Studies so far show that BA seems to have significant impact in business, but understanding how BA investments create business value has been quite limited (Krishnamoorthi & Mathew, 2018).

The BA tool has evolved over the years and has become a consideration for many uses, particularly from the quantum and dynamics of data involved (G. Hindle et al., 2020). These large data interactions help the process of modeling descriptive, predictive, and prescriptive outcomes that help to align purpose with strategy and define the business value that assures business sustainability in a challenging business environment (Balog, 2019; G. A. Hindle & Vidgen, 2018). De Luca et al., 2020) argued that big data technologies improved business outcomes, but the full benefits is yet to be harnessed. Affordances in technology aid result-driven capabilities (De Luca et al., 2020; George & Lin, 2017; Volkoff & Strong, 2017). George & Lin, 2017) posited that evolution of big data is leading organizations to integrate technology into their processes for improved business results. Business adaptation and evolution has been aided by the leverage of these technology tools and their unique capabilities (Schildt, 2017). Business analytics has shown potential for significant synergies and opportunities for business-wide application and to forge a data-driven business model (G. Hindle et al., 2020). These numerous benefits from the adoption of business analytics provide support for understanding and fulfilling the objectives of this study which intends to assess the impact of using business analytics as a tool for driving market adaptation and establishing if there are differential results in the adoption of business analytics on market share. Consequently, fully integrated business analytics, product management, and market adaptation capabilities are insufficient in the homegrown industry, and these are necessary to drive innovative outcomes and sustainability. Similarly, a correlation exist between changing market demand and market adaptation (Dombrowski et al., 2014); Yahya-Imam & Aranuwa, 2020) Recent studies have established that several organizations have adopted the use of BA, however, the record of successes from implementation across these organizations have been very few (Duan et al., 2020; S. Singh et al., 2020). These views point to the need for additional research that could help understand the requirements for achieving success with business analytics adoption.

Market adaptation

The reality of today's business environment, particularly that of e-commerce businesses, has shown a need to re-evaluate their business model based on the impact of the Covid-19 pandemic (Srinivas et al., 2020; Staegemann et al., 2020; Vidgen et al., 2020) including upgrading or re-aligning their digital infrastructure capabilities so they can be better efficient and be more flexible in adapting to the business environment and market changes. (Cirera & Muzi, 2020; Ekka, 2020; Seetharaman, 2020; Tim et al., 2020) in their work conclude that the survival of businesses in an era of global volatility and uncertainty heavily depends on adaptation capabilities and mechanisms that enable them to define appropriate responses to achieve market stability with zero, less, or minimal impact from the changes in the market. Market adaptation defines as an innovative approach that follows a robust delivery framework in delivering sustained value to customers while achieving positive market adaptation outcomes and remaining competitive (Fosso Wamba et al., 2020; Quang Trung et al., 2019; Shamim et al., 2020). Pollák et al., 2021 posited a dual assumption of innovation and continuous change in the market as two basic and critical functions of business and areas where capabilities need to be developed in addressing market adaptation strategies. Deploying the right e-business tool and effective data gathering will support the development of insightful information about the market and enhance gaining competitive advantages (Muthukumar, 2020; Pollák et al., 2021). Organizations are often limited by the sophistication and adaptiveness of their technology infrastructure, and they struggle to respond effectively or adapt to the changes in their external environment, particularly customers and product fit (Vitari & Raguseo, 2020). Customer satisfaction is an essential consideration in market adaptation, and a measure of how goods and services meet the expectations of the customers or users (Vitari & Raguseo, 2020), hence customer satisfaction is a major mediating variable in achieving market adaptation results. In the study by Chatterjee et al., 2021, he found out that data and tools acquisition propels the successes associated with the adoption of business analytics in driving business value and improving the performance of the organization. His findings showed further correlation and complementarity between the acquisition of business analytics capabilities and business process performance.

The leverage placed on data science and information technology and the adoption of analytics capabilities by organizations has helped them improve their understanding of and relationship with the external market and realized the advantages of insightful decision making, how to adapt to the market and environmental challenges, business growth, and sustainability (Barlette & Baillette, 2020; Sharma et al., 2019). Organizations must be strategic in defining their business model and ensure that such business model has resilient and adaptable capabilities to maintain its presence and continuity in the market to foster continuous competitive advantage in the market (Baden-Fuller & Teece, 2020; Rahmasari & Syafitri, 2018). Such a resilient business model will allow the organization to remain aligned with evolutions in the industry and business environment and provide a tool for enabling market leadership and data-driven performance (Ramadan et al., 2020). Organizations now look at developing dynamic service analytics on the back of their data analytics capabilities to gather intelligence and explore and transform their service systems through innovative upgrades and adaptation in alignment with market requirements (Baden-Fuller & Teece, 2020). It is important to develop a resilient and dynamic data analytics technique that extracts dynamic data about the dynamic business environment that ensures an appropriate response for superior performance (Akter, Motamarri, et al., 2020). Existing literature gives credence to how service adaptation enhances trust relationship sustainability between the organization and its customers (Motamarri et al., 2017; Mou et al., 2020) because services have become a major form of business exchange or trade globally and information from data analytics makes the services system more robust, smarter and resilient to enhance dynamic adaptation, knowledge, and decision making under uncertainty (Akter, Gunasekaran, et al., 2020) Business analytics has been tested to improve customer information gathering, reduce customer acquisition costs, enhance product customization and improve the overall experience of the customers (Chen & Cheng, 2009; Dubey et al., 2016; Hoang et al., 2021; Wu et al., 2020). Côrte-Real et al., 2017; Helfat & Peteraf, 2009 recommended that organizations should embrace dynamic capability nature to be better prepared for changes in the environment and achieve competitive advantage. This capability will further be strengthened by the robustness of the analytics capabilities available internally (Akter, Gunasekaran, et al., 2020; De Luca et al., 2020) Within the e-commerce ecosystem, the adoption and use of business analytics have increased in recent decades (Gao, 2021), but there are theoretical and practical gaps in the existing research that requires expanded development (Gao, 2021; Odularu, 2020; Sun et al., 2018). Business analytics supports e-commerce businesses with better ways of data collection, processing, and management and more focused use of data and insights to improve customer acquisition, understand the behavior and sentiments of customers, pursue an effective product management effort, including product innovation and drive an effective market adaptation agenda (Enyinna & C, 2020; Gao, 2021; Olagunju et al., 2020). Based on existing literature and studies, it is evident that market leadership, competitiveness, and sustainability are among the outcomes when a business effectively and positively adapts to market changes. These help to fulfill the objectives of this study and provide contexts for the research questions and hypotheses.

