Data modelling for business intelligence solutions: Investigation into Edtech and Fintech businesses in Nigeria

International Journal of Business Sustainability

Omolade Sunday Adeyemi
Department of Business Administration, Christopher University, Ogun State, Nigeria

Oluwatoyin Damilola Adeyemi
Department of Economics and Business Administration, Aletheia University, Ago-Iwoye, Ogun State, Nigeria

Babalola Raphael Adesunloro
Department of Accounting, Finance and Investment, Wesley University, Ondo, Ondo State, Nigeria

Oluwatoyin Alice Jayeoba
Department of Business Administration, Osun State University, Osogbo, Nigeria

Received: 14 August 2025
Revised: 12 September 2025
18 March 2026
Accepted: 18 March 2026
Published: 31 March 2026

Abstract

Purpose: This study investigated the influence of data modelling for business intelligence solution using the comprehensiveness of the business model, physical model and decision-making speed on business performance in Nigeria's EdTech and FinTech industries.

Design/methodology/approach: A quantitative approach was employed, the cross-sectional survey research design was adopted, data were obtained from 495 Nigerian EdTech and FinTech practitioners. Partial Least Square Structural Equation Modelling (PLS-SEM) utilising SmartPLS 4 was used to evaluate hypothesised relationship among latent constructs of data modelling and business performance.

Findings: A quantitative approach was employed, the cross-sectional survey research design was adopted, data were obtained from 495 Nigerian EdTech and FinTech practitioners. Partial Least Square Structural Equation Modelling (PLS-SEM) utilising SmartPLS 4 was used to evaluate hypothesised relationship among latent constructs of data modelling and business performance.

Limitations and Research implications: This study focused on two sectors within the Nigerian environment, which may restrict generalisability. Future studies should investigate cross-sectoral and multi-country comparisons to validate and enhance the integrated RBV-TOE model suggested.

Practical Implications: Managers should emphasise the development of complete and strategically aligned business models that include enhanced data structuring to speed effective decision-making. Policymakers are encouraged to support digital infrastructure enhancements to foster durable competitive advantages in emerging digital marketplaces.

Originality/value: This research gives empirical support for the combined Resource-Based View and Technology-Organisation-Environment frameworks applied to data modelling's function in increasing organisational performance in emerging markets. It uniquely situates advanced data modelling principles within the context of Nigeria's flourishing EdTech and FinTech sectors, providing a valuable position for researchers, practitioners, and policymakers.

Keywords: Data Modelling, Comprehensiveness of Business Model, Physical Model, Business Intelligence, Decision-making Speed, Business Performance

e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

Introduction

In today's quickly expanding era of digital transformation, data-driven decision-making has emerged as a primary priority in business sustainability, especially so in high-growth industries such as EdTech and Fintech in Nigeria. In pursuit of becoming flexible and resilient, the ability to make good use of data effectively, translating raw data into actionable knowledge, has been a distinct competitive edge (Ravi & Radhakrishna, 2024). Nonetheless, data gathering to usable insights is influenced by data modelling strength, encompassing essential stages: business modelling, logical modelling, dimensional modelling, and physical modelling. All these steps are pillars of business intelligence solution architecture strength that not only affect data processing efficiency but also strategic outcomes for firms functioning in difficult and unstable marketplaces (Kushwaha et al., 2021; Solomon et al., 2025).

Nigeria's EdTech sector is growing rapidly; the market is projected to surpass $400 million in 2025, driven by a vast youth population, rising mobile internet adoption, and confidence from local and global investors. Nigeria hosts about 34% of Africa's top EdTech startups and, therefore, is one of the foremost frontiers for first-mobile and hybrid education (Agbeche et al., 2024; Al-Qararah, 2023). Similarly, the Nigerian fintech industry has grown by roughly 70% annually due to rapidly changing regulations, record volumes of digital payments, and investment in groundbreaking innovations such as embedded finance and artificial intelligence integration (Abbas et al., 2025; Agbeche et al., 2024). Consequently, it remains one of the largest fintech hubs on the continent. In contrast to studies that are primarily situated within the Global contexts and the West African context, this research therefore situates data modelling practices within the specific economic and regulatory environment of Nigeria, which is defined by unique challenges and opportunities that shape business intelligence adoption (Alt et al., 2024; Goswami et al., 2025).

Despite rising investment and interest in fintech and edtech, empirical research on the influence of the subtle data modelling procedures on corporate performance remains fragmented. Initial business intelligence research has generally focused on the technical challenges of model design or the technical performance of analytics systems and has tended to be positioned in a Western or global North context. This has uncovered glaring gaps in understanding, primarily regarding how personalised data modelling procedures can drive sustainable development within Nigeria's specific economic and regulatory space, where Fintech and Edtech increasingly occupy roles of a revolutionary nature (Agbeche et al., 2024). Most existing work fails to cross over theoretical underpinnings of data modelling with empirical measurements of business performance, and context-specific elements that may affect the effectiveness of such techniques within the African marketplace have been poorly examined (Ionescu et al., 2025; Joel & Oguanobi, 2024).

Against such a backdrop, this study seeks to fill this gap by systematically analysing how data modelling, the comprehensiveness of the business model, the physical model, and decision-making speed impact business growth and sustainability among Nigerian Fintech and Edtech organisations. The question guiding this study is: Does each of the phases of data modelling promote business intelligence capacity building toward performance and sustainability?

Theoretically, this study enriches the theoretical picture of the data-to-value chain, revealing the confluence of technological design and strategic delivery. In reality, the findings offer the potential for effective recommendations for corporate leaders, data architects, technology providers, and legislators committed to developing a platform for data-driven growth (Hamzat et al., 2023; Joel & Oguanobi, 2024). By identifying data modelling techniques and concrete economic outcomes, this study aims to offer insights into best practices, guide investment in data infrastructure and skills, and build stronger, more flexible enterprises in Nigeria's digital economy. This study established the framework, argued for its place in business sustainability, identified significant scholarly gaps, outlined the research issue, and highlighted the study's dual theoretical and practical relevance. This study examines existing literature on data modelling and business intelligence for sectors. This is followed by a comprehensive explanation of the research method and analytical approach. The next section on findings includes actual evidence from the EdTech and FinTech sectors. The discussion section analyses these findings in the context of the study objectives, and the study concludes with ideas for practical implications and recommendations.

Literature Review

Conceptual Review

Business Performance

Business performance is the primary focus in technology-enabled enterprises, encompassing financial outcomes, operational efficiency, innovation capacity, customer satisfaction, and strategic adaptability. Solomon et al. (2025) and Verma (2024) assert that business performance in digital sectors, such as Nigerian EdTech and FinTech, is significantly affected by the degree to which data-driven insights are incorporated into product design and development, risk management, customer engagement, and market development. These industries face significant competition, rapid innovation cycles, and regulatory ambiguity, necessitating strategic-level data-driven business intelligence.

Empirical evidence demonstrates that business intelligence (BI) enhances organisational performance through predictive analytics, improved operational decision-making, enhanced customer insights, and digital innovation, as noted by Hamzat et al. (2023) and Joel and Oguanobi (2024). Nevertheless, the majority of the study does not examine how the maturity of successive phases of data modelling influences performance outcomes, particularly in emerging economies. The limited number of empirical publications addressing emerging nations, such as Nigeria, reveals a performance disparity in how quality data modelling impacts the performance of digital firms constrained by infrastructural and legal limitations.

Comprehensiveness of the Business Model

Business model comprehensiveness refers to the clarity and thoroughness with which an organisation defines its value proposition, core operations, customer segmentation, revenue mechanisms, and performance objectives. In BI contexts, the business model provides the strategic framework for determining data requirements and aligning modelling processes with company objectives. Prior studies underscore the fact that only when BI systems' data structures are positioned to directly support strategic imperatives do important insights get obtained, whether it is Ionescu et al. (2025), Modesta Oluoha et al. 2019), and Solomon et al. (2025) themselves.

