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COMPETITIVE INTELLIGENCE AND MARKETING PERFORMANCE AMONG SOME SELECTED BANKING INDUSTRIES IN NORTH CENTRAL, NIGERIA: A MEDIATING ROLE OF ORGANIZATIONAL LEARNING

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Abstract
The objective of this study is to investigate competitive intelligence and marketing performance in the banking industry in North Central Nigeria, with organisational learning as a mediating variable. The research is grounded in Dynamic Capabilities Theory and uses a cross-sectional survey to collect data from respondents. The study population comprised 323 employees from five metropolitan banks: Access Bank, Fidelity Bank Plc, Sterling Bank Plc, Wema Bank Plc, and Zenith Bank Plc, operating in Abuja, Benue, Nasarawa, and Kogi States. The data were collected via a structured five-point Likert scale questionnaire and analysed using structural equation modelling using Smart PLS. For direct relationships, the results revealed that marketing intelligence and organizational learning have positive and significant effects on marketing performance, while technological intelligence has a negative and non-significant relationship with marketing performance. For the mediating role, organizational learning does not mediate the relationship between marketing intelligence and marketing performance, whereas technological intelligence mediates the relationship between technological intelligence and marketing performance. This study recommends that the management of the banks should strengthen their capacity for market intelligence by investing in research units, analytics tools, and staff training, enabling them to design strategies that boost customer satisfaction, competitiveness, and marketing performance.

Keywords: Competitive Intelligence, Marketing Intelligence, Technological Intelligence, Marketing Performance

INTRODUCTION

Globally, marketing performance has become a major indicator of banks' competitiveness worldwide. According to Standard & Poor's Global (2024), ICBC recorded $6.898 trillion in assets, $13.84 billion in annual profit, and a 38% increase in stock value, while JPMorgan Chase and HSBC reported $4.567 trillion and $3.017 trillion in total assets, respectively. In Nigeria, Access Bank reported $23.26 billion in assets and $149.43 million profit before tax, followed by UBA with $18.12 billion in assets and $148.07 million profit before tax (KPMG, 2024). These performances demonstrate the importance of competitive intelligence (CI) in improving marketing performance. However, many banks continue to face challenges related to poor data quality, untimely information, and rapidly changing market conditions, reducing the effectiveness of CI in marketing decisions (Maluleka & Chummun, 2023; Cavallo et al., 2021; Syamria et al., 2023). Organizational learning facilitates the acquisition, sharing, and application of intelligence, but studies examining its mediating role between CI and marketing performance remain limited, especially in developing economies. Furthermore, North Central Nigeria has received limited scholarly attention compared to the South-West. This study therefore investigates the effect of competitive intelligence on marketing performance through organizational learning among deposit money banks in North Central Nigeria

Statement of the Problem

The banking industry in North Central Nigeria faces increasing competition and rapid technological changes, making Competitive Intelligence (CI) essential for improving marketing performance. However, many banks have not fully utilized CI, while existing studies (Ali & Anwar, 2021; Ezenwa et al., 2018; Kunle et al., 2017; Tahmasebifard, 2018) have relied on similar proxies and largely overlooked the mediating role of organizational learning. This study addresses these gaps by examining marketing intelligence and technological intelligence within a unified framework. Despite the aforementioned challenges in this study, previous research indicates that the positive relationship between competitive intelligence and market performance may help uncover the mechanisms underlying observed relationships (Baron & Kenny, 1986). Numerous studies (Ali & Anwar, 2021; Asri et al., 2020; Kunle et al., 2017; Nnabuife et al., 2023; Shawaly, 2024; Tahmasebifard, 2018) indicate that the positive relationship between competitive intelligence and marketing performance is significantly enhance model precision and explanatory power by identifying the processes through which an independent variable affects an outcome providing valuable insights for policymakers, businesses, and organizations to develop evidence-based strategies (Preacher & Hayes, 2008). While some scholars may not apply rigorous statistical techniques such as checking for bias, using robustness checks, and validating findings with different samples, this study introduces organisational learning as a mediating variable in the relationship between competitive intelligence and marketing performance to obtain more accurate results.

