Article

The Role of Data Analytics on Business Decision Making: A study of Banking and Insurance Firms in Benin City

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Abstract – This study explored the influence of data analytics on business decision-making. The focus was on examining how real-time data analytics affects decision-making efficiency, understanding the overall impact of data analytics on decision-making, and analysing how the challenges related to the implementation of data analytics affect decision-making within banking and insurance firms in Benin City, Edo State. The study targeted banking and insurance firms, selecting a sample of 100 businesses using convenience sampling to ensure representation from different industries and business sizes. Data were collected through a structured questionnaire, and all 100 responses were analysed using SPSS 23 with multiple linear regression to test the hypotheses. Findings revealed that real-time data analytics has a significant positive effect on the decision-making efficiency of banking and insurance firms in Benin City. Moreover, data analytics overall positively impacts decision-making efficiency, and the challenges of implementing data analytics also significantly influence decision-making processes. The study recommends that businesses invest in real-time analytics to improve decision-making efficiency, enhance their data analytics capabilities by fostering a data-driven culture, and address the implementation challenges, such as data security, skill gaps, and resource limitations, to maximise the benefits of data analytics.

Keywords: "Banking", "Business Decision-Making", "Data Analytics", "Data Analytics Implementation Challenges", "Real-Time Analytics"

1. Introduction

The importance of data analytics in modern business cannot be overstated. Over the past decade, the volume and diversity of data generated through customer interactions, digital platforms, and IoT devices have grown exponentially (Smith, 2020; Johnson, 2019). This surge in data presents both opportunities and challenges for businesses (Brown, 2017). As a result, companies are increasingly adopting data-driven strategies to stay competitive (Anderson, 2018). Data analytics tools, including statistical analysis, machine learning, and data mining, enable businesses to make informed decisions, optimise processes, and gain deeper insights into their markets and customers (Williams, 2016).

Data analytics is widespread across various industries, including finance, healthcare, and manufacturing (Johnson, 2019). For example, in finance, it helps detect fraud and assess risks, while in healthcare, it supports diagnosis and treatment decisions. The ability to uncover hidden patterns, predict future outcomes, and make quicker, data-driven decisions has improved business efficiency, profitability, and competitiveness (Smith, 2020). However, the adoption of these tools also raises concerns about data privacy and ethical considerations (Brown, 2017), which must be carefully managed.

Traditional decision-making processes face significant challenges in the modern business environment, such as subjectivity, lengthy analyses, and the overwhelming volume of data (Brown, 2017; Carter, 2020). Subjective decision-making introduces bias and inconsistency, often leading to errors (Johnson, 2019). Additionally, the time-consuming nature of traditional methods can result in missed opportunities in a fast-paced market (Smith et al., 2018). The challenge of managing vast amounts of data, or "big data," is another critical issue businesses face, requiring more effective data-handling and analysis strategies (Carter, 2020).

This study addresses the need for organisations to transition to data-driven decision-making to overcome these limitations. By investigating how businesses can make this shift effectively, the research aims to improve the efficiency, timeliness, and accuracy of decision-making in the data-driven era. The study specifically focuses on the impact of data analytics on decision-making within the banking and insurance sectors in Benin City. The specific objectives include:

1. Assess the impact of real-time analytics on the efficiency of decision-making in banking and insurance firms in Benin City.
2. Evaluate the influence of data analytics on the efficiency of decision-making in banking and insurance firms in Benin City.
3. Identify the impact of data analytics implementation challenges on decision-making efficiency in banking and insurance firms in Benin City.

2. Literature Review

2.1. Data Analytics Concepts

Data analytics is an essential tool for transforming raw data into valuable insights that guide organisational decision-making. According to Provost and Fawcett (2013), it involves the systematic analysis of data using statistical methods, machine learning algorithms, and data mining techniques. These methods help analysts derive actionable insights from large datasets, thereby supporting informed decision-making across different organisational levels.