A well-articulated business model often specifies what data to obtain, how to preserve it, and which analytics provide a competitive edge for EdTech and FinTech firms. There is empirical evidence that a business model aligned with strategy enhances data utilisation, innovation, and organisational agility (Mochama, 2021; Ravi & Radhakrishna, 2024). However, few studies have studied the comprehensiveness of the business model as an early stage of data modelling or as a driver of effectiveness in BI applications in the Nigerian digital industries. This produces a conceptual gap in appreciating the strategic-technical link in BI deployment.

Physical Data Model

The physical data model specifies all the real storage structures, indexing techniques, partitions, and performance improvements needed to implement the logical and dimensional models. Effective physical modelling enhances system scalability, reduces latency, and meets the computing demands of BI applications (Alam & Mohanty, 2022; Ogeawuchi et al., 2025).

e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

In places like Nigeria, where infrastructure can be severely restrictive for digital enterprises, this may include intermittent connectivity, volatility in data hosting, and increased regulatory constraints. Physical model optimisation is crucial for numerous reasons, including enabling real-time analytics, ensuring system stability, and enabling organisations to respond to user expectations for speed and reliability (Fagbore et al., 2022). However, the literature is scarce on how effectively physical modelling translates into operational efficiency or competitive advantage in EdTech and FinTech organisations. This is, in fact, a call for an empirical study within such situations.

The Mediating Role of Decision-Making Speed

Decision-making speed is the rate at which an organisation interprets data to evaluate alternatives and then strategically or operationally acts. Research evidence indicates that BI has a positive impact on performance only when it improves the timeliness of managerial decision-making processes (Desai & Desai, 2025; Kumar & Aithal, 2025). Different data modelling stages directly influence decision-making speed: logical models improve accuracy, dimensional models enable faster understanding, while physical models govern system response times. In fast-moving digital marketplaces, rapid decision-making boosts responsiveness to customer needs, enables rapid product iteration, and amplifies competitive agility (Chebrolu, 2025; Vudugula & Chebrolu, 2025). While all this is true, empirical research has failed to analyse how decision-making speed may act as a key conduit in the relationship between data modelling and performance in EdTech and FinTech organisations.

Theoretical Foundations

Resource-Based View (RBV)

The Resource-Based View also states that companies have superior performance to the extent that they have resources that are priceless, distinctive, inimitable, and non-substitutable (Barney, 1991). Data modelling capabilities, such as business model comprehensiveness and logical, dimensional, and physical models, satisfy the RBV criteria because they generate exclusive data architecture and analytical capabilities that are difficult for rival businesses to duplicate (Alam & Mohanty, 2022; Kushwaha et al., 2021). These levels of modelling strengthen internal skills, improve decision-making accuracy, and drive innovation in EdTech and FinTech businesses.

Technology Organisation Environment Framework

The TOE framework demonstrates that technological attributes, organisational preparation, and environmental influences determine technology adoption and its performance implications (Abdulrazaq et al., 2023; Ravi & Radhakrishna, 2024). Data modelling stages highlight the technological factor, the comprehensiveness of the business model represents organisational readiness, and regulatory and competitive issues represent environmental implications (Desai & Desai, 2025; Kumar & Aithal, 2025; Nguyen, 2022). These combined characteristics characterise the level of performance improvement achieved by BI initiatives in the digital industries in Nigeria.

Hypothesis Development

This study conceptualises data modelling and business intelligence capabilities as strategic organizational resources that can be achieved through the comprehensiveness of the business model, physical data model, decision-making speed, and business performance. Based on RBV and TOE, and supported by appropriate empirical evidence, the following hypotheses are proposed:

H1: Comprehensiveness of the business model has significant positive effect on decision-making speed in Nigerian EdTech and FinTech business.

According to the RBV, a robust business model is an important and integrative organisational resource that synchronises information flows, operational procedures, and strategic goals. When business models are clearly described and internally consistent, they eliminate uncertainty, promote cross-functional coordination, and expedite management cognition. Empirical studies suggest that businesses with well-defined business models exhibit faster, more accurate decision-making processes due to greater information openness and interpretability (Alam & Mohanty, 2022). In technologically demanding areas such as EdTech and FinTech, where responsiveness is crucial, this effect is predicted to be more significant.

H2: Physical data model has a significant positive effect on decision-making speed in Nigerian EdTech and FinTech businesses.

Physical data models reflect the practical reality of data architecture, determining system efficiency, processing speed, and accessibility. TOE theory highlights that technical infrastructure quality directly affects organisational results by shaping how well information systems support management activity. Optimised physical data models reduce latency, boost system robustness, and improve real-time access to information, ultimately expediting decision cycles. Empirical evidence shows that well-engineered physical data structures significantly reduce decision-making time in data-intensive businesses (Solomon et al., 2025).

H3: Decision-making speed has a significant positive effect on business performance in Nigerian EdTech and FinTech businesses.

Decision-making speed reflects a dynamic organisational capability that helps firms to notice, comprehend, and respond to environmental changes more effectively. Within the RBV framework, such dynamic capabilities are important processes through which resources are turned into performance results. Prior BI and analytics research consistently shows that timely, informed decision-making promotes profitability, operational efficiency, and competitive positioning (Desai & Desai, 2025; Solomon et al., 2025). Accordingly, decision-making speed processes are expected to translate directly into greater business success.

H4: Decision-making speed mediates the relationship between the comprehensiveness of the business model and business performance in Nigerian EdTech and FinTech businesses.

According to the RBV, a robust business model is an important and integrative organisational resource that synchronises information flows, operational procedures, and strategic goals. When business models are clearly described and internally consistent, they eliminate uncertainty, promote cross-functional coordination, and expedite management cognition. Empirical studies suggest that businesses with well-defined business models exhibit faster, more accurate decision-making processes due to greater information openness and interpretability (Alam & Mohanty, 2022). While a comprehensive business model provides the strategic logic that structures organisational priorities, its impact on business performance is not intended to be direct. Rather, the performance advantage of business model comprehensiveness is delivered through its activation of faster, better-informed decision-making mechanisms. Without the decision-making process to turn structural comprehensiveness into timely organisational action, the latent performance potential of the company model remains unrealised. DDMS is therefore postulated as the mediating channel through which CB exerts its performance benefits, with no substantial direct link expected between CB and BP in the presence of the mediator (Desai & Desai, 2025; Solomon et al., 2025).

© UIR Press
e-ISSN: 3110-7737
DOI:
10.25299/ijbs.2026.24557

H5: Decision-making speed mediates the relationship between physical data model and business performance in Nigerian EdTech and FinTech business.

Physical data models reflect the practical reality of data architecture, determining system efficiency, processing speed, and accessibility. TOE theory highlights that technical infrastructure quality directly affects organisational results by shaping how well information systems support management activity. Optimised physical data models reduce latency, boost system robustness, and improve real-time access to information, ultimately expediting decision cycles. Empirical evidence demonstrates that well-engineered physical data structures greatly boost decision-making time in data-intensive businesses (Solomon et al., 2025). However, the physical data model does not generate business performance irrespective of the organisational mechanisms via which data is translated into choices. The performance value of data infrastructure depends on decision-making speed; it is at the moment of decision, not at the point of data storage or retrieval, that data assets generate competitive returns. DDMS consequently mediates the relationship between PD, and BP, operating as the conversion mechanism through which data architecture quality is transformed into organisational performance outcomes. A considerable indirect effect of PD on BP through DDMS is therefore expected, with no significant direct relationship anticipated when DDMS is included in the model.

Empirical Review

The empirical literature review of the study further examines existing studies assessing the association between data-driven technologies, particularly in Fintech and Edtech, and corporate performance in Nigeria. This growing corpus of research provides useful findings on the adoption and utilisation of emerging technologies, affecting operational effectiveness, sustainability, and business growth across different industries.

There has been extensive empirical research on the effects of fintech penetration on the growth and efficiency of Nigerian SMEs. (Agbeche et al., 2024; Mochama, 2021; Santosh Kumar, 2024) find that fintech services, such as mobile payment systems, online banks, and blockchain platforms, are associated with higher operating efficiency, increased revenues, and greater market reach for SMEs. These studies utilised quantitative and mixed-methods research strategies, including surveys and structural equation modelling, to rigorously test these links. They underline the significance of Fintech in overcoming conventional silos, such as limited access to financing and entry restrictions, which are vital to sustaining business growth in emerging economies like Nigeria.