Gaps in the literature

Exploration of existing literature on this study shows that past studies are much more concerned with the impact of business analytics on the performance of an organization rather than market adaptation (Chatterjee et al., 2021) Others are concerned with the effect of business analytics on product innovation (Chaudhuri et al., 2021) among others. It appears that none of the existing literature focused on the effect of business analytics on market adaptation. On the other, market adaptation also enjoys less patronage from researchers few studies that the study explores focus on foreign market adaption while others are concerned with marketing environment or strategies. Based on the foregoing this study appears to be making original contributions to literature in this area.

Theoretical literature

Dynamic capability (DC) theory Dynamic capability posits that dynamic capability help businesses to align with the reality of internal and external conditions and sustain competitiveness (Helfat & Peteraf, 2009). Recent, many businesses have leveraged the RBV for improved business outcomes (Côrte-Real et al., 2017). The RBV and its gaps has fostered usage of other theories like DC and KBV. DC supports the KBV (Newey & Zahra, 2009). Numerous emerging studies support the DC model and its importance as an enabler for business success (Duan et al., 2020). Dynamic capabilities connects information processing with organisation enablers and resources (Côrte-Real et al., 2017).

3. Methodology

This aspect of the study discusses the research method employed to achieve the objectives of the study.

Research design

The study collects primary data from the target respondents using a questionnaire. Quantitative analysis is used to analyze the data and they are interpreted and discussed. This forms the bases of inferences.

The population of the study

The study focuses on businesses in the eCommerce industry in Nigeria. It is worth noting that there are no available statistics on the number of entrepreneurs that are in the eCommerce industry in Nigeria.

Samling and sampling techniques

A multistage sampling technique is adopted by the study. This comprises the usage of both probability and nonprobability sampling techniques The Purposive sampling technique was initially adopted to select 40 businesses that are in the eCommerce industry in the Lagos area of Nigeria (Akpa, Victoria O. et al., 2021)**.** The second stage of the sampling technique embraced random sampling techniques which enable the random representation of the businesses so that all of them will not be on the same line of businesses in that wise, equal probability was given to the respondents for being selected to partake in the survey. Generally, the 40 respondents were randomly selected from various companies so that their responses will not be lopsided.

Method of data collection

The major approach to the collection of data for the study is through a well-structured questionnaire. The survey instrument is divided into three main parts. Part A contains questions on bio-data and demographic information of respondents, Part B includes questions on business analytics, and Part C contains questions on market adaptation. Apart from the biodata which used categorical responses, other responses on the remaining part of the questionnaire used the five-point Likert scale.

Validity and Reliability of the research instrument

Both the validity and reliability tests were carried out on the survey tool. The Cronbach Alpha test was used for the reliability test which shows a value of 0.74. The validity test used the KMO Bartlet test which gave a value of 0.64. The two values indicate that the survey tool measured what was expected and they also consistently measured them.

Method of data analysis

In the work of Chatterjee et al., 2021 who studied the role of business analytics in organizational performance, five salient features of business analytics were identified this is data and information collection on customers and services, Data and information analysis, Utilization of data analyzed for future planning, Policy and decision making following the results of the data analysis, Management of analyzed data for marketing, product development, and management, sales, finance, people and process, supply chain, for actionable insights. Consequently, the components of business analytics are divided into five namely; Data collection (DC), Data analysis (DA), data analysis results utilization (DARU), Data analysis result application for decision making (DARADM), and Data analysis results management (DARM)

A model describing the relationship between business analytics and market adaptation is expressed thus

$$MA = f(BA) \tag{1}$$

Where MA is market Adaptation and BA in Business and Analytics. Equation (1) shows that Market adaptation depends on business analytics. It should be noted that from the initial discussion business analytics has been divided into 5 major areas. Consequently, equation (1) can be simplified further as

$$MA = f(DC, DA, DARU, DARADM, DARM) \tag{2}$$

Equation 1 is expressed in linear regression form as follows

$$MA = \alpha_0 + \alpha_1 DC + \alpha_2 DA + \alpha_3 DARU + \alpha_4 DARADM + \alpha_5 DARM + \mu \tag{3}$$

All variables are as defined above in the previous discussion. μ is the error term capturing the stochastic variable.