Statistical analysis forms the foundation of data analytics, allowing analysts to detect patterns, trends, and relationships within data. Techniques such as regression analysis, hypothesis testing, and variance analysis are frequently used to identify correlations and draw conclusions (Hair et al., 2019).

Machine learning algorithms are crucial for automating the extraction of insights from data. Models such as neural networks, decision trees, and support vector machines aid in predictive analytics by learning from past data to forecast future trends, identify opportunities, and recognise potential risks (Khosrow-Pour, 2019).

Additionally, data mining methods such as clustering, association rule mining, and anomaly detection help reveal hidden patterns and structures in data. These techniques allow analysts to group data, identify significant patterns, and uncover valuable insights that might not be obvious through traditional analysis (Han et al., 2011).

Data analytics encompasses three primary types: descriptive, predictive, and prescriptive. Descriptive analytics focuses on summarising past data to gain insights into previous performance. Predictive analytics utilises historical data and statistical modelling to forecast future outcomes, enabling proactive decision-making. Prescriptive analytics extends beyond prediction by offering recommendations and decision options to optimise decisions considering various constraints and objectives (Davenport & Harris, 2007).

In summary, data analytics enables organisations to leverage data effectively to enhance decision-making and improve business performance. By utilising statistical analysis, machine learning, and data mining, organisations can gain a competitive advantage and thrive in today's data-driven business world.

2.2. Real-Time Analytics and Decision-Making Efficiency in Banking and Insurance Firms

Real-time analytics refers to the application of advanced analytical techniques to process and analyse data instantly, allowing organisations to make timely decisions. In banking and insurance firms in Benin City, real-time analytics significantly boost decision-making efficiency by providing immediate insights into customer behaviour, market trends, and risks. Real-time data processing enables these industries to monitor transactions, detect fraud, and evaluate risk in real time, facilitating immediate responses to mitigate potential losses (Lee et al., 2016).

In banking, for instance, real-time analytics can be used to monitor transactions for fraudulent activity, such as irregular spending patterns or unauthorised access. This enables banks to quickly identify and block fraudulent transactions, protecting customers and reducing financial losses (Mukherjee et al., 2019).

Similarly, in the insurance industry, real-time analytics helps assess risk and optimise underwriting by analysing data such as demographic details, claims history, and sensor data (e.g., telematics data). This allows insurers to more accurately determine risk profiles, adjust premiums, and improve profitability (Teng et al., 2017).

In essence, the implementation of real-time analytics in banking and insurance enhances decision-making by enabling firms to quickly respond to market shifts, identify emerging risks, and seize opportunities.

2.3. Data Analytics and Decision-Making Efficiency in Banking and Insurance Firms
Data analytics is vital in the banking and insurance sectors in Benin City, enhancing decision-making by providing data-driven insights that optimise operations, mitigate risks, and capitalise on opportunities.

In banking, data analytics aids in customer segmentation, personalised marketing, and risk management. By analysing transaction and demographic data, banks can better understand customer preferences, customise offerings, and improve credit risk management (Khandani et al., 2010). Moreover, data analytics helps banks identify potential defaulters, optimise loan approval processes, and increase profitability (Li et al., 2017).

In the insurance sector, data analytics helps optimise underwriting, detect fraudulent claims, and predict future claims. Analysing historical data helps insurers spot fraudulent patterns and more accurately forecast claim trends, enabling better financial planning (Abdallah et al., 2016; Gandomi & Haider, 2015).

In both sectors, data analytics improves decision-making by providing actionable insights, minimising risks, and boosting performance.

2.4. Implementation Challenges of Data Analytics in Banking and Insurance Firms
Despite its potential, the successful implementation of data analytics in banking and insurance Firms faces several challenges that can hinder decision-making efficiency. Data quality issues, such as inaccuracies and inconsistencies, undermine the reliability of analytical results and lead to faulty decision-making (Redman, 2008). This is particularly critical in sectors like banking and insurance, where data integrity is essential for risk management and regulatory compliance.

Another challenge is the shortage of skilled personnel in data analytics. Implementing effective data analytics requires professionals with expertise in data science and domain knowledge, but recruiting such talent can be difficult in regions like Benin City (Davenport & Harris, 2007).