Other empirical research places the broader sectoral impact of Fintech innovation on financial institutions and businesses in perspective, noting that digitally enabled financial services not only contribute to more inclusive access to finance but also enhance strategic and operational performance. Alam and Mohanty (2022), Mochama (2021), and Solomon et al. (2025) found that the adoption of fintech solutions is associated with greater employment generation, profitability, and business expansion. However, these studies also suggest that contextual considerations, such as legal frameworks and infrastructural constraints, shape the extent to which Fintech might influence distinct Nigerian business contexts.

While empirical studies of EdTech in Nigeria's market are comparatively few compared to FinTech, parallel research indicates that digital teaching and learning technologies enhance organisational adaptation and performance. Edtech accelerates the digital revolution to render service delivery more effective, more interactive for users, and scalable for education enterprises, just like in the case of fintech organisations (Abdulrazaq et al., 2023; Modesta Oluoha et al., 2019)

Despite such noteworthy contributions, modern empirical research rarely explores the effect of specific data modelling processes that fuel business intelligence systems, such as the various business roles and logical, dimensional, and physical models. Subsequently, there remains a crucial knowledge gap regarding how these technological stages of data modelling contribute to improved performance metrics in Nigerian EdTech and FinTech organisations (Ibrahim & Handayani, 2022; Solomon et al., 2025).

This study thus draws on an empirical base through a detailed investigation of how the planned and formal deployment of distinct data modelling methodologies affects business performance as a whole. By applying rigorous quantitative analysis through structural equation modelling, it seeks to provide in-depth insights that link the process and architecture of data modelling to sustainable growth outcomes across two of Nigeria's most active technology industries. This focus on business intelligence's middle mechanisms provides a more differentiated empirical contribution to the literature and practical advice for organisations seeking to optimise their data-driven potential.

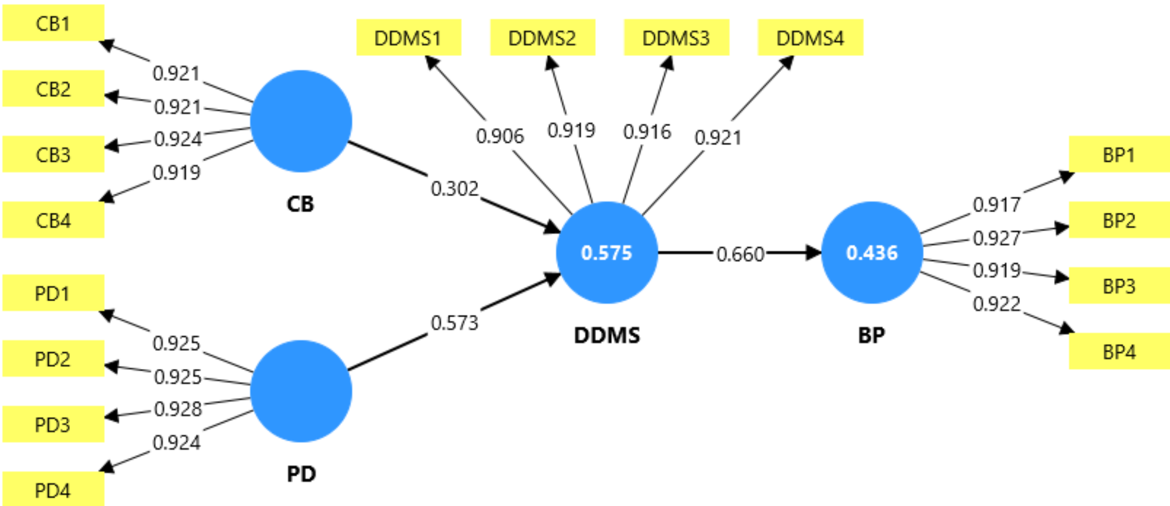

Figure 1
PLS Path Model
Note: CB = Comprehensiveness of the Business Model, PD= Physical Data Model, DDMS = Decision Making Speed, and BP = Business Performance

Methodology

This study adopted a quantitative research approach; a cross-sectional survey design was used to examine the relationships among data modelling, the comprehensiveness of the business model, decision-making speed in physical model selection, and business performance in Nigeria's Fintech and Edtech sectors. A quantitative approach is most ideal, as it allows statistical testing of predicted construct relationships, yielding objective and generalisable findings that align with the study's aims. The constructs of the study, comprehensiveness of the business model, physical model, decision-making speed, and business performance were operationalised using validated measurement scales adapted from existing literature and tailored to the Nigerian EdTech and FinTech contexts to enhance relevance and comprehension. Each construct was clearly defined: the comprehensiveness of the business model captures strategic alignment and operational completeness; the physical data model represents the technical infrastructure for data storage and retrieval optimisation; the decision-making speed was used to mediate the relationship between the dependent and independent variable and business performance encompasses market penetration, revenue growth, operational efficiency, innovation potential, and customer satisfaction.

International Journal of Business Sustainability

© UIR Press
e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

The target population comprised organisational respondents who possessed adequate knowledge of their firm's business model architecture, data infrastructure, and decision-making processes to furnish educated self-report data on all four constructs. The target population consisted of organisational respondents who possessed adequate knowledge of their firm's business model architecture, data infrastructure, and decision-making processes to furnish educated self-report data on all four constructs. Primary data were acquired using a structured, closed-ended questionnaire delivered to 495 respondents selected through a combination of stratified and convenience sampling. Stratified sampling guaranteed representation across organisational sizes, ages, and subsectors within the Nigerian EdTech and FinTech sectors. In contrast, convenience sampling facilitated access to relevant practitioners in business intelligence and data analytics roles. The sample size was deemed appropriate, providing adequate statistical power for the complex analyses performed, ensuring the robustness and stability of the model results. Descriptive statistics confirmed that there were no missing values among the 16 indicators, and the sample had sufficient statistical power for PLS-SEM estimation, including five structural paths and four reflective constructs (Hair et al., 2019).

The structured questionnaire captured the demographic profile of respondents, and the study constructs were used using reflective measurement models. Each construct was measured using 4 indicators, all yielding a total of 16 items. All items were anchored on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Items ranged from 2.88 to 2.94, with standard deviations approximating unity across all indicators, indicating adequate distributional variability. Skewness (-0.053 to 0.111) and excess kurtosis (-0.714 to -0.465) with values within the ±2.0 thresholds acceptable for PLS-SEM analysis. Convergent validity was assessed for all constructs, with outer loadings ranging from 0.906 to 0.928 and average variance extracted (AVE) values ranging from 0.838 to 0.857. Internal consistency and reliability were assessed for all constructs using the Cronbach’s alpha coefficients, which fall between 0.936 and 0.944, and composite reliability values between 0.954 and 0.960. Discriminant Validity was confirmed through the HTMT with all values below the conservative 0.85 threshold and corroborated by the Fornell-Larcker criterion. Data analysis was carried out using the Partial Least Square Structural Equation Modelling (PLS-SEM) with 5000 sub-sample bootstrapping, Bias-Corrected and accelerated (BCa) confidence intervals, PLSpredict cross-validated predictive assessment, and Cross-Validated Predictive Ability (CVPAT) using SmartPLS 4, chosen for its potential to simultaneously evaluate measurement models (validating how well survey items represent latent components) and structural models (testing theoretical causal links) (Al-MSloum, 2021; Hair Jr et al., 2021). These rigorous analytical methods ensured both instrument reliability and the validity of inferences generated from the structural model (Al-MSloum, 2021). Research ethics were properly adhered to throughout the investigation. Participation was voluntary, and informed consent was obtained from all responders. Anonymity and confidentiality were maintained through the de-identification of survey data and secure data management practices, thereby ensuring research integrity and reliability.