Estimation technique

Quantitative analysis is embraced for the estimation of the equation. Particularly multiple regression approach is applied. Before the application, some initial pre-estimation tests were carried out. This includes the factors analysis and the normality test. The normality test is necessary to determine the type of regression applied since this study uses primary data. After the normality test, it was discovered that instead of linear regression, ordinal regression analysis is more suitable for the estimation of the regression model and the results of both the test and the regression are presented and interpreted in the next section of the paper.

4. Results and Discussion

This aspect of the paper discusses the empirical result. It starts with the descriptive statistics of the bio-data information of the respondents

Biodata analysis of respondents

A total of 40 respondents are included in the survey and the major features of these respondents demographically are analyzed as follows

Table 1. Education Qualification Distribution

Education	Frequency	Percent	Valid Percent	Cumulative Percent
HND	1	2.5	2.5	2.5
Graduate Degree	27	67.5	67.5	70.0
Post-Graduate Degree	12	30.0	30.0	100.0
Total	40	100.0	100.0	

Source: Authors computation, 2022

Results presented in table 1 shows that the majority of the respondents are highly educated at least about 67.5% of them are university graduate. In addition, nearly 30% also have postgraduate qualifications. The implication of this is that the respondents are well educated to understand the questions in the research instrument and provide the needed answers to them.

Table 2. Years in Service Distribution

	Frequency	Percent	Valid Percent	Cumulative Percent
Less than 1 year	12	30.0	30.0	30.0
1-3 years	17	42.5	42.5	72.5
4-6 years	8	20.0	20.0	92.5
Above 10 years	3	7.5	7.5	100.0
Total	40	100.0	100.0	

Source: Authors computation, 2022

Table 2 indicated that the respondents have relatively long years of experience in their respective organizations. More than 40% of them have spent around 3 years while 20% have spent about 8 years. Some have even spent more than 10 years. The length of experience is important for the questions included in the research instrument

Table 3. Gender Distribution

	Frequency	Percent	Valid Percent	Cumulative Percent
Female	11	27.5	27.5	27.5
Male	29	72.5	72.5	100.0
Total	40	100.0	100.0	

Source: Authors computation, 2022

The percentage of males in the respondents' distribution is more than that of females. It is about 70% of the population. This might not be unconnected to the fact that the online trading business is male dominant profession across the globe (Rodgers & Harris, 2003). The same situation is playing out in this study.

Table 4. Number of Employees

	Frequency	Percent	Valid Percent	Cumulative Percent
Less than 100	28	70.0	70.0	70.0
100-499	4	10.0	10.0	80.0
500-999	1	2.5	2.5	82.5
1,000 - 1,999	3	7.5	7.5	90.0
2,000 - 2,999	2	5.0	5.0	95.0
3,000 - 3,999	1	2.5	2.5	97.5
4,000 - 4,999	1	2.5	2.5	100.0
Total	40	100.0	100.0	

Source: Authors computation, 2022

The results in table 4 show that many organizations with a workforce of less than 100. it shows that the idea that e-commerce business is more capital intensive than labor intensive still holds sway in this study as well. More than 70% have a workforce that is less than 100. Very few organizations have employees in their thousands.

Table 5. Nature of Ownership

	Frequency	Percent	Valid Percent	Cumulative Percent
100% Homegrown	22	55.0	55.0	55.0
Majorly Homegrown	9	22.5	22.5	77.5
100% Foreign	4	10.0	10.0	87.5
Majorly Foreign	5	12.5	12.5	100.0
Total	40	100.0	100.0	

Source: Authors computation, 2022

The belief that the eCommerce business in a foreign company dominated in Nigeria is refuted going by the result presented in table 5. Results from the descriptive statistics of the ownership structure of the organizations show that about 55% of the respondents are with 100% homegrown ownership organizations. Notwithstanding, about 23% have co-ownership with foreign investors. Very few of the organizations covered in the study have foreign ownership.

Other attributes of the organizations involved in the survey

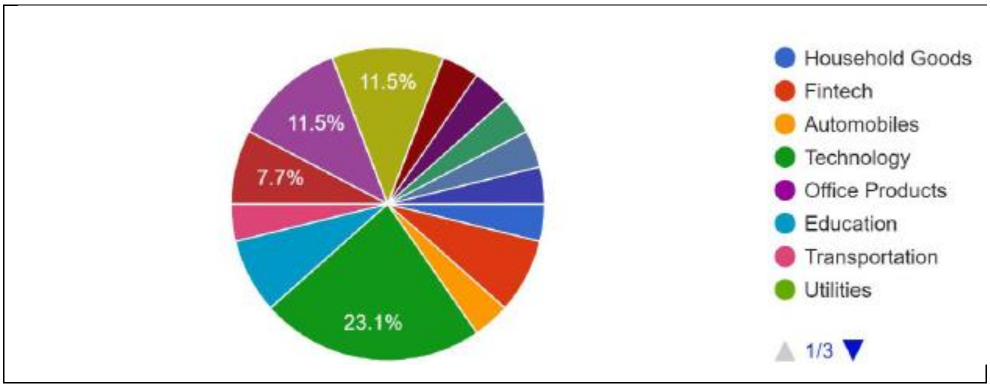

Figure 1. Core Business
Source: Authors computation, 2022

Utilities and technology dominated the product line of the organization included in the study. Nearly 24% of the organization are into technological base product line notwithstanding both Fintech and utilities are also very common among the product line of the organizations. Office products are also included in the core business occupying about 11.5% of the total population of the organizations covered by the study.