The broad question of this research is to determine the extent to which marketing intelligence affects marketing performance among the banking industry in North Central, Nigeria; to investigate the extent of influence of technological intelligence on marketing performance among the banking industry; and whether organisational learning mediates the relationship between competitive intelligence (marketing intelligence and technological intelligence) and marketing performance among the banking industry in North Central.

Theoretically, this study advances Competitive Intelligence Theory by demonstrating that marketing intelligence and technological intelligence are distinct but complementary dimensions that jointly influence marketing performance through organizational learning. Practically, Nigerian banks need to adopt advanced competitive intelligence platforms such as Customer Relationship Management (CRM) analytics, social listening tools, and fintech trend monitors to continually update their marketing strategies based on real-time intelligence. They should also invest in continuous skill development to enhance employees' ability to effectively use competitive intelligence in marketing decision-making.

LITERATURE REVIEW

Marketing performance is a multidimensional concept that reflects the effectiveness of marketing activities through indicators such as revenue growth, customer acquisition, market share, brand awareness, customer satisfaction, and customer loyalty. According to Morgan et al. (2019), it represents the contribution of marketing strategies to overall organizational performance, while Gao (2010) emphasized that measuring marketing performance enables organizations to refine strategies, adapt to market changes, and sustain competitiveness. Competitive intelligence (CI) enhances marketing performance by providing information on competitors, market trends, and customer preferences, although concerns remain regarding the accountability and credibility of marketing, requiring marketers to demonstrate their contribution to organizational performance (Edy & Halim, 2010; Morgan et al., 2019).

Organizational learning is the continuous process through which organizations acquire, create, transform, and apply knowledge to improve organizational performance and innovation. Gomes et al. (2022) describe it as the adaptation of organizational knowledge and routines, while Jiménez-Jiménez et al. (2011) define it as the creation of new knowledge and shared insights that influence organizational behaviour. This study adopts the definition of Aun et al. (2025) because it integrates innovation, capacity building, collective vision, and continuous learning to achieve organizational objectives.

Competitive intelligence involves the systematic collection and analysis of information about competitors, customers, and the business environment to support strategic decision-making and competitive advantage (Nnabuife et al., 2023; Kunle et al., 2017). Ali and Anwar (2021) viewed CI as monitoring competitors to improve competitive positioning, while Maina (2022) emphasized its role in supporting strategic planning. Following Tahmasebifard (2018), this study conceptualizes CI as the strategic collection and analysis of valuable information regarding competitors, market trends, customer preferences, and internal and external environments. Within the banking sector, CI includes monitoring competitors' products, pricing strategies, marketing campaigns, customer service quality, digital transformation initiatives, and regulatory changes (Maina, 2022).

DIMENSIONS OF COMPETITIVE INTELLIGENCE

According to Kunle et al. (2017**),** marketing intelligence is the continuous collection of information about developments in the marketing environment to support marketing planning and decision-making. It gathers data from internal sources, such as CRM systems, transaction records, sales reports, and customer feedback, as well as external sources, including competitors' activities, market research, pricing strategies, advertising campaigns, and online reviews (Shawaly, 2024; Maina, 2022**).** This study defines marketing intelligence as the systematic acquisition, analysis, and dissemination of information on customers, competitors, market trends, and environmental conditions to improve marketing decisions. In the banking sector, it assists managers in understanding customer needs, market changes, and regulatory conditions **(**Maluleka & Chummun, 2023).

Syamria et al. (2023) defined technological intelligence as systematic monitoring of technological developments to identify business opportunities and threats, improve technology performance, and promote innovation. Abrokwah-Larbi and Awuku-Larbi (2024) further describe it as the process of collecting and analyzing information on emerging technologies, technological trends, competitor strategies, and market demands to strengthen innovation and competitive advantage. In the banking sector, technological intelligence supports the adoption of technologies such as AI, blockchain, and digital wallets, improving customer experience, market share, competitiveness, and strategic decision-making through timely information on technological opportunities and risks **(**Vishnoi et al., 2021**)**

REVIEW OF EMPIRICAL STUDIES

Prior studies have consistently shown that intelligence capabilities and organizational learning improve organizational performance; however, they reveal several research gaps. Rehman (2025) found, using PLS-SEM on 256 SMEs**,** that market intelligence and entrepreneurial orientation positively influenced international performance through the mediating role of global technological competence; the study's reliance on cross-sectional data limits the ability to establish causality between intelligence and performance.