Results

The Demographic Profile of Respondents

Table 1 provides the demographic profile of the 495 respondents engaged in the study. Regarding gender, the sample was roughly balanced, with males accounting for 52.32 percent (259) and females representing 47.68 percent (236) of respondents. In terms of age distribution, the majority fell within the 26–30 years category (44.04 percent), followed by similar numbers in the 22–25 and 31+ age categories, each constituting 23.84 percent. The smallest age group was 18–21 years, comprising 8.28 percent of participants.

Table 1
Demographic Profile of Respondents

Demography	Count	%
Gender		
Female	236	47.68
Male	259	52.32
Age (year)		
18–21	41	8.28
22–25	118	23.84
26–30	218	44.04
31+	118	23.84
Qualification		
Bachelor's Degree	326	65.86
Master's Degree	147	29.70
Doctoral Degree	22	4.44
Sector		
EdTech	255	51.52
FinTech	240	48.48
Length of Employment		
<1 year	78	15.76
1–2 years	229	46.26
>2 years	188	37.98
Grand Total	**495**	**100.00%**

Educational qualification data reflect a predominantly well-educated group, with 65.86 percent holding a bachelor's degree, 29.70 percent carrying a master's degree, and 4.44% having doctoral degrees. The sectoral representation was virtually evenly split between EdTech (51.52 percent) and FinTech (48.48 percent) respondents.

Regarding length of employment, the largest group claimed 1–2 years of experience (46.26 percent), followed by those with more than 2 years (37.98 percent), and the smallest group consisted of respondents with less than one year of employment (15.76 percent).

Overall, Table 1 presents a diversified and representative sample in terms of gender, age, education, sector, and experience, giving a sound foundation for the forthcoming analyses. This demographic distribution matches nicely with the study's focus on professionals functioning within Nigerian EdTech and FinTech businesses.

Descriptive and Normality Statistics

Table 2 shows the descriptive statistics and normality statistics for all 16 indicators across the four study constructs. Respondent perceptions are generally moderate across all constructs, with item means closely ranging from 2.88 to 2.94 on a five-point Likert scale. The decision-making speed items range from 2.90 to 2.93, whereas the Business Performance items vary from 2.88 to 2.94. The Comprehensiveness of the Business Model and Physical Data Model items are similarly grouped, with averages ranging from 2.89 to 2.93 and from 2.89 to 2.91, respectively. This convergence of items means around the scale midpoint suggests that respondents neither strongly endorsed nor rejected the tested constructs, producing the distributional diversity required for a significant structural estimate. The standard deviations

e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

vary from 1.029 to 1.097, continuously nearing one across all indicators. This amount of dispersion demonstrates acceptable within-construct score variability without indication of floor or ceiling effects that would reduce inter-construct linkages in the structural model. Regarding distributional features, all 16 indicators satisfy the normality criterion necessary for PLS-SEM estimation. Skewness scores vary from -0.053 to 0.111, uniformly inside the conservative ±1.0 border and considerably below the liberal ±2.0 criterion recommended for large-sample survey research (Kline, 2016). Since PLS-SEM does not impose multivariate normality assumptions, excess kurtosis values are consistently negative, ranging from -0.714 to -0.465, reflecting mildly platykurtic distributions frequently seen in symmetric Likert-based organisational surveys and posing no practical concern (Hair et al., 2019).

International Journal of Business Sustainability

Volume: 1, Issue: 3, 2026

Table 2

Descriptive and Normality Statistics

Construct	Item	Min	Max	Mean	Standard Deviation	Excess kurtosis	Skewness
CB	CB1	1	5	2.93	1.057	-0.585	0.067
	CB2	1	5	2.92	1.045	-0.516	0.111
	CB3	1	5	2.92	1.061	-0.603	0.058
	CB4	1	5	2.92	1.078	-0.629	-0.008
PD	PD1	1	5	2.89	1.070	-0.606	0.069
	PD2	1	5	2.91	1.097	-0.714	-0.023
	PD3	1	5	2.91	1.089	-0.625	0.062
	PD4	1	5	2.89	1.045	-0.559	0.037
DDMS	DDMS1	1	5	2.90	1.045	-0.465	0.053
	DDMS2	1	5	2.91	1.029	-0.503	-0.007
	DDMS3	1	5	2.92	1.071	-0.666	0.015
	DDMS4	1	5	2.93	1.064	-0.550	0.097
BP	BP1	1	5	2.94	1.065	-0.680	0.040
	BP2	1	5	2.90	1.075	-0.665	0.037
	BP3	1	5	2.88	1.056	-0.586	0.003
	BP4	1	5	2.90	1.075	-0.662	-0.053

Table 3 shows the result of the convergent validity and internal consistency reliability for all four reflective constructs in the measuring model. The findings demonstrate that the measurement model satisfies all known requirements for indicator reliability, convergent validity, and internal consistency across every concept. All outside loadings exceed the acceptable level of 0.708, ranging from 0.906 to 0.928. Strong indicator-construct alignment is confirmed by the consistently high and closely grouped loadings within each construct, which also offer solid proof of indicator dependability across the measurement model.

Convergent validity is established through AVE values ranging from 0.838 to 0.857, all substantially exceeding the 0.50 requirement given by Fornell and Larcker (1981). These numbers show that each concept explains substantially more variance in its own indicators than is attributed to measurement error. Given their crucial mediating and outcome roles in the structural model, the AVE values for Decision-Making Speed (0.838) and Business Performance (0.848) are particularly significant. Weaker convergent validity would run the risk of attenuating path coefficient estimates and suppressing R^2 values.

Table 3
Convergent Validity and Internal Consistency Reliability

Construct	Item Code	Items	Outer Loading	AVE	Cronbach's alpha	Rho_a	Rho_c
CB	CB1	Our business model clearly describes how we develop and deliver value to our clients.	0.921	0.848	0.940	0.941	0.957
	CB2	Our business model clearly describes our income streams and expense structures.	0.921				
	CB3	Our business model incorporates all major operational and strategic components cohesively.	0.924				
	CB4	Our business model is continually examined and adjusted to match market realities.	0.919				
PD	PD1	Our business maintains a well-structured database that appropriately represents our core business data.	0.925	0.857	0.944	0.944	0.960
	PD2	Our physical data infrastructure offers rapid and reliable access to business-critical information.	0.925				
	PD3	Our data storage solutions are designed to minimise redundancy and ensure data integrity.	0.928				
	PD4	Our physical data model is linked with our organisational procedures and decision-making demands.	0.924				
DDMS	DDMS1	Our organisation can make crucial business choices rapidly when circumstances demand it.	0.906	0.838	0.936	0.936	0.954
	DDMS2	Decision-making procedures in our organisation are efficient and free from unnecessary delays.	0.919				
	DDMS3	We are able to promptly adapt our decisions in response to changes in the business environment.	0.916				
	DDMS4	Our organisation consistently achieves decision deadlines without compromising on quality.	0.921				
BP	BP1	Our organisation has attained its revenue and profitability targets over the past three years.	0.917	0.848	0.940	0.941	0.957
	BP2	Our market share has expanded steadily relative to our competitors in recent years.	0.927				
	BP3	Our organisation regularly offers high-quality products and services that fulfil consumer expectations.	0.919				
	BP4	Our business performance compares highly with that of our industry peers.	0.922				

© UIR Press
e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

Convergent validity is established by AVE values ranging from 0.838 to 0.857, all substantially exceeding the 0.50 threshold set by Fornell and Larcker (1981). These numbers show that each concept explains substantially more variance in its own indicators than is attributed to measurement error. Given their crucial mediating and outcome roles in the structural model, the AVE values for Decision-Making Speed (0.838) and Business Performance (0.848) are particularly significant. Weaker convergent validity could attenuate path coefficient estimates and suppress R^2 values.