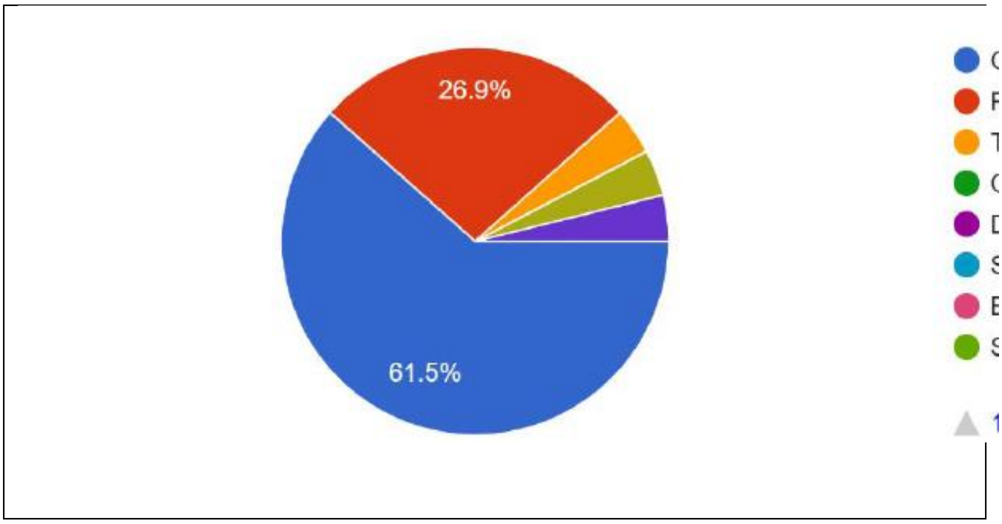

Figure 2. Business Analytics Tool Used

Source: Authors computation, 2022

Since the focus of this study is examining the effect of Business analytics on the market adaption of the organizations, the nature of the tool used for carrying out business analytics is investigated and the result is in figure 2. The result shows that in the majority of the organizations, about 70% of them use google analytics for their eCommerce business. This further attests to the dominance of google tools in the eCommerce industry across the globe (Gaur et al., 2016).

Analysis of the impact of business analytics on market adaptation

The main objective of the study is subjected to empirical analysis under this sub-section of the study. From the methodology, it was stated that some pre-estimation tests were carried out before the analysis.

Factor analysis (examining the validity and sphericity of the research instrument)

The validity in terms of sampling adequacy and sphericity are tested and the results are presented in Table 6.

Table 6. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.648
Bartlett's Test of Sphericity	Approx. Chi-Square	103.880
	Df	15
	Sig.	.000

Source: Authors computation, 2022

The test shown in table 6 explains the sampling adequacy and the KMO statistics give 0.648. This figure is an indication that the sample is adequate to examine the effect of business analytics on the market adaption of the organizations. In terms of sphericity as well the chi-square value is 103.880 which is okay and is also statistically significant thus indicating that the sampling and the research instrument are in good order for usage in the analysis.

Table 7. Normality test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Variables	Statistic	df	Sig.	Statistic	df	Sig.
Data collection DC	.275	40	.000	.726	40	.000
Data Analysis DA	.389	40	.000	.730	40	.000
data analysis results utilization (DARU)	.369	40	.000	.755	40	.000
Data analysis result application for decision making (DARADM)	.300	40	.000	.761	40	.000
Data analysis results management (DARM)	.346	40	.000	.755	40	.000
Market Adaptation (MA)	.263	40	.000	.795	40	.000
a. Lilliefors Significance Correction						

Source: Authors computation, 2022

Results in table 7 show that all the variables have significant statistics in terms of both Kolmogorov-Smirnov[a] and Shapiro-Wilk tests. The implication is that the ordinal regression approach will be more suitable for the analysis than linear regression and also for the correlation, spearman rank correlation is preferred to the product-moment correlation coefficient. Since the sample size is below 100, the Shapiro-Wilk test results are more appropriate to be used in the study although they both give the same result.

Table 8. Correlation Result

Correlations							
		Data collection DC	Data Analysis DA	data analysis results utilization (DARU)	Data analysis result application for decision making (DARADM)	Data analysis results management (DARM)	MA
Data collection DC	Pearson Correlation	1	.116	-.082	.098	-.291	.279
	Sig. (2-tailed)		.475	.616	.546	.069	.081
	N	40	40	40	40	40	40
Data Analysis DA	Pearson Correlation	.116	1	.743**	.491**	.381*	.469**
	Sig. (2-tailed)	.475		.000	.001	.015	.002
	N	40	40	40	40	40	40
data analysis results utilization (DARU)	Pearson Correlation	-.082	.743**	1	.401*	.486**	.262
	Sig. (2-tailed)	.616	.000		.010	.001	.103
	N	40	40	40	40	40	40
Data analysis result application for decision making (DARADM)	Pearson Correlation	.098	.491**	.401*	1	.664**	.673**
	Sig. (2-tailed)	.546	.001	.010		.000	.000
	N	40	40	40	40	40	40
Data analysis results management (DARM)	Pearson Correlation	-.291	.381*	.486**	.664**	1	.362*
	Sig. (2-tailed)	.069	.015	.001	.000		.022
	N	40	40	40	40	40	40
Market Adaptation (MA)	Pearson Correlation	.279	.469**	.262	.673**	.362*	1
	Sig. (2-tailed)	.081	.002	.103	.000	.022	
	N	40	40	40	40	40	40
**. Correlation is significant at the 0.01 level (2-tailed).							
*. Correlation is significant at the 0.05 level (2-tailed).							