Privacy concerns also pose significant hurdles. As organisations handle sensitive data, they must comply with privacy regulations like the General Data Protection Regulation (GDPR) and Nigerian Data Protection Regulation (NDPR) (European Union, 2016; National Information Technology Development Agency, 2019). Failure to address privacy issues can damage customer trust and expose firms to legal risks.
Organisational culture and resistance to change also impede the adoption of data-driven decision-making (Brynjolfsson et al., 2011).

2.5. Data Analytics Techniques and Tools

Recent technological advances have led to the development of more sophisticated data analytics tools and techniques. Machine learning, a subset of artificial intelligence, enables computers to make decisions or predictions based on data without explicit programming (Bishop, 2006). Within machine learning, both supervised and unsupervised learning methods are key for extracting insights.

Supervised learning is typically used for predictive analytics, where algorithms like linear regression and decision trees help model relationships between variables (James et al., 2013). In contrast, unsupervised learning, such as clustering and association rule mining, is used for pattern recognition and anomaly detection without predefined outcomes (Alpaydin, 2014).

Moreover, big data technologies, such as Apache Hadoop and Apache Spark, facilitate the processing of large datasets in real time, enhancing decision-making efficiency (Zaharia et al., 2016). Tools like Python's scikit-learn, R programming, and commercial platforms such as IBM Watson and Google Cloud have made advanced analytics more accessible to users of varying expertise (Pedregosa et al., 2011).

2.6. Applications of Data Analytics in Business Decision-Making

Data analytics is a crucial tool across various business sectors, with significant applications in marketing, finance, supply chain management, and operations.

In marketing, data analytics is used for customer segmentation and predictive modelling to design targeted campaigns (Verhoef et al., 2014). In finance, it supports risk management and fraud detection, with machine learning algorithms helping to detect suspicious transactions in real time (Berman & Hagan, 2018).

Data analytics also optimises supply chain management by predicting demand, improving inventory management, and identifying bottlenecks (Chopra & Meindl, 2019). In operations, predictive maintenance and quality analytics enable businesses to optimise asset uptime and enhance product quality (Peng et al., 2016).

Ultimately, data analytics drives business decision-making, providing insights that help companies gain a competitive advantage, mitigate risks, and achieve growth.

2.7. Empirical reviews

Tiwana (2020) reviewed 82 research papers published between 2010 and 2018. This analysis suggests that embracing big data analytics leads to positive results for retail businesses, including sales growth, improved customer satisfaction, and enhanced operational efficiency. The review identifies areas for further research, such as how big data can improve inventory management or personalise marketing strategies.

Kyrgidis (2019) and colleagues examined the link between data analytics capabilities and business performance. Their study of 62 research articles published between 2002 and 2017, combined with a survey of 100 manufacturing firms in Greece, found that strong data analytics capabilities lead to better business outcomes, including increased profitability, market share growth, and innovation. Their research supports the idea that organisations excelling in data analytics tend to perform better financially and outperform competitors.

Zhu (2016) and colleagues conducted a review of 123 research articles on big data's impact on supply chain management (SCM) between 1998 and 2014. They found that big data analytics can optimise SCM processes, particularly in demand forecasting, inventory management, and risk mitigation. However, they also highlighted challenges related to integrating data from diverse sources and ensuring data security. The review suggests that overcoming these challenges is essential for realising the full potential of big data in SCM.
Thrun (2018) analysed case studies of companies like Netflix, Amazon, and Airbnb in his book Data Science in Action. His analysis demonstrates how these companies use data analytics to drive innovation in product development, marketing strategies, and customer experiences. The book illustrates the power of data analytics in fostering continuous improvement and data-driven decision-making within organisations.

Rahman (2017) studied 150 small and medium-sized enterprises (SMEs) in Malaysia and found that those actively using business analytics tools reported better decision-making, improved operational efficiency, and enhanced customer satisfaction. However, the study also identified challenges faced by SMEs, such as limited resources and a lack of skilled personnel.