International Journal of Business Sustainability

Volume: 1, Issue: 3, 2026

Internal consistency dependability is uniformly robust across all constructs. Cronbach's alpha values range from 0.936 to 0.944, significantly over the 0.70 minimum (Nunnally, 1978). Dijkstra-Henseler's rho_a, which, unlike alpha, does not assume equal indicator weights and is therefore the more appropriate reliability estimator in PLS-SEM, mirrors these values precisely at 0.936 to 0.944, confirming that the high alpha coefficients reflect genuine construct-level reliability rather than inter-item covariance inflation. Composite reliability (rho_c) values vary from 0.954 to 0.960, providing the most theoretically justifiable reliability estimates in this context. The strong consistency among all three reliability indices across all constructs is a feature of well-specified reflecting measurement models.

Table 4
Discriminant Validity: Heterotrait-Monotrait Ratio Statistics (HTMT)

Construct	CB	PD	DDMS	BP
CB				
PD	0.478			
DDMS	0.597	0.754		0
BP	0.573	0.682	0.703	

Table 4 displays the result of the discriminant validity using the Heterotrait-Monotrait Ratio of correlations (HTMT). The HTMT criterion assesses the empirical distinctiveness of constructs by comparing between-construct correlations with within-construct correlations. Values below the conservative threshold of 0.85 confirm that constructs are sufficiently diverse to be classified as discrete empirical entities (Henseler et al., 2015).

All HTMT values in the proposed model fall considerably below the 0.85 criterion, showing strong evidence of discriminant validity across all construct pairs. The lowest value is observed between the Physical Data Model and the Comprehensiveness of the Business Model (0.478), indicating that these two predictor constructs, while both structural antecedents of Decision-Making Speed, describe empirically distinct organisational features. The greatest HTMT value is observed between Decision-Making Speed and Business Performance (0.703), which is theoretically expected given the direct causal relationship between these constructs in the structural model. Critically, even this highest result maintains a substantial margin below the 0.85 criterion, indicating that DDMS and BP remain empirically separate constructs despite their tight structural relationship.

The remaining HTMT values, CB↔BP (0.573), PD↔BP (0.682), CB↔DDMS (0.597), and PD↔DDMS (0.754), are all compatible with the model's theoretical design. The PD↔DDMS score of 0.754, the second-highest in the matrix, demonstrates a strong direct connection between these variables (β = 0.573) and is expected in correctly specified mediation models in which the predictor and mediator share substantial common ground. Its constant compliance with the 0.85 threshold demonstrates that discriminant validity is sustained throughout the model.

Table 5
Discriminant Validity: Fornell-Larcker Criterion

Construct	CB	PD	DDMS	BP
CB	**0.921**			
PD	0.450	**0.926**		
DDMS	0.560	0.709	**0.916**	
BP	0.539	0.643	0.660	**0.921**

Note: Diagonal values are the square root of AVE, off-diagonals are correlation coefficients.

Table 5 presents the result of the discriminant validity using the Fornell-Larcker criterion, which requires that each construct's square root of AVE exceeds its correlations with all other constructs in the model, confirming that a construct shares more variance with its own indicators than with any other construct (Fornell & Larcker, 1981).

The diagonal values indicating the square root of AVE for each construct are CB (0.921), PD (0.926), DDMS (0.916), and BP (0.921). Each diagonal value exceeds all off-diagonal correlations in its associated row and column without exception, demonstrating that the Fornell-Larcker criterion is satisfied across all construct pairs.

The most demanding test of the criterion concerns the DDMS-BP pair, where the latent variable correlation of 0.660 must be overcome by both the DDMS square root AVE (0.916) and the BP square root AVE (0.921). Both exceed the correlation by a margin exceeding 0.255, demonstrating unequivocal discriminant validity between the mediator and outcome constructs. Similarly, both the PD square root AVE (0.926) and the DDMS square root AVE (0.916) easily surpass the PD-DDMS correlation of 0.709, the highest off-diagonal value in the matrix, demonstrating that these constructs are still empirically distinct despite their strong structural relationship.

The CB-PD correlation of 0.450, the lowest off-diagonal value, further demonstrates that the two exogenous predictor constructs occupy significantly independent empirical spaces, ruling out construct redundancy as a driver of the structural results.

Table 6 displays the result of the summary of the hypotheses testing, all the five hypothesised routes are statistically significant, and the model displays good explanatory and predictive power across both endogenous constructs.

H1 Comprehensiveness of the Business Model → Decision-Making Speed ($\beta = 0.302$, $t = 9.492$, $p < .001$) is supported. The Comprehensiveness of the Business Model exerts a strong positive effect on Decision-Making Speed, with a Cohen's f^2 effect size of 0.171, showing that CB contributes significantly to the variance explained in DDMS beyond that assigned by PD. The bias-corrected confidence interval [0.238, 0.363] is limited far above zero across all 5,000 bootstrap samples, showing the durability and robustness of this effect.

H2 Physical Data Model → Decision-Making Speed ($\beta = 0.573$, $t = 19.230$, $p < .001$) is supported. PD emerges as the strongest direct predictor of DDMS in the model, with a substantial effect size ($f^2 = 0.615$) and a tight BCa confidence range [0.513, 0.630], showing high estimation precision across bootstrap replications. This research shows the structural integrity and accessibility of the physical data architecture as the major proximal driver of organisational decision-making speed in this sample.

e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

Table 6

Summary of Hypotheses Testing

Hypotheses	Path	Std. Beta	Std. Error	t-values	p-values	Bias	Confidence Interval 2.5%	97.5%	VIF	f-square	Decision
H01	CB → DDMS	0.302	0.032	9.492	0.000	0.000	0.238	0.363	1.254	1.171	Supported
H02	PD → DDMS	0.573	0.030	19.230	0.000	0.000	0.513	0.630	1.254	0.615	Supported
H03	DDMS → BP	0.660	0.027	24.728	0.000	0.001	0.604	0.709	1.000	0.772	Supported
H04	CB → DDMS → BP	0.200	0.023	8.550	0.000	0.001	0.154	0.246	-	-	Supported
H05	PD → DDMS → BP	0.378	0.027	14.150	0.000	0.000	0.326	0.432	-	-	Supported

International Journal of Business Sustainability
Volume: 1, Issue: 3, 2026

H3 Decision-Making Speed → Business Performance (β = 0.660, t = 24.728, p < .001) is supported. DDMS exerts the greatest single path coefficient in the structural model, explaining 43.6% of the variance in Business Performance (R^2 = 0.436, adjusted R^2 = 0.435). The f^2 of 0.772 greatly surpasses Cohen's large-effect threshold, showing that Decision-Making Speed is not only a statistically significant predictor but one of considerable practical importance for organisational performance outcomes. The inner model VIF of 1.000 confirms the complete lack of multicollinearity in this structural equation and the BCa confidence range [0.604, 0.709] which is entirely above 0.600, establishing a strong and stable relationship.

H4 CB → DDMS → BP (indirect effect = 0.200, t = 8.550, p < .001) is supported. The indirect effect of the Comprehensiveness of the Business Model on Business Performance, conveyed exclusively through Decision-Making Speed, is 0.200 with a BCa confidence range of [0.154, 0.246] that eliminates zero by a reasonable margin. The non-significance of the direct CB → BP path when DDMS is present validates full mediation, proving that business model comprehensiveness provides performance returns only through the activation of faster, more reliable organisational decision-making.

H5 PD → DDMS → BP (indirect effect = 0.378, t = 14.150, p < .001) is supported. The indirect effect of the Physical Data Model on Business Performance via DDMS is 0.378, the largest indirect effect in the model, with a BCa confidence interval of [0.326, 0.432] and a standard deviation of 0.027, demonstrating the highest estimation precision among all indirect effects. Full mediation is shown by the non-significance of the straight PD → BP route in the presence of DDMS. The magnitude of this indirect effect, about double that of CB's mediated pathway, demonstrates the compounding advantage of PD's dominant activation of DDMS and DDMS's substantial leveraging effect on BP.