Source: Authors computation, 2022

The result of the correlation analysis shown in table 8 is an indication that market adaptation shared some positive and significant correlations with some components of business analytics. For example, there is a strong positive correlation between data analysis and market adaptation, also the same strong and positive correlation is between data analysis results application for decision making and market adaptation. The correlation coefficients of the two are 0.469 and 0.673. Both are significant at the 1% level. Similarly, data analysis result management with a correlation coefficient of 0,362 also has a significant correlation with market adaptation at a 5% level. The implication is that out of the four components of business analytics three of them shared a positive and significant correlation with market adaptation.

Ordinal Regression analysis

The impact of business analytics is examined using ordinal regression and the steps used and the results are presented and discussed as follows.

Table 10. Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	132.538			
Final	102.193	30.345	5	.000
Link function: Logit.				

Source: Authors computation, 2022

The null hypothesis in the model fitting information test is that the data does not fit the model estimated. The result in table 10 has shown the model is statistically significant at 1% thus showing that the null hypothesis is rejected and it is concluded that the data fits the estimated model very well. Therefore it is suitable for inferences.

Table 11. Goodness of Fit

Goodness-of-Fit			
	Chi-Square	Df	Sig.
Pearson	1177.928	191	.098
Deviance	98.121	191	1.000
Link function: Logit.			

Source: Authors computation, 2022

The null hypothesis under the goodness of fit is stated in a reverse from different from the model fitting information. Consequently, for the model to have a good fitting it is expected that both the Pearson and Deviance chi-square are not statistically significant. This is the situation in table 11. Therefore the goodness of fit of the estimated ordinal regression model is in order and appropriate for inferences.

Table 12. Pseudo R Square

Pseudo R-Square	
Cox and Snell	.532
Nagelkerke	.647
McFadden	.214
Link function: Logit.	

Source: Authors computation, 2022

Just like the normal R square in linear regression, the pseudo R square of the ordinal regression explains the systemic variation in the dependent variable that is explained by the independent variables. The focus here is the Nagelkerke value which is 0.647. This value implies that business analytics explains about 64.7% variation in market adaptation. This is a strong coefficient of determination because it shows that business analytics explains market adaptation very well.

Table 13, Ordinal Regression Result

Parameter Estimates								
		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[MA = 1.00]	7.039	2.574	7.478	1	.006	1.994	12.084
	[MA = 1.50]	8.853	2.738	10.459	1	.001	3.488	14.219
	[MA = 2.00]	9.352	2.771	11.389	1	.001	3.921	14.783
	[MA = 3.00]	10.283	2.838	13.125	1	.000	4.720	15.846
	[MA = 3.50]	10.714	2.869	13.949	1	.000	5.092	16.337
	[MA = 4.00]	12.150	2.975	16.678	1	.000	6.319	17.981
	[MA = 4.50]	14.128	3.161	19.975	1	.000	7.933	20.324
Location	DC	.686	.382	3.235	1	.072	-.062	1.434
	DA	.191	.012	.194	1	.049	-.657	1.038
	(DARU)	-.371	.441	.708	1	.400	-1.235	.493
	DARADM	1.660	.498	11.100	1	.001	.684	2.637
	DARM	.804	.528	2.317	1	.128	-.231	1.839
Link function: Logit.								

Source: Authors computation, 2022

The regression result presented in table 13 shows two areas where business analytics have a significant impact on market adaptation. Firstly, the coefficient of data analysis DA is 0.191 the probability significance is 0.49. This is an indication that data analysis has a significant impact on market adaptation at a 5% significant level. This underscores the importance of data analysis to market adaptation. It will be recalled that the two also shared a significant relationship under the correlations analysis. The results support the findings from the studies like analyzing data on customer satisfaction and business attributes generally are very important for business performance (Chatterjee et al., 2021).

Secondly, Data analysis result application for decision making (DARADM) has a coefficient of 1.660 which is also statistically significant at a 5% level of significance. The result has also shown that this aspect of business analytics is very germane to market adaptation. The result has shown that application of the result of the data analysis to decision making is the most important aspect of business analytics before it can positively influence market adaptation. It follows the conclusion from the study of Duan, Cao, & Edwards, (2020) that most of the processes and efforts of businesses to improve performance cannot be effective until they allow it to influence the decision-making of their organization. It shows that the effectiveness of business analytics on market adaptation depends on its utilization for decision-making.

Other aspects of business analytics that do not have a significant impact but maintain a positive relationship with market adaptation are data collection, data utilization, and data management. All these aspects of business analytics have been shown by this study not to be as important as data analysis and data analysis results application for decision making.

5. Conclusions and Recommendation

Findings from the study have underscored the importance of business analytics in market adaptation. The results obtained from the study imply that it does not sufficient enough to just collect data, utilize and manage it but the most important thing in business analytics before it can influence market adaptation positively is that the data must be analyzed and applied to taking of important decisions in the organization. There is no point in data collection only if it has not been analyzed. Again, there is no point in just managing or utilizing the data analysis results if it has not been applied to decision-making in the organization.