Wu and Monfort (2023) examine the role of marketing intelligence in marketing strategies and performance with a sample size of 278 food firms, using structural equation modelling and the fuzzy set qualitative comparative analysis (FsQCA) approach. The findings show that marketing capabilities, customer value co-creation, and market orientation are positively related to performance. Finally, the results highlight that marketing capabilities, customer value co-creation, and market orientation affect the development of marketing intelligence strategies. While the study identifies important relationships, it does not assess how contextual factors (e.g., firm size or market type) might moderate the impact of intelligence on performance.

Similarly, Ismaeel et al. (2023), using 256 respondents**,** found that market research, competitive intelligence, and consumer intelligence significantly improved organizational efficiency, whereas marketing analytics and product intelligence had no significant effect. The limited effect of some intelligence dimensions highlights that not all intelligence activities are equally relevant, but the study does not explore why certain dimensions fail to impact efficiency.

In technological intelligence research, Mekimah et al. (2024) examined the necessity of technological intelligence for start-ups' performance: Insights from Algerian start-ups using neural network modelling and fuzzy logic with a sample of 213 start-up companies. The study reveals that the elements of technological intelligence collectively exhibit a weak impact on the performance improvement of start-ups in Algeria. Approximately 31% of the observed weak impact of technological intelligence elements on start-up performance is attributed to the underutilization of available market technology for product development**.** The weak impact suggests that technological intelligence alone may not drive performance unless effectively leveraged in product development.

Chukuigwe (2022) conducted a study on technology intelligence and organizational performance of firms in Rivers State. The findings revealed that Technology Intelligence has a positive relationship with the Organizational Performance of Firms in Rivers State. It was therefore recommended that firms in Rivers State should emphasize building a positive Strategic Intelligence to meet customers' expectations and offer more benefits to customers. The study did not empirically examine the mechanisms (e.g., mediating variables) through which technology intelligence translates into performance, limiting actionable insights.

Pham et al. (2019) found, using 160 respondents from Vietnamese firms, that organizational learning capability positively affects business performance, particularly through management commitment to learning and knowledge transfer and integration, although the use of MBA students limits the generalizability of the findings. Similarly, AlMujaini et al. (2021) analyzed data from 354 SMEs with SmartPLS and found that organizational learning significantly improves organizational performance, while digital transformation moderates the relationship between organizational learning and innovation, and innovativeness mediates the relationship between corporate foresight and performance. However, the insignificant effect of corporate foresight indicates the need to examine additional mediating and contextual factors

CONCEPTUAL FRAMEWORK

The conceptual framework in this study illustrates the interdependence of the independent, dependent, and mediating variables. Competitive intelligence (CI) helps to clarify these links by detailing its influence on marketing intelligence (MI) and organizational learning (OL), thereby defining the connection between the independent and dependent variables and expounding on the mediating effects within the model.

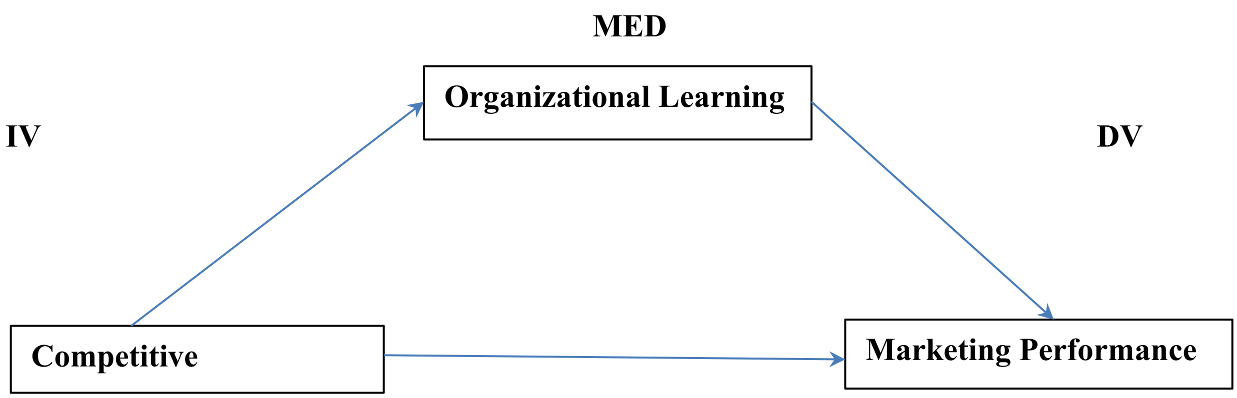

Figure 1: Conceptual Framework for the Research
Source: Author's Computation, 2026