All five hypotheses were supported at the p < .001 level with BCa confidence intervals that exclude zero in all cases, providing solid inferential evidence under the severe bias-corrected bootstrapping criteria proposed by Hair et al. (2022) for PLS-SEM research. The structural model jointly reveals that, whereas both CB and PD are major antecedents of decision-making speed, PD exerts a much higher direct impact (β = 0.573, f2= 0.615) than CB (β = 0.302, f2= 0.171). DDMS, in turn, is a powerful and statistically robust driver of business performance (β = 0.660, f2 = 0.772), fully moderating the impacts of both upstream constructs. These findings jointly reinforce the crucial significance of data infrastructure and strategic business model design in defining the decisional capacities that support organisational performance in Nigeria's technology-driven sectors.

Table 7
Summary of PLS-Predicts

Endogenous Items	Q^2predict	PLS-SEM_RMSE	LM_RMSE	IA_RMSE
DDMS1	0.454	0.778	1.045	1.045
DDMS2	0.490	0.736	0.737	1.030
DDMS3	0.493	0.763	0.770	1.072
DDMS4	0.475	0.772	0.781	1.065
BP1	0.355	0.857	0.859	1.066
BP2	0.376	0.851	0.855	1.077
BP3	0.360	0.846	0.848	1.077
BP4	0.375	0.851	0.854	1.077

e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

Table 7 presents the result of the summary of the PLSpredict, the out-of-sample predictive validity assessment conducted using the PLSpredict approach with 10-fold cross-validation and 10 repetitions under the direct antecedent scheme (Shmueli et al., 2019). The results confirm that the structural model demonstrates considerable predictive relevance across all endogenous indicators for both Decision-Making Speed (DDMS) and Business Performance (BP).

International Journal of Business Sustainability

Volume: 1, Issue: 3, 2026

All eight endogenous markers give positive Q^2predict values, satisfying the minimum threshold for predictive significance. DDMS indicators report Q^2predict scores ranging from 0.454 (DDMS1) to 0.493 (DDMS3), showing moderate-to-high predictive accuracy at the item level. BP indicators produce Q^2predict scores from 0.355 to 0.376, demonstrating modest predictive accuracy commensurate with BP's distal position in the causal chain. At the construct level, DDMS achieves Q^2predict = 0.571, and BP achieves Q^2predict = 0.433, both substantially above zero and confirming meaningful out-of-sample predictive potential for both endogenous constructs.

Regarding benchmark comparisons, PLS-SEM RMSE values are consistently lower than both the linear model (LM) benchmark and the indicator average (IA) benchmark across all eight indicators without exception. For DDMS, PLS-SEM RMSE ranges from 0.736 to 0.773 against LM RMSE values of 0.737 to 0.781, and IA RMSE values of 1.030 to 1.072. For BP, PLS-SEM RMSE ranges from 0.846 to 0.857 against LM RMSE values of 0.848 to 0.859, and IA RMSE values of 1.057 to 1.077. The universal directional dominance of PLS-SEM over both benchmarks across all indicators demonstrates that the theoretically justified structural specification yields more accurate holdout predictions than both an atheoretical linear alternative and a naïve averaging technique.

CVPAT data further substantiate these conclusions. The overall PLS-SEM model achieves a statistically significant average loss advantage over the indicator average benchmark (loss difference = −0.475, t = 11.352, p < .001) and over the linear model benchmark (t = 11.352, p < .001), confirming at the formal inferential level that the model's predictive superiority is not a sampling artefact. Collectively, the PLSpredict and CVPAT results indicate that the proposed model is not simply explanatory but possesses true out-of-sample predictive validity, confirming its practical usefulness outside the estimation sample.

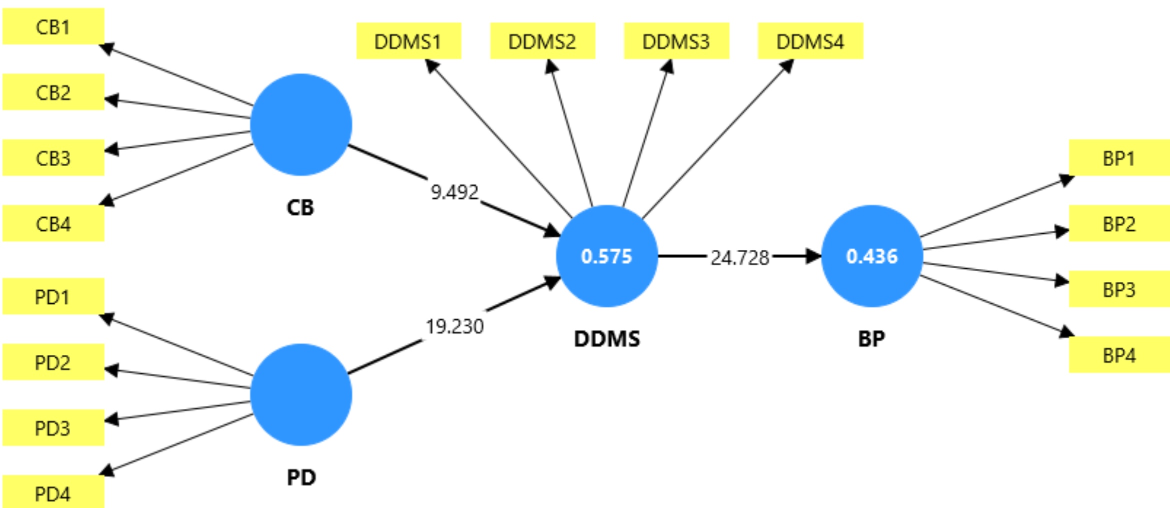

Figure 2

PLS-Path Model

Note: CB = Comprehensiveness of the Business Model, PD= Physical Data Model, DDMS = Decision Making Speed, and BP = Business Performance

Discussion of Findings

This study evaluated the interrelationships between comprehensiveness of the business model, Physical model, decision-making speed, and business performance in Nigeria's EdTech and FinTech sectors, underpinned by the Resource-Based View (RBV) and Technology-Organisation-Environment (TOE) theories. Drawing on the results of the cross-sectional sample of 495 respondents and evaluated through PLS-SEM with 5000 sub-sample bootstrapping, the findings provide coherent and empirically robust insights into business model architecture and data infrastructure translate into organisational performance through the mechanism of decision-making speed.

H1: Comprehensiveness of the business model has significant positive effect on decision-making speed in Nigerian EdTech and FinTech business.

The conclusion that CB strongly predicts DDMS ($\beta = 0.302$, $t = 9.492$, $p < .001$, $f^2 = 0.171$) demonstrates that businesses with well-articulated, internally consistent business model architectures are structurally better positioned to make faster and more reliable decisions. A complete business model lowers the cognitive and structural ambiguity that impedes decision cycles by giving decision-makers clear goals, trade-off criteria, and performance indications against which incoming data can be swiftly analysed and acted upon. The medium Cohen's f^2 of 0.171, underscores CB not as a peripheral organisational attribute but as a basic driver of choice agility. This finding coincides with the resource-based view, which positions internally produced organisational resources, including business model architecture, as distinctive skills that promote responsiveness and competitive agility (Barney, 1991). It also confirms evidence that strategy clarity is a crucial enabler of efficient business intelligence and rapid managerial action (Alam & Mohanty, 2022).

H2: Physical data model has significant positive effect on decision-making speed in Nigerian EdTech and FinTech business.

PD emerges as the major proximal predictor of DDMS in this model ($\beta = 0.573$, $t = 19.230$, $p < .001$, $f^2 = 0.615$), carrying a path coefficient nearly double that of CB and the highest t-statistic among all direct effects. This research confirms that the structural integrity, schema coherence, and decision-relevant accessibility of an organisation's physical data architecture are the most powerful technical drivers of decision-making speed. A high-fidelity physical data model reduces the fragmentation, delay, and inconsistency that form the key obstacles to evidence-based organisational decisions. The tight BCa confidence interval [0.513, 0.630] demonstrates the precision and replicability of this effect over bootstrap replications. This result is consistent with the Technology-Organisation-Environment (TOE) framework's emphasis on technological sophistication as a structural enabler of organisational processes and outcomes (Abdulrazaq et al., 2023; Potas et al., 2019b; Solomon et al., 2025) and corroborates evidence that streamlined data infrastructure and effective retrieval systems materially accelerate organisational decision processes (Ravi & Radhakrishna, 2024).