Conclusively, this study has shown that business analytics can only contribute positively to market adaptation if the data collected on customer satisfaction, and service deliveries among others are analyzed and the results of the analysis are applied for decision-making in the organizations in this case in the eCommerce industry. It is therefore recommended that entrepreneurs in the eCommerce industry should endeavor to embrace business analytics and also make sure the results from it are applied for decision making or else business analytics will just be a mere academics exercise and as such constitute an exercise in futility.

Again, the main challenge encountered by the study during the survey was the inability to know and cover the whole organization into online business in Nigeria as there are no such statistics. Notwithstanding, the forty samples selected were done randomly in a way that they will be near representative of the population.

Finally, further studies on this subject may attempt to verify the veracity of the findings of this study by using some other lines of businesses apart from eCommerce. This will enable readers to understand if the discoveries in this research can be generalized for other organizations that are not under eCommerce

References

Akpa, Victoria O., Asikhia, Olalekan U., & Okusanya, Adedoyin, O. (2021). Leadership Styles and Organisational Performance in Nigeria: Qualitative Perspective. *International Journal of Engineering and Management Research*, *11*(1), pp. 46–53. https://doi.org/10.31033/ijemr.11.1.7

Akter, S.; Gunasekaran, A.; Wamba, S. F.; Babu, M. M. & Hani, U. (2020). Reshaping competitive advantages with analytics capabilities in service systems. *Technological Forecasting and Social Change*, *159*(May 2019), 120180. https://doi.org/10.1016/j.techfore.2020.120180

Akter, S.; Motamarri, S.; Hani, U.; Shams, R.; Fernando, M.; Mohiuddin Babu, M. & Ning Shen, K. (2020). Building dynamic service analytics capabilities for the digital marketplace. *Journal of Business Research*, *118*(May), pp. 177–188. https://doi.org/10.1016/j.jbusres.2020.06.016.

Baden-Fuller, C. & Teece, D. J. (2020). Market sensing, dynamic capability, and competitive dynamics. *Industrial Marketing Management*, *89*(November), pp. 105–106. https://doi.org/10.1016/j.indmarman.2019.11.008

Balog, K. (2019). *Agile Organizations and Sustainability*, pp. 111–121.

Barlette, Y. & Baillette, P. (2020). Big data analytics in turbulent contexts: towards organizational change for enhanced agility. *Production Planning and Control*, *0*(0), pp. 1–18. https://doi.org/10.1080/09537287.2020.1810755

Bradberry, C.; Ray, A.; Wayman, M.; Dhami, J.; Charnock, J. & Pittges, J. (2017). *Explaining and Predicting First Year Student Retention via Card Swipe Systems*.

Chatterjee, S.; Rana, N. P. & Dwivedi, Y. K. (2021). How does business analytics contribute to organisational performance and business value? A resource-based view. *Information Technology and People*, pp. 0–33. https://doi.org/10.1108/ITP-08-2020-0603.

Chaudhuri, R.; Chatterjee, S., Vrontis, D., & Thrassou, A. (2021). Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture. *Annals of Operations Research*, *January 2022*. https://doi.org/10.1007/s10479-021-04407-3.

Chen, C. W. D. & Cheng, C. Y. J. (2009). Understanding consumer intention in online shopping: A respecification and validation of the DeLone and McLean model. *Behaviour and Information*

Technology, 28(4), pp. 335–345. https://doi.org/10.1080/01449290701850111.

Cirera, X., & Muzi, S. (2020). Measuring innovation using firm-level surveys: Evidence from developing countries. *Research Policy*, 49(3), pp. 103912. https://doi.org/10.1016/j.respol.2019.103912.

Côrte-Real, N.; Oliveira, T. & Ruivo, P. (2017). Assessing business value of Big Data Analytics in European firms. *Journal of Business Research*, 70, pp. 379–390. https://doi.org/10.1016/j.jbusres.2016.08.011.

De Luca, L. M.; Herhausen, D.; Troilo, G. & Rossi, A. (2020). How and when do big data investments pay off? The role of marketing affordances and service innovation. *Journal of the Academy of Marketing Science*. https://doi.org/10.1007/s11747-020-00739-x.

Dombrowski, U.; Krenkel, P. & Ebentreich, D. (2014). Adaptability within a multi-variant serial production. *Procedia CIRP*, 17, pp. 124–129. https://doi.org/10.1016/j.procir.2014.01.047.

Duan, Y.; Cao, G. & Edwards, J. S. (2020). Understanding the impact of business analytics on innovation. In *European Journal of Operational Research* (Vol. 281, Issue 3). Elsevier B.V. https://doi.org/10.1016/j.ejor.2018.06.021.

Dubey, R.; Gunasekaran, A.; Childe, S. J.; Wamba, S. F. & Papadopoulos, T. (2016). The impact of big data on world-class sustainable manufacturing. *International Journal of Advanced Manufacturing Technology*, 84(1–4), pp. 631–645. https://doi.org/10.1007/s00170-015-7674-1.

Ekka, S. (2020). *Big Data Analytics Tools and Applications for Modern Business World*. *Icesc*, pp. 587–592.