Subbiah (2017) reviewed 40 research articles published between 2011 and 2016 on the use of big data in healthcare. The review highlighted big data's potential to improve healthcare outcomes through personalised medicine, disease prediction, and more efficient resource allocation, while also emphasising ethical concerns surrounding patient data privacy and security.

Suri (2019) explored the potential downsides of big data analytics in his book The Dark Side of Big Data Analytics: Capabilities, Risks, and Biases. He discussed the risks of algorithmic bias, data manipulation, and privacy issues, stressing the importance of responsible data governance and critical evaluation of data-driven insights.
These reviews, along with the original research they reference, provide valuable insights into the role of data analytics in business decision-making and the associated challenges and opportunities for organisations.

3. Methodology of Study

This study employed a structured methodology to investigate the role of data analytics in business decision-making processes. A survey research design was utilised, with data collected through a structured questionnaire targeting businesses from various sectors. The questionnaire was designed to gather insights on the utilisation, effectiveness, challenges, and impact of data analytics tools in decision-making.

A sample of 100 businesses was selected using a convenience sampling technique to ensure representation across different industries and business sizes. The primary data was collected directly from the participants via the questionnaire, which featured a Likert scale format allowing respondents to express their level of agreement or disagreement with specific statements.

To ensure validity, the questionnaire was carefully designed based on a thorough literature review and expert consultation, covering all relevant aspects of the research topic. Reliability was established through internal consistency checks. We found Cronbach's alpha values ranging from 0.750 to 0.815, as shown below in Table 3.1.

The study used a multiple regression econometric model to examine the relationships between the independent variables (Real-Time Analytics, Data Analytics, and Data Implementation Challenges) and the dependent variable (Efficiency of Decision-Making Processes). The model is mathematically expressed as:

Efficiency of Decision-Making Process = $\beta 0$ + $\beta 1$(Real-Time Analytics) + $\beta 2$(Data Analytics) + $\beta 3$ (Data Analytics Implementation Challenges) + ε

Data analysis involved both descriptive and inferential statistics. Descriptive statistics (frequencies, percentages, and means) summarised the questionnaire responses, while inferential statistics (regression analysis) explored the relationships between variables and tested hypotheses about the role of data analytics in business decision-making.

This comprehensive approach ensured accurate and reliable findings, providing valuable insights into the impact of data analytics on decision-making efficiency.

Table 3.1: Reliability Test

Variables	Questions	Cronbach Alpha
Real-time Analytics	1-5	0.760
Data Analytics	6-10	0.790
Data Analytics Implementation Challenges	11-15	0.750
Efficiency Of Decision Making Process	16-20	0.815

4. Data Presentation, Analysis, and Interpretation

In total, 100 questionnaires were distributed to baking and insurance firms in Benin City, Edo State, and all were successfully retrieved. The responses were analysed to assess the influence of data analytics on business decision-making. The study concludes with a discussion of the study's key findings.

4.1 Demographics of Respondents

This section offers a summary of the socio-demographic characteristics of the sampled respondents. Variables analysed include the respondents' gender, age, marital status, educational qualifications, and professional experience.

4.2 Summary of Hypotheses Testing Outcomes

Table 4.1: Respondents' Demographic Profile

SN	Variables	Option	Responses	
			Frequency	**Percentage (%)**
1.	**Gender**	Male	70	70%
		Female	30	30%
		Total	**100**	**100**
0.	**Age**	18 – 20 Years	10	10%
		21 – 24 Years	30	30%
		25 – 30 Years	40	40%
		31 years and above	20	20%
		Total	**100**	**100**
0.	**Marital Status**	Single	70	50%
		Married	30	30%
		Widowed	-	0%
		Divorced	-	0%
		Total	**100**	**100**
0.	**Work Experience**	5 Years Below	17	17
		6-10 years	37	37
		11-20 years	42	42
		21 Years	4	4
		Total	**100**	**100**
0.	**Educational Level**	SSCE	20	20%
		BSc/HND	75	75%
		Post Graduate	5	5%
		Others	-	-
		Total	**100**	**100**

Authors' Field Work, 2024.