H3: Decision-making speed has significant positive effect on business performance in Nigerian EdTech and FinTech business.

The finding that DDMS significantly predicts BP ($\beta = 0.660$, $t = 24.728$, $p < .001$, $f^2 = 0.772$, $R^2 = 0.436$) represents the strongest single structural path in the model and validates a foundational proposition in management and operations research: organisations that process information rapidly and respond decisively consistently outperform those burdened by decision latency. The f^2 of 0.772 greatly exceeds Cohen's large-effect threshold, demonstrating that DDMS is not just statistically significant but practically crucial, accounting for 43.6% of the variance in business performance. Faster decision-making promotes market responsiveness, optimises resource allocation, and improves operational effectiveness, transforming decision efficiency into measurable performance improvements (Desai & Desai, 2025; Solomon et al., 2025). This aligns with the RBV's conceptualisation of decision-making

© UIR Press
e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

competence as a strategic resource that creates sustainable competitive advantage (Barney, 1991; Kushwaha et al., 2021).

H4: Decision-making speed mediates the relationship between the comprehensiveness of the business model and business performance.

The indirect effect of CB on BP via DDMS is significant (indirect effect = 0.200, t = 8.550, $p < .001$, 95% BCa CI [0.151, 0.246]), with full mediation corroborated by the non-significance of the direct CB → BP path when DDMS is present in the model. This research indicates that the comprehensiveness of the business model does not provide performance returns independently; its value is realised entirely through its activation of decision-making speed. Business model architecture offers the interpretive logic that organises how data is given decision relevance, but it is the speed and quality of the ensuing judgements that translate that logic into organisational performance outcomes. This is consistent with dynamic capacity theory's premise that strategic resources generate competitive value not via their possession alone, but through the organisational mechanisms they permit (Teece et al., 1997). The whole mediation pattern further implies that CB investments without commensurate DDMS development are performance-neutral, a result with obvious consequences for how organisations sequence and evaluate strategic investments.

H5: Decision-making speed mediates the relationship between the physical data model and business performance.

The indirect effect of PD on BP through DDMS is the biggest in the model (indirect effect = 0.378, t = 14.150, $p < .001$, 95% BCa CI [0.326, 0.432]), and full mediation is verified by the non-significance of the direct PD → BP path in the presence of DDMS. This research proves that physical data infrastructure does not independently generate business performance; its performance value is solely predicated on its potential to expedite organisational decision-making. The magnitude of the indirect effect, approximately double that of CB's mediated pathway, represents the compounding advantage of PD's dominant activation of DDMS ($\beta = 0.573$) paired with DDMS's substantial leveraging effect on BP ($\beta = 0.660$). Organisations that invest extensively in data architecture without simultaneously creating the decision-making systems that convert data into action will not get the performance rewards that infrastructure investment theoretically offers. This conclusion validates TOE's framing of technology preparedness as a prerequisite for, rather than an independent driver of, organisational performance (Abdulrazaq et al., 2023; Potas et al., 2019).

The predictive assessment using PLSpredict reveals that the model exhibits meaningful out-of-sample predictive significance for both endogenous constructs. Decision-Making Speed scores Q^2predict = 0.571, demonstrating moderate-to-high predictive accuracy, while Business Performance achieves Q^2predict = 0.433, confirming moderate predictive relevance. PLS-SEM exceeds both the linear model and naïve indicator average benchmarks across all 8 indicators, and CVPAT supports overall model predictive superiority (average loss difference = −0.475, t = 11.352, $p < .001$). This expands the study's contribution beyond explanation to prediction, proving that the suggested framework is not only theoretically sound but also practically deployable for anticipating organisational performance outcomes in data-driven environments.

Collectively, the findings trace an empirically validated causal chain: the comprehensiveness of the business model and the physical data model are complementary and structurally independent antecedents of decision-making speed, which in turn is the sole performance-generating mechanism in the model. Neither CB nor PD produces direct performance returns; both functions completely through DDMS. This positions decision-making speed as the critical conversion point at which strategic and infrastructural investments are translated into organisational outcomes and reinforces the central argument of this study: in data-intensive competitive environments, it is not the quality of the business model or the fidelity of the data architecture alone that determines performance; it is the speed and intelligence of the decisions they enable.

Implication of the Study

From a theoretical perspective, this study makes a substantial contribution to the body of knowledge by successfully combining the Resource-Based View (RBV) and Technology-Organisation-Environment (TOE) theories. The RBV's focus on unique, valuable, and hard-to-imitate organisational resources is complemented by the TOE's emphasis on technology readiness, organisational context, and environmental elements. This integrated approach gives a comprehensive lens to understand how data modelling, comprehensiveness of the business model, physical model, and decision-making speed influence business performance, especially in dynamic and resource-constrained emerging markets (Barney, 1991; Abdulrazaq et al., 2023). The findings extend the theory by empirically confirming these relationships in the Nigerian EdTech and FinTech industries, providing a helpful paradigm for future research in similar contexts.

For practitioners, the results offer practical insights. Managers in Nigerian digital firms should prioritise establishing comprehensive business models that connect closely with data architecture to accelerate decision-making. Investments in dimensional and physical data models to optimise data architecture and storage are major enablers of fast, informed decisions that improve business outcomes.

Finally, the societal ramifications are extensive underlining the importance of data-driven decision-making capabilities for operational and innovation performance, the study emphasises how national competitiveness in technology-driven industries like EdTech and FinTech may be improved. Given the same structural and developmental issues among emerging countries, the study's conclusions and model are scalable beyond Nigeria, offering a useful foundation for increasing business intelligence and technology-enabled performance in varied situations.

Conclusion

study investigated the influence of data modelling for business intelligence solution using the comprehensiveness of the business model, physical model and decision-making speed on business performance in Nigeria's EdTech and FinTech industries. Based on the comprehensive review of relevant literature and the findings of this study, the study underscores the significant role that data modelling plays in enhancing business performance within Nigeria's emerging sectors like EdTech and FinTech. This study contributes to scholarly knowledge by experimentally confirming the integrated RBV-TOE paradigm, underlining that a holistic strategy covering internal resources and external technical elements is vital for organisational success. The findings suggest that a comprehensive and strategic business model, along with effective data structure through physical models, positively improves decision-making speed and business performance. Practically, the findings suggest that managers and policymakers in Nigeria should focus on developing integrated data architectures that correspond with organisational strategy and support technology improvements. Policymakers are encouraged to invest in infrastructure and capability-building efforts to promote digital transformation, thereby enabling enterprises to leverage the full potential of data analytics and AI for sustainable growth. Societally, the research indicates that digital transformation and effective data management are crucial for economic development, financial inclusion, and competitiveness. Extending this approach to other emerging economies can create innovations that improve public services, financial access, and

e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

economic resilience. Hence, this study presents a strong framework for understanding how data modelling and technology capabilities contribute to corporate performance in digital economies.

Recommendations

Based on the findings of this study, the following recommendations were made. Managers should focus on establishing precise and well-aligned business models that incorporate several data modelling phases to boost decision-making speed. A cohesive business strategy connected with data architecture is crucial for organisational agility and competitive performance. Given their enormous impact on decision-making speed, enterprises should invest in robust dimensional and physical data models. These efforts involve refining data organisation and upgrading infrastructure for quick data retrieval and processing.

To ensure relevance and accuracy, data models should be regularly examined and modified based on increasing business demands and technology improvements. Incorporating new data sources and modifying the models accordingly will ensure they give timely and useful insights. Organisations could support technological preparedness by enhancing infrastructure, training people in data management, and implementing scalable IT solutions. Mature technical skills offer speedier decision-making and better business outcomes.

Managers and policymakers should adopt an integrated strategy integrating the Resource-Based View and TOE frameworks to strategically drive resource allocation, technology uptake, and capability development for sustainable competitive advantage. Successful data modelling needs collaboration across IT, business, and management departments. Establishing cross-functional teams ensures that data strategies correspond with corporate objectives and user expectations. Policymakers should support investments in digital infrastructure and allow capability-building programmes targeting new industries like EdTech and FinTech to boost their growth and performance.