Figure 1 illustrates the conceptual framework for this research. The independent variable, competitive Intelligence, is depicted by marketing intelligence and technological intelligence. Marketing intelligence serves as the dependent variable, and organisational learning as the mediating variable.

THEORETICAL FRAMEWORK

The study used Dynamic Capabilities Theory propounded by Teece et al. (1997). DCT posits that firms succeed in dynamic environments not because of what resources they own, but because of their capacity to renew, integrate, and transform those resources in ways that sustain competitive advantage. This means that firms achieve and sustain competitive advantage in environments characterized by rapid technological, market, and institutional change. Scholars such as Eisenhardt and Martin

(2000) and Zollo and Winter (2002) argued that dynamic capabilities are not necessarily unique; in moderately dynamic markets, they can resemble best practices, making them hard to measure as firm-specific, and pointed out that capabilities are hard to measure empirically, as they reside within organizational routines and are not openly observable. This lens is highly relevant in the banking industry where marketing intelligence equips banks with the ability to monitor and interpret customer behaviours, competitor strategies, and market trends. This enables banks to identify evolving customer preferences and design services that foster greater satisfaction. Such intelligence further supports the introduction of innovative digital solutions, improved operational efficiency, and the development of marketing strategies that strengthen customer engagement and overall performance. Likewise, through continuous learning routines and feedback mechanisms, banks can adjust to changes, fine-tune marketing approaches, and maintain long-term competitiveness. Consequently, when banks effectively utilize intelligence to sense changes, capitalize on opportunities, and restructure through learning, they experience enhanced market share, stronger customer retention, and higher profitability.

Research Hypotheses

Guided by the existing scholarly evidence, the subsequent hypotheses are clearly articulated for empirical testing.

H_{01}: There is no relationship between marketing intelligence and marketing performance among some selected banking industries in North Central, Nigeria.

H_{02}: There is no relationship between marketing intelligence and organisational learning among some selected banking industries in North Central, Nigeria.

H_{03}: There is no relationship between organisational learning and marketing performance among some selected banking industries in North Central, Nigeria.

H_{04}: There is no relationship between technological intelligence and marketing performance among some selected banking industries in North Central, Nigeria.

H_{05}: There is no relationship between technological intelligence and organisational learning among some selected banking industries in North Central, Nigeria.

H_{06}: Organisational learning does not mediate the relationship between marketing intelligence and marketing performance among some selected banking industries in North Central, Nigeria.

H_{07}: Organisational learning does not mediate the relationship between technological intelligence and marketing performance among some selected banking industries in North Central, Nigeria.

METHODOLOGY

This study utilized a descriptive survey research design with a cross-sectional orientation. The design was considered appropriate because it provides an effective means of describing the present status of study variables, allows the gathering of data from a broad population at one point in time, facilitates statistical analysis, and is both economical and time-saving, aligning well with the research goals. The target population comprised employees of five metropolitan banks: Access Bank, Fidelity Bank Plc, Sterling Bank Plc, Wema Bank Plc, and Zenith Bank Plc operating in Abuja, Benue, Nasarawa, and Kogi States within North Central Nigeria. These banks were selected because of their ranking as leading strategic banks, as reported in the 2024 annual bulletin of the Central Bank of Nigeria (CBN). The precise number of employees within the population could not be ascertained, as the banks withheld such information due to likely regulatory and confidentiality concerns. This left the researcher with no other choice except to adopt an infinite population and sample size determination formula of Krejcie and Morgan (1970) for the study, which made the study population proportion (P=0.70), assumed to be 70% for maximum variability at a 95% confidence level =1.96 (Cochran, 1977; Yamane, 1967).