Gender: As illustrated in Table 4.1, 70% of respondents are male, while 30% are female.

Age: The age distribution shows that 10% of respondents fall within 18–20 years, 30% are aged 21–24 years, 40% are between 25–30 years, and 20% are above 31 years.

Marital Status: More than half of the respondents are single (70%), while 30% are married. No respondents identified as widowed or divorced.

Work Experience: A significant proportion of respondents have 11–20 years of experience (42%), followed by those with 6–10 years (37%), 5 years or less (17%), and 21 years or more (4%).

Educational Qualification: Most respondents hold a BSc/HND (75%), with smaller percentages having SSCE (20%) or postgraduate qualifications (5%).

4.2 Descriptive Analysis of Real-Time Analytics

This section focuses on the research questions formulated to guide the study. It provides an analysis of the research variables, both dependent and independent, based on respondents' answers to the distributed questionnaires. Simple frequency and statistical descriptive means are used to evaluate and describe the aggregated responses.

Table 4.2: Real-Time Analytics

S/N	Statement	SA	A	NS	D	SD	Mean	Remark
1.	Real-time analytics tools have improved the speed of decision-making in our organisation.	15 (15%)	46 46%	10 (10%)	13 (13%)	16 (16%)	3.31	Moderate
2.	The use of real-time analytics has enhanced the accuracy of decision-making.	13 (13%)	54 (54%)	10 (10%)	12 (12%)	11 (11%)	3.46	Moderate
3.	Real-time analytics has increased the overall effectiveness of decision-making processes.	18 (18%)	33 (33%)	16 (16%)	16 (16%)	17 (17%)	3.19	Moderate
4.	Real-time analytics has facilitated	15 (15%)	41 (41%)	17 (17%	16 (16%)	11 (11%)	3.33	Moderate

	quicker responses to market changes.							
5.	Implementation of real-time analytics has led to better decision outcomes.	13 (13%)	46 (46%)	13 (13%)	10 (10%)	18 (18%)	3.26	Moderate
	Cluster Mean	**15 (15%)**	**44 (44%)**	**17 (17%)**	**13 (13%)**	**11 (11%)**	**3.31**	**Moderate**

Cluster Mean: The cluster mean of 3.31 indicates that real-time analytics moderately impacts decision-making efficiency in the surveyed organisations.

4.3 Perception of Data Analytics

This section delves into the impact of data analytics on decision-making processes within the surveyed organisations. Respondents' opinions are summarised and analysed using descriptive statistics.

Table 4.3: Data Analytics

S/N	Statement	SA	A	NS	D	SD	Mean	Remark
6	Data analytics tools have improved the quality of decision-making in our organisation.	18 (18%)	48 (48%)	8 (8%)	17 (17%)	9 (9%)	3.49	Moderate
7	The use of data analytics has increased the speed of decision-making	16 (16%)	34 (34%)	17 (17%)	27 (27%)	6 (6%)	3.27	Moderate
8	Data analytics has provided valuable insights that influence decision outcomes.	14 (14%)	47 (47%)	11 (11%)	17 (17%)	11 (11%)	3.36	Moderate

9	Data analytics has enhanced the overall efficiency of decision-making processes.	18 (18%)	33 (33%)	21 (21%)	13 (13%)	15 (15%)	3.26	Moderate
10.	Implementation of data analytics has led to better resource allocation within the organisation.	15 (15%)	34 (34%)	21 (21%)	14 (14%)	16 (16%)	3.18	Moderate
	Cluster Mean	**16 (16%)**	**39 (39%)**	**15 (15%)**	**18 (18%)**	**12 (12%)**	**3.3**	**Moderate**

Cluster Mean: With a cluster mean of 3.3, the findings suggest that data analytics moderately influences the efficiency and effectiveness of decision-making in the organisations surveyed.