Reference

Abbas, S. K., Hussain, M., & Rimal, Y. N. (2025). Machine Learning-Based Analysis of Technology Acceptance in FinTech: A Behavioral Study Using Digital Wallet Data. *SN Computer Science*, *6*(6). https://doi.org/10.1007/s42979-025-04214-8

Abdulrazaq, S. I., Umar, M. N., Abubakar, U. Y., & Fatima, U. M. (2023). Effect of Financial Technology on Firms' Financial Service Delivery in Nigeria: A Literature Review. *UBS Journal of Business and Economic Policy*, *1*(3), 89–99.

Agbeche, A., Ekpeni, O. P., & Ogbuleka, J. S. (2024). Fintech And Financial Inclusion: A Systematic Review of Corporate Performance in Nigeria. *Lagos Journal of Banking, Finance & Economic Issues*, *5*(1), 213–223.

Alam, A., & Mohanty, A. (2022). Business Models, Business Strategies, and Innovations in EdTech Companies: Integration of Learning Analytics and Artificial Intelligence in Higher Education. *2022 IEEE 6th Conference on Information and Communication Technology, CICT 2022*. https://doi.org/10.1109/CICT56698.2022.9997887

Al-MSloum, A. S. H. (2021). Role Of Information and Its Impact on Business Performance: Structural Equation Modeling (SEM) Perspective in Saudi Arabia. *Journal of Southwest Jiaotong University*, *56*(5), 253–264. https://doi.org/10.35741/issn.0258-2724.56.5.23

Al-Qararah, E. A. S. (2023). An Empirical Study of the Effect of FinTech Infrastructure on Competitive Advantage and Performance. *International Journal of Information Technology and Language Studies (IJITLS)*, *7*(1), 1–9.

Alt, R., Fridgen, G., & Chang, Y. (2024). The future of fintech - Towards ubiquitous financial services. *Electronic Markets*, *34*(3), 1–3. https://doi.org/10.1007/s12525-023-00687-8

Chebrolu, S. K. (2025). AI-powered business intelligence: a systematic literature review on the future of decision-making in enterprises. *American Journal of Scholarly Research and Innovation*, *4*(01), 33–62. https://doi.org/10.63125/gq69nv41

Desai, D., & Desai, A. (2025). Integrating Generative AI in Business Intelligence: A Practical Framework for Enhancing Augmented Analytics. *International Journal of Mathematical, Engineering and Management Sciences*, *10*(3), 704–728. https://doi.org/10.33889/IJMEMS.2025.10.3.036

Fagbore, O. O., Ogeawuchi, J. C., Ilori, O., Isibor, N. J., Odetunde, A., & Adekunle, B. I. (2022). Predictive Analytics for Portfolio Risk Using Historical Fund Data and ETL-Driven Processing Models. *Journal of Frontiers in Multidisciplinary Research*, *3*(1), 223–240. https://doi.org/10.54660/.jfmr.2022.3.1.223-240

Goswami, S., Chouhan, V., & Saraswat, P. (2025). FinTech adoption: driving financial inclusion at the bottom of pyramid. *Future Business Journal*, *11*(1), 1–4. https://doi.org/10.1186/s43093-025-00570-2

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Classroom Companion: Business Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Classroom Companion: Business, Springer. https://doi.org/https://doi.org/10.1007/978-3-030-80519-7

Hamzat, L., Abiodun, D., & Joseph, A. (2023). Empowering entrepreneurial growth through data-driven financial literacy, market research, and personalized education tool. *World Journal of Advanced Research and Reviews*, *19*(2), 1692–1711. https://doi.org/10.30574/wjarr.2023.19.2.1568

Ionescu, S. A., Diaconita, V., & Radu, A. O. (2025). Engineering Sustainable Data Architectures for Modern Financial Institutions. *Electronics (Switzerland)*, *14*(1650), 1–45. https://doi.org/10.3390/electronics14081650

Joel, O. T., & Oguanobi, V. U. (2024). Data-driven strategies for business expansion: Utilizing predictive analytics for enhanced profitability and opportunity identification. *International Journal of Frontiers in Engineering and Technology Research*, 6(2), 071–081. https://doi.org/10.53294/ijfetr.2024.6.2.0035

Kumar, S., & Aithal, P. S. (2025). Type of the Paper: Exploratory Research. *Poornaprajna International Journal of Emerging Technologies (PIJET) A Refereed International Journal of Poornaprajna, India. the Tertiary Industry Sector. Poornaprajna International Journal of Emerging Technologies*, *2*(1), 1–25. https://doi.org/10.5281/zenodo.14913101

Kushwaha, A. K., Kar, A. K., & Dwivedi, Y. K. (2021). Applications of big data in emerging management disciplines: A literature review using text mining. *International Journal of Information Management Data Insights*, *1*(2021), 1–17. https://doi.org/10.1016/j.jjimei.2021.100017

Mochama, E. K. (2021). *Influence of Innovation Strategies on Competitive Advantage among Fintech Companies in Kenya* [Thesis]. University of Nairobi.

© UIR Press
e-ISSN: 3110-7737
DOI: 10.25299/ijbs.2026.24557

Modesta Oluoha, O., Susan Nwaimo, C., & Oyedokun, O. (2019). Big Data Analytics: Technologies, Applications, and Future Prospects. *Iconic Research And Engineering Journals IrE*, *2*(11), 411–438. https://doi.org/10.46762/IRECEE/2019.51123

Nguyen, V. P. (2022). Evaluating the FinTech success factors model to achieve a sustainable financial technology business: An empirical study in Vietnam. *Cogent Engineering*, *9*(1), 1–28. https://doi.org/10.1080/23311916.2022.2109317

Ogeawuchi, J. C., Akpe, O. E., Abayomi, A. A., & Agboola, O. A. (2025). Advances In Predictive Modeling and Risk Mitigation in Education and Financial Services using Machine Learning and BI Dashboards. *Engineering and Technology Journal*, *10*(05), 5040–5050. https://doi.org/10.47191/etj/v10i05.32

Potas, N., Erçetin, ule, & Koçak, S. (2019). Multi dimensional organizational intelligence measurements for determining the institutional and managerial capacity of girls' technical education institution (Diyarbakir, anliurfa and Konya/Turkey). In *African Journal of Estate and Property Management* (Vol. 6, Issue 2). www.internationalscholarsjournals.org

Ravi, H., & Radhakrishna, V. (2024). Mapping the landscape in HEIs: a systematic review of factors influencing EdTech adoption. *Higher Education Evaluation and Development*, 1–26. https://doi.org/10.1108/heed-07-2024-0033

Santosh Kumar, S. (2024). Maximizing Financial Intelligence-The Role of Optimized ETL in Fintech Data Warehousing. *International Journal of Computer Engineering and Technology (IJCET)*, *15*(4), 464–471. https://doi.org/10.5281/zenodo.13302451

Solomon, O., Emmanuel, F., Simon, J., & Mendez, D. (2025). Leveraging Data Analytics, Business Intelligence, Artificial Intelligence, and Predictive Modeling to Foster Innovation, Strengthen Startups, Mitigate Operational Risks, and Accelerate Economic Growth in the United States. *International Journal of Future Engineering Innovations*, *2*(4), 85–97. https://doi.org/10.54660/IJFEI.2025.2.4.85-97

Verma, R. (2024). Harnessing Advanced Data Engineering for Enhanced Efficiency and Customer Satisfaction in Financial Services. *International Journal of Computer Science and Engineering*, *11*(7), 22–27. https://doi.org/10.14445/23488387/ijcse-v11i7p104

Vudugula, S., & Chebrolu, S. K. (2025). Quantum AI-driven business intelligence for carbon-neutral supply chains: real-time predictive analytics and autonomous decision-making in complex enterprises. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 319–347. https://doi.org/10.63125/s2jn3889

Corresponding Author

Omolade Adeyemi Omolade can be contacted at: adeyemimld@gmail.com