$$no = \frac{Z^2 x\ Px(1-P)}{e^2}$$

Where:
Z=1.96 (for 95% confidence level)
e=0.05 (margin of error)
p= 0.3
1−p=0.7

$$no = \frac{(1.96)^2 x\ 0.3x(1-0.3)}{(0.05)2}$$

$$= \frac{3.8416\ x\ 0.7x0.3}{0.0025}$$

$$= \frac{3.8416\ x\ 0.21}{0.0025}$$

$$= \frac{0.806736}{0.0025}$$

$$= 322.69$$

$$= 323$$

Therefore, the sample size of 323 was determined using the Krejcie and Morgan (1970) formula designed for unknown population sizes. The study employed a simple random sampling technique in selecting participants. This method was considered appropriate as it guarantees that every member of the population has an equal chance of being included, thereby minimizing researcher bias and enhancing the reliability of the results (Kothari, 2004; Saunders et al., 2019). In line with established survey research guidelines (Israel, 2013; Salkind, 2014; Dillman et al., 2014), this study increased the sample size by 50%, resulting in a total of 162 + 323 = 485 respondents. Data were collected using a validated, self-administered questionnaire consisting of closed-ended questions measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), specifically developed for this study. Descriptive statistics, specifically simple percentages, were used to analyze demographic data, while structural equation modelling (SEM) using SmartPLS 4 was used to test the proposed hypotheses.

Model specification

This study investigates competitive intelligence (CI) and marketing performance (MP) among the banking industry in North Central Nigeria. CI is conceptualized using two proxy variables: marketing intelligence (MI) and Technology Intelligence (TI). Additionally, organizational learning (OL) is introduced as a mediating variable that explains the indirect effect of CI on marketing performance.
Competitive Intelligence (CI) =f (Competitive Intelligence) ……………….…………………... (1).

Where:
Competitive Intelligence = f (MI, TI)
MP =f (MI, TI).
This indicates that marketing performance is a function of marketing intelligence and technology intelligence

Econometric Model:
MP=β0+β1MI+β2TI+β3(MP×MI) +β4 (MP×TI) +μτ
Where:
MP = Marketing performance (Dependent Variable)
MI = Marketing intelligence (CI Proxy 1)
TI = Technology Intelligence (TI Proxy 2)
OL = Organisational learning (Mediator)
β_0 = Intercept
B_1–β_4 = Coefficients of interest

μ_τ = Error term representing other unobserved factors

The study aims to examine how CI technologies (MI and TI) influence marketing performance both directly and indirectly through the mediating effect of organisational learning (OL). The primary parameters of interest are β_1, β_2, and β_4, which capture the direct effects of the CI proxies and their interaction with organisational learning on marketing.

RESULTS AND DISCUSSION

Rate of Response

The researchers distributed 485 questionnaires on 20th May 2025 to employees of banks in Abuja, Benue, Nasarawa, and Kogi States, Nigeria. The data collection continued from 30th May to 1st September 2025, covering slightly over three months. A total of 359 questionnaires were returned, yielding an impressive 74% response rate. This excludes incomplete submissions; 323 valid responses, representing 67%, were available for analysis, exceeding the benchmark response rates (Baruch & Holtom, 2008; Sekaran & Bougie, 2016).

Table 1: Response Rate of the Questionnaires

Response rate	Frequency/Rate
No. of distributed questionnaires	485
Returned questionnaires	359
Returned and usable questionnaires	323
Returned and excluded questionnaires	36
Questionnaires not returned	126
Overall Response Rate	74%
Valid Response Rate	67%

Note: Response rate calculation is the total number of responses received divided by the total number of questionnaires, multiplied by 100. Also, the valid response rate is the number of usable responses divided by the total number of distributed questionnaires, multiplied by 100.

Descriptive analysis of respondent and business characteristics

This subsection presents a descriptive analysis of the respondents' demographic information, specifically focusing on age, gender, years of operation, and educational qualification. Table 2 summarizes the descriptive statistics for these demographic variables.