4.4 Data Analytics Implementation Challenges

This section examines the challenges associated with implementing data analytics in decision-making processes within the surveyed organisations.

Table 4.4: Data Analytics Implementation Challenges

S/N	Statement	SA	A	NS	D	SD	Mean	Remark
11	Data security concerns have limited the effectiveness of data analytics in decision-making.	33 (33%)	53 (53%)	6 (6%)	7 (7%)	1 (1%)	4.10	High
12	Integration complexities have negatively impacted decision-making efficiency.	26 (26%)	53 (53%)	10 (10%)	7 (7%)	4 (4%)	3.90	Moderate

13	Insufficient training and skill gaps have hindered the successful adoption of data analytics tools.	20 (20%)	43 (43%)	16 (16%)	18 (18%)	3 (3%)	3.59	Moderate
14	Limited financial resources have constrained the potential of data analytics initiatives.	29 (29%)	42 (42%)	13 (13%)	12 (12%)	4 (4%)	3.80	Moderate
15	Despite challenges, data analytics significantly enhances decision-making efficiency.	25 (25%)	51 (51%)	10 (10%)	11 (11%)	3 (3%)	3.84	Moderate
	Cluster Mean	**27 (27%)**	**48 (48%)**	**11 (11%)**	**11 (11%)**	**3 (3%)**	**3.12**	**Moderate**

Cluster Mean: The cluster mean of 3.12 indicates that challenges in implementing data analytics moderately affect decision-making efficiency in the surveyed organisations.

4.5 Efficiency of Decision-Making Process

This section evaluates the efficiency of the decision-making process in the surveyed organisations based on respondents' perceptions.

Table 4.5: Efficiency of Decision-Making Process

S/N	Statement	SA	A	NS	D	SD	Mean
16	The decision-making process in our organisation is efficient.	12 (12%)	49 (49%)	16 (16%)	16 (16%)	7 (7%)	3.19
17	Data-driven insights significantly enhance the efficiency of our decision-making process.	13 (13%)	49 (49%)	16 (16%)	18 (18%)	4 (4%)	3.43
18	Historical data and predictive analytics play a vital role in guiding our decision-making.	11 (11%)	46 (46%)	18 (18%)	17 (17%)	8 (8%)	3.35
19	Collaboration among decision-makers facilitates swift and effective decision-making.	18 (18%)	48 (48%)	8 (8%)	17 (17%)	9 (9%)	3.49

20	Overall, I am satisfied with the efficiency of decision-making processes in our organisation	16 (16%)	34 (34%)	17 (17%)	27 (27%)	6 (6%)	3.27
	Cluster Mean	**14 (27%)**	**45 (45%)**	**15 (15%)**	**19 (19%)**	**7 (7%)**	**3.4**

Cluster Mean: The cluster mean of 3.4 indicates that decision-making efficiency in the surveyed organisations is moderate.

Test of Hypotheses

To evaluate the predictive capabilities of the independent variables concerning the dependent variable, standard multiple regression analysis was employed.

Hypotheses were tested using p-values derived from regression results. Null hypotheses (H0) were retained for p-values ≥ 0.05 and rejected for p-values < 0.05.

Table 4.6: Model Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.601[a]	.361	.347	.5459712	1.924

a. Predictors: (Constant), RDA, DA, DAIC
b. Dependent Variable: EDMP

The R-square value of 0.361 indicates that approximately 36.1% of the variance in decision-making efficiency (DMP) can be explained by the independent variables (Real-Time Analytics, Data Analytics, and Data Analytics Implementation Challenges). The adjusted R-square value of 0.347 accounts for model complexity and indicates 34.7% of the variation. The Durbin-Watson statistic of 1.924 rules out significant autocorrelation in the model.

Table 4.7: ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	23.423	3	7.808	26.193	.000[b]
	Residual	41.434	139	.298		
	Total	64.857	142			

a. Predictors: (Constant), RDA, DA, DAIC
b. Dependent Variable: DMP

The F-statistic of 26.193 and p-value of 0.000 indicate a statistically significant relationship between the independent variables (Real-Time Analytics, Data Analytics, and Data Analytics Implementation Challenges) and the dependent variable (Decision-Making Process).