Enyinna, U. K., & C, N. N. (2020). *Transatlantic Journal of Multidisciplinary Research*. *2*(1), pp. 57–80. https://doi.org/10.5281/zenodo.3948156.

Fosso Wamba, S.; Akter, S.; Edwards, A.; Chopin, G. & Gnanzou, D. (2015). How "big data" can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, 165, pp. 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031.

Fosso Wamba, S.; Queiroz, M. M.; Wu, L. & Sivarajah, U. (2020). Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03812-4.

Gao, Y. (2021). Big Data Analysis on E-commerce Platform. *Proceedings of the 2021 International Conference on Economic Development and Business Culture (ICEDBC 2021)*, *182*(Icedbc), pp. 191–195. https://doi.org/10.2991/aebmr.k.210712.031.

Gaur, L.; Singh, G. Jeyta & Kumar, S. (2016). Google Analytics: A Tool to make websites more Robust. *ACM International Conference Proceeding Series*, 04-05-March-2016(March). https://doi.org/10.1145/2905055.2905251.

George, G. & Lin, Y. (2017). *Institutional Knowledge at Singapore Management University Analytics , innovation , and organizational adaptation*, pp. 16–22.

Helfat, C. E. & Peteraf, M. A. (2009). Understanding dynamic capabilities: Progress along a developmental path. *Strategic Organization*, *7*(1), pp. 91–102. https://doi.org/10.1177/1476127008100133.

Hindle, G. A. & Vidgen, R. (2018). Developing a business analytics methodology: A case study in the foodbank sector. *European Journal of Operational Research*, 268(3), pp. 836–851. https://doi.org/10.1016/j.ejor.2017.06.031.

Hindle, G.; Kunc, M.; Mortensen, M.; Oztekin, A., & Vidgen, R. (2020). Business analytics: Defining the field and identifying a research agenda. *European Journal of Operational Research*, *281*(3), pp. 483–490. https://doi.org/10.1016/j.ejor.2019.10.001

Hoang, G. T.; Luu, T. T.; Nguyen, T. T.; Le, L. P. & Pham, N. T. (2021). Entrepreneurial Leadership and Product Innovation in Construction SMEs. *Academy of Management Proceedings*, *2021*(1), p. 10361.

Işik, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information and Management*, *50*(1), pp. 13–23. https://doi.org/10.1016/j.im.2012.12.001

Jahan, S., Alrajawy, I., Abid, S., & Martin, P. (2021). Analysing the Impact of Globalisation on Business Performance: Case of Uae Food Industry. *International Journal for Quality Research*, *15*(2), 665–678. https://doi.org/10.24874/IJQR15.02-19

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *The International Journal of Logistics Management*.

Kiron, D., Prentice, P. K., & Ferguson, R. B. (2012). Innovating with analytics. *MIT Sloan Management Review*, 54(1), P. 47.

Krishnamoorthi, S. & Mathew, S. K. (2018). Business analytics and business value: A comparative case study. *Information and Management*, 55(5), pp. 643–666. https://doi.org/10.1016/j.im.2018.01.005

Levinthal, D. A. (1991). *Organizational adaptation and environmental selection-interrelated processes of change. Organization science*, 2(1), pp. 140-145.).

Motamarri, S.; Akter, S. & Yanamandram, V. (2017). Does big data analytics influence frontline employees in services marketing? *Business Process Management Journal*, 23(3), pp, 623–644. https://doi.org/10.1108/BPMJ-12-2015-0182

Mou, J., Cui, Y. & Kurcz, K. (2020). Trust, risk and alternative website quality in B-buyer acceptance of cross-border e-commerce. *Journal of Global Information Management*, *28*(1), pp. 167–188. https://doi.org/10.4018/JGIM.2020010109

Muthukumar, T. (2020). Business Analytics: Current State & Challenges. *Indian Journal of Scientific Research*, *10*(2), p. 143. https://doi.org/10.32606/ijsr.v10.i2.00022

Nalchigar, S. & Yu, E. (2020). Designing Business Analytics Solutions. *Business & Information Systems Engineering*, *62*(1), pp. 61–75. https://doi.org/10.1007/s12599-018-0555-z.

Newey, L. R. & Zahra, S. A. (2009). The evolving firm: how dynamic and operating capabilities interact to enable entrepreneurship. *British Journal of Management*, *20*, S81–S100.

Odularu, G. (2020). Strategic policy options for bracing Nigeria for the future of trade. In *Strategic Policy Options for Bracing Nigeria for the Future of Trade*. https://doi.org/10.1007/978-3-030-34552-5

Olagunju, T.; Oyebode, O. & Orji, R. (2020). Exploring Key Issues Affecting African Mobile eCommerce Applications Using Sentiment and Thematic Analysis. *IEEE Access*, *8*, pp. 114475–114486. https://doi.org/10.1109/ACCESS.2020.3000093

Pappas, I. O.; Mikalef, P.; Giannakos, M. N.; Krogstie, J. & Lekakos, G. (2018). Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. *Information Systems and E-Business Management*, 16(3), pp. 479–491. https://doi.org/10.1007/s10257-

018-0377-z

Pollák, F.; Konečný, M. & Ščeulovs, D. (2021). Innovations in the Management of E-Commerce: Analysis of Customer Interactions during the COVID-19 Pandemic. *Sustainability*, *13*(14), p. 7986. https://doi.org/10.3390/su13147986

Quang Trung, D.; Yoke Beng, A. N. & Bhaumik, A. (2019). The environmental dynamism, dynamic capabilities and marketing innovation of fertiliser firms in Vietnam. *International Journal of Innovation, Creativity and Change*, 8(2), pp. 116–128.