Table 2: Descriptive Results of Demographic Variables

Characteristics	Frequency	Frequency	Valid Percentage	Cumulative Percentage
Gender				
Male	221	68.4	68.4	68.4
Female	102	31.6	31.6	**100.0**
Total	**323**	**100.0**	**100.0**	
Age	**Frequency**	**Percentage**	**Valid Percentage**	**Cumulative Percentage**
01-20years	8	2.5	2.5	2.5
21-30 years	24	7.4	7.4	9.9
31-40 years	157	48.6	48.6	58.5

41-50 years	134	41.5	41.5	**100.0**
Total	**323**	**100.0**	**100.0**	
Qualification	**Frequency**	**Percentage**	**Valid Percentage**	**Cumulative Percentage**
PhD/DBA/Mphil	13	4.0	4.0	4.0
M.Sc./MBA	83	25.7	25.7	29.7
B.Sc./HND	124	38.4	38.4	68.1
Diploma/NCE	79	24.5	24.5	91.8
SSCE	24	7.4	7.4	**100.0**
Total	**323**	**100.0**	**100.0**	
Position	**Frequency**	**Frequency**	**Valid Percentage**	**Cumulative Percentage**
Strategy Dir.	120	37.2	37.2	37.2
Branch Mgr	40	12.4	12.4	49.5
Heads of Dept	63	19.5	19.5	69.0
R/D Units	97	30.0	30.0	99.1
Others	3	0.9	0.9	**100.0**
Total	**323**	**100.0**	**100.0**	
Experience	**Frequency**	**Frequency**	**Valid Percentage**	**Cumulative Percentage**
01-7 years	31	9.6	9.6	9.6
8-14 years	64	19.8	19.8	29.4
15-20 years	137	42.4	42.4	71.8
21-35 years	86	26.6	26.6	98.5
36 above	5	1.5	1.5	**100.0**
Total	**323**	**100.0**	**100.0**	

Source: Author's Computation (2026) using SPSS version 27

Table 2 shows that among the 323 valid participants, 68.4% were male and 31.6% were female. Most respondents were aged between 31-40 years (48.6%) and 41-50 years (41.5%), showing that the workforce is largely middle-aged. The dominant qualification was BSc/HND (38.4%), followed by MSc/MBA (25.7%), and Diploma/NCE (24.5%), while doctoral holders represented only 4%. In terms of job roles, Strategy Directors (37.2%) formed the largest group, with Research/Development staff (30.0%), Heads of Department (19.5%), and Branch Managers (12.4%) making up the rest. Work experience data revealed that the majority had 15–20 years (42.4%) or 21–35 years (26.6%), suggesting an experienced employee base.

Measurement Model Assessment

The evaluation of reflective constructs in PLS-SEM involves several steps. Outer loadings are first examined to test item reliability, with acceptable scores between 0.4 and 0.7. Cronbach's Alpha and composite reliability are then used to confirm internal consistency, requiring values from 0.7 to 0.9. AVE values of 0.50 or higher are needed to establish convergent validity. Finally, discriminant validity is checked using the Fornell-Larcker criterion, which demands that the square root of AVE exceed inter-construct correlations, ideally kept below 0.85–0.90.

Individual Item Reliability

The reliability of individual items in PLS-SEM is typically assessed through the outer loadings of indicators for each latent variable (Hair et al., 2014). Outer loadings of 0.7 and above indicate strong reliability, while those in the 0.40–0.70 range are retained only if they do not weaken composite reliability (CR) or average variance extracted (AVE). Deletion is recommended when their removal raises CR above 0.70 and AVE above 0.50. Based on Figure 1 and Table 2, the structure explains over 50% of the indicator variance, signifying that the items achieve acceptable reliability.