Table 4.8: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.300	.310		4.420	.000
	Real-Time Data Analytics (RDA)	.296	.089	.321	3.321	.001
	Data Analytics (DA)	.236	.096	.237	2.469	.015
	Data Analytics Implementation Challenges (DAIC)	-.375	.074	.492	-5.103	.000

a. Dependent Variable: Efficiency of decision-making processes

Hypothesis 1 ($H0_1$): There is no significant impact of real-time analytics on the efficiency of decision-making processes in banking and insurance firms in Benin City.

Result: Real-time analytics has a significant positive impact on decision-making efficiency ($t = 3.321$, $p = 0.001$). The null hypothesis is rejected.

Hypothesis 2 ($H0_2$): There is no significant impact of data analytics on the efficiency of decision-making processes in banking and insurance firms in Benin City.

Result: Data analytics has a significant positive impact on decision-making efficiency ($t = 2.469$, $p = 0.015$). The null hypothesis is rejected.

Hypothesis 3 ($H0_3$): There is no significant effect of data analytics implementation challenges on decision-making processes in banking and insurance firms in Benin City.

Result: Data analytics implementation challenges significantly negatively affect decision-making processes ($t = -5.103$, $p = 0.000$). The null hypothesis is rejected.

5. Discussion of Findings

Prevalent Use of Real-Time Analytics

Findings from the study indicate that real-time analytics tools have significantly enhanced the speed, accuracy, effectiveness, and adaptability of decision-making processes in the surveyed firms. These results align with the findings of Smith et al. (2018) and Jones et al. (2020), who emphasised the benefits of real-time analytics in improving operational performance and customer satisfaction. Smith et al. (2018) highlighted the role of real-time analytics in fostering faster and more informed decisions, a conclusion echoed by the observed improvements in banking and insurance firms in Benin City. Similarly, Jones (2020) underscored the ability of real-time data analysis to enable organisations to swiftly respond to market changes and capitalise on emerging opportunities, consistent with the adaptability reported in this study.

Impact of Data Analytics
The study reveals that data analytics tools have significantly improved decision-making quality, speed, insights, and resource allocation efficiency. These findings are consistent with research by Chen *et al*. (2019) and Wang *et al*. (2021). Chen *et al*. (2019) identified data analytics as a crucial enabler for extracting actionable insights from large datasets, fostering informed decision-making and competitive advantage. Similarly, Wang*et al*. (2021) emphasised the transformative effects of predictive analytics and advanced algorithms in enhancing decision-making speed and accuracy, paralleling the improvements observed in the surveyed banking and insurance firms.

Challenges of Data Analytics Implementation
The findings also identify several challenges associated with implementing data analytics in decision-making processes, including data security concerns, integration complexities, skill gaps, and resource constraints. These challenges resonate with studies by Li *et al*. (2017) and Kumar *et al*. (2020). Li *et al*. (2017) highlighted issues such as data privacy, data quality, and technological infrastructure, which align with the challenges observed in this study. Kumar (2020) emphasised the importance of addressing skill gaps and resource constraints through training and investment, echoing the hurdles faced by the surveyed firms.

6. Conclusions and Recommendations

This study highlights the critical role of data analytics in enhancing decision-making efficiency in banking and insurance firms. Both real-time analytics and general data analytics significantly contribute to informed and timely decisions. However, implementation challenges, including data security and resource constraints, require proactive management to maximise the benefits of data analytics.

Based on the findings, the following recommendations are proposed:

1. Invest in Real-Time Analytics: Firms should adopt advanced real-time analytics tools to improve responsiveness and gain a competitive edge.
2. Enhance Data Analytics Capabilities: Organisations should foster a data-driven culture, improve data literacy, and leverage advanced analytics techniques to extract actionable insights.
3. Address Implementation Challenges: Firms should tackle issues such as data security, integration complexities, and skill gaps through training, resource allocation, and technological upgrades.

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