Rahmah, M.; Ameen, A.; Isaac, O.; El, A.-E.; Abu-Elhassan, S.; & Khalifa, G. S. A. (2020). Effect of Organizational Innovation (Product Innovation, Process Innovation, and Administrative Innovation) On Organizational Learning. *TEST Engineering & Management*, *82*(2), pp. 12101–12113.

Rahmasari, A. & Syafitri, W. (2018). *Traditional Market Adaptation Srategy in Addresing*. 63–67.

Ramadan, M.; Shuqqo, H.; Qtaishat, L.; Asmar, H. & Salah, B. (2020). Sustainable competitive advantage driven by big data analytics and innovation. *Applied Sciences (Switzerland)*, *10*(19). https://doi.org/10.3390/app10196784

Rodgers, S. & Harris, M. A. (2003). Gender and E-commerce: An exploratory study. *Journal of Advertising Research*, *43*(3), pp. 322–329. https://doi.org/10.1017/S0021849903030307.

Schaffner, M. (2020). Industry 4.0—Flexibility of Technical Infonomics by Knowledge Management. In *German and Chinese Contributions to Digitalization*, pp. 39–46. Springer.

Schildt, H. (2017). Big data and organizational design–the brave new world of algorithmic management and computer augmented transparency. *Innovation: Management, Policy and Practice*, 19(1), pp. 23–30. https://doi.org/10.1080/14479338.2016.1252043.

Seetharaman, P. (2020). Business models shifts: Impact of Covid-19. *International Journal of Information Management*, 54(June), pp. 1–4. https://doi.org/10.1016/j.ijinfomgt.2020.102173.

Shamim, S.; Zeng, J.; Khan, Z. & Zia, N. U. (2020). Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technological Forecasting and Social Change*, 161(August), p. 120315. https://doi.org/10.1016/j.techfore.2020.120315.

Sharma, N.; Chakrabarti, A. & Balas, V. E. (2019). Data management, analytics and innovation. *Proceedings of ICDMAI*, *1*.

Singh, A. & Pawale, M. S. (2020). Redesigning Strategies in a Turbulent Business Environment. *Studies in Indian Place Names*, 40(74), pp. 1593–1601.

Singh, S.; Weeber, M., Birke, K. P., & Sauer, A. (2020). Development and Utilization of a Framework for Data-Driven Life Cycle Management of Battery Cells. *Procedia Manufacturing*, *43*(2019), pp. 431–438. https://doi.org/10.1016/j.promfg.2020.02.191.

Srinivas, S.; Gill, A. Q. & Roach, T. (2020). *Analytics-Enabled Adaptive Business Architecture Modeling*. *23*, pp. 23–43.

Staegemann, D.; Volk, M.; Daase, C. & Turowski, K. (2020). *Discussing Relations Between Dynamic Business Environments and Big Data Analytics*. 23, pp. 58–82.

Sun, Z.; Sun, L. & Strang, K. (2018). Big Data Analytics Services for Enhancing Business Intelligence. *Journal of Computer Information Systems*, 58(2), pp. 162–169. https://doi.org/10.1080/08874417.2016.1220239.

Tim, Y.; Hallikainen, P.; Pan, S. L. & Tamm, T. (2020). Actualizing business analytics for organizational transformation: A case study of Rovio Entertainment. *European Journal of Operational Research*, *281*(3), pp. 642–655. https://doi.org/10.1016/j.ejor.2018.11.074.

Van Den Bosch, F. A. J.; Volberda, H. W. & De Boer, M. (1999). Coevolution of Firm Absorptive Capacity and Knowledge Environment: Organizational Forms and Combinative Capabilities. *Organization Science*, 10(5), pp. 551–568. https://doi.org/10.1287/orsc.10.5.551.

Vidgen, R.; Hindle, G. & Randolph, I. (2020). Exploring the ethical implications of business analytics with a business ethics canvas. *European Journal of Operational Research*, *281*(3), pp. 491–501. https://doi.org/10.1016/j.ejor.2019.04.036.

Vitari, C. & Raguseo, E. (2020). Big data analytics business value and firm performance: linking with environmental context. *International Journal of Production Research*, *58*(18), pp. 5456–5476. https://doi.org/10.1080/00207543.2019.1660822.

Volkoff, O. & Strong, D. M. (2017). Affordance theory and how to use it in is research. *The Routledge Companion to Management Information Systems*, pp. 232–246. https://doi.org/10.4324/9781315619361

Wu, L.; Liu, H. & Su, K. (2020). Exploring the dual effect of effectuation on new product development speed and quality. *Journal of Business Research*, *106*(135), pp. 82–93. https://doi.org/10.1016/j.jbusres.2019.09.016.

Yahya-Imam, M. K. & Aranuwa, F. O. (2020). An Empirical Study on Big Data Analytics: Challenges and Directions. *Intelligent Computing and Innovation on Data Science* pp. 669–677. Springer.

Yin, J. & Fernandez, V. (2020). A systematic review on business analytics. *Journal of Industrial Engineering and Management*, 13(2), pp. 283–295. https://doi.org/10.3926/jiem.3030