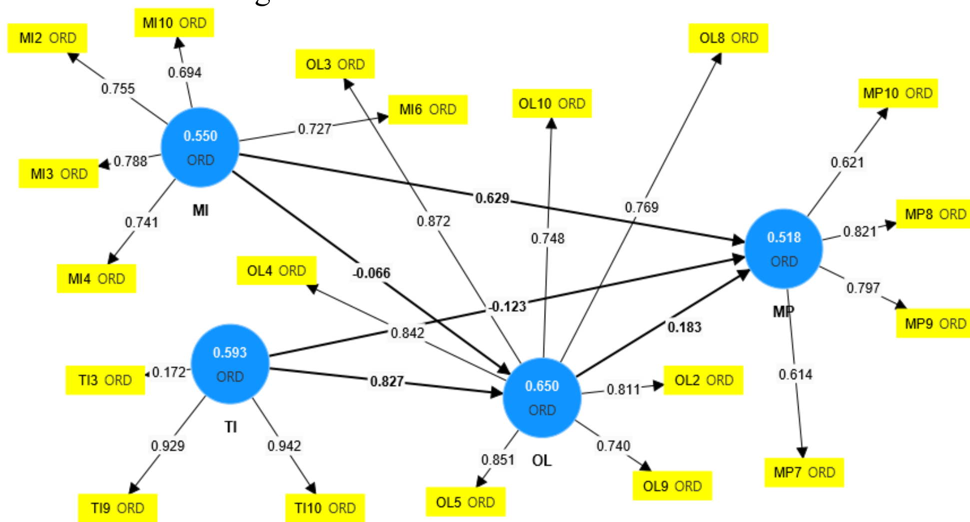

Figure 1: Path Diagram of measurement model

Internal Consistency Reliability

The internal consistency of the measurement model was assessed using Cronbach's alpha and composite reliability (CR). Cronbach's alpha operates under the assumption that all indicators contribute equally, meaning they possess identical outer loadings (Hair et al., 2014). In contrast, CR takes into account variations in outer loadings across indicators. Because of this distinction, both measures are applied together to provide a reliable assessment of internal consistency (Hair et al., 2014). The accepted thresholds require CR values above 0.708 and Cronbach's alpha above 0.70. As shown in Table 2, these conditions are met for all constructs, except for Cronbach's alpha values of 0.560 and 0.686, which are below 0.70 but offset by CR values of 0.774 and 0.808.

Table 3: Individual Item Reliability, Internal Consistency Reliability, Convergent Validity and Discriminant Validity

	Outer loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
MI		0.796	0.802	0.859	**0.550**
M10	0.694				
MI2	0.755				
MI3	0.788				
MI4	0.741				
MI8	0.727				

MP		0.686	0.721	0.808	**0.518**
MP10	0.621				
MP7	0.614				
MP8	0.821				
MP9	0.797				
OL		0.910	0.920	0.928	**0.650**
OL10	0.748				
OL2	0.811				
OL3	0.872				
OL4	0.842				
OL5	0.851				
OL8	0.769				
OL9	0.740				
TI		0.560	0.849	0.774	**0.593**
TI10	0.809				
TI3	0.079				
TI9	0.723				

Source: Author's Computation (2026) using Smart PLS 4.0.9.9 released in 2023.

Convergent Validity

To test convergent validity, the Average Variance Extracted (AVE) was computed for each latent construct by averaging and squaring the indicator loadings. A threshold value of 0.50 or higher indicates adequacy (Hair et al., 2014). Table 3 demonstrates that all AVE values surpassed this benchmark. Therefore, convergent validity is confirmed for the constructs. The results further indicate that at least 50% of the variance in the indicators is explained by their respective constructs.

The goal of discriminant validity is to demonstrate that each construct is distinct and free from overlap with others, thereby reflecting a unique dimension of the model. In SEM, three techniques are often used for this purpose: cross-loadings, the Heterotrait-Monotrait ratio (HTMT), and the Fornell-Larcker criterion. This study adopts the Fornell-Larcker criterion (Hair et al., 2014), which verifies discriminant validity by comparing the square root of each construct's AVE with its correlations, ensuring the AVE value is higher. The findings are displayed in Table 4.4.

Discriminant Validity

Table 4: Discriminant Validity- Fornell-Larcker Criterion

	MI	MP	OL	TI
MI	**0.742**			
MP	0.622	**0.720**		
OL	0.091	0.140	**0.806**	
TI	0.190	0.145	0.814	**0.770**

Source: Author's Computation (2026) using Smart PLS 4.0.9.9 released in 2023

From Table 4, the AVE for Market Intelligence is 0.550, with its square root at 0.7416 and a Fornell-Larcker value of 0.742, slightly exceeding the AVE. Marketing Performance yields an AVE of 0.518, a square root value of 0.7197, and a Fornell-Larcker value of 0.720. For Organizational Learning, the AVE is 0.650, while both the square root and Fornell-Larcker values stand at 0.806. Technological Intelligence shows an AVE of 0.593, with both its square root and Fornell-Larcker values at

0.770. Based on these results, the constructs (MI, MP, OL, and TI) are shown to be distinct, demonstrating no evidence of multicollinearity or overlap. Therefore, discriminant validity is established through the Fornell-Larcker approach.

Structural (or Inner) Model

After analyzing the measurement model's reliability and validity, the study proceeded to evaluate the structural model by testing the relationships between marketing performance and the exogenous constructs, organizational learning and competitive intelligence (market intelligence and technological intelligence). Using a bootstrapping procedure of 5,000 resamples across 323 respondents, the analysis was conducted in line with the recommendations of Hair et al. (2011, 2012, 2014, 2017) and Henseler et al. (2012). The evaluation focused on β-values, t-statistics, p-values, R^2, Q^2, and f^2 to determine both model significance and predictive power.

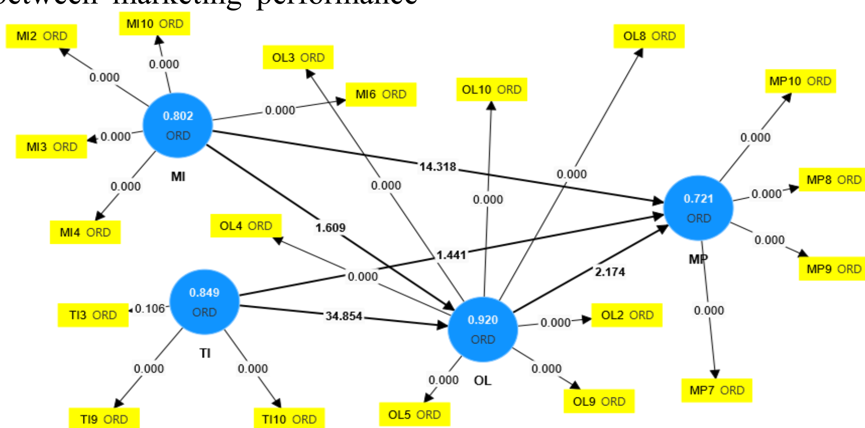

Figure 2: Path Diagram of Structural (Inner) Model

Hypothesis Testing for Direct Relationship

This section of the analysis investigates the direct impact of the exogenous latent variable, Competitive Intelligence, on the endogenous latent variable, Marketing Performance. Table 5 summarizes the path coefficients for these relationships, as well as their T-statistics and p-values, in line with the study's hypothesized links. The null hypothesis (H_0) assumes that the effects of Competitive Intelligence, particularly marketing intelligence and technological intelligence, on marketing performance are not statistically significant.

Table 5: Path Coefficients for Direct Effects in the Inner Model

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
HO1	MI -> MP	0.629	0.634	0.044	14.318	0.000	Accepted
HO2	MI -> OL	-0.066	-0.065	0.041	1.609	0.108	Rejected
HO3	OL -> MP	0.183	0.183	0.084	2.174	0.030	Accepted
HO4	TI -> MP	-0.123	-0.125	0.085	1.441	0.150	Rejected
HO5	TI -> OL	0.827	0.829	0.024	34.854	0.000	Accepted

Source: Author's Computation (2026) using Smart PLS 4.0.9.9 released in 2023.

The study hypothesized (H1) that competitive intelligence, proxy marketing intelligence, and technological intelligence would exert a significant and positive influence on performance, opposing the null hypothesis (H0). However, the empirical results in Table 4.5 demonstrate that H01: The statistical results presented in Table 5 revealed that marketing intelligence has a positive and significant effect on marketing performance (β = 0.629, t=14.318, p<.001). Since the p-value is less than the 0.05 level of significance, the null hypothesis is rejected, and the alternative hypothesis is accepted, indicating that marketing intelligence significantly influences marketing performance among deposit money banks.

H02: The structural path coefficient result shown in Table 5 indicates that marketing intelligence has a negative and non-significant relationship with organizational learning (β = -0.066, t=0.108, p >.001). Since the p-value is above the conventional 0.05 level of significance, the null hypothesis is accepted, and the alternative hypothesis is rejected, indicating that marketing intelligence is negative and non-significant relationship with organizational learning.

H03: From the path coefficient results presented in Table 4.5, it is found that organizational learning has a positive and significant influence on marketing performance (β=0.183, t= 2.174, p <.001). As the p-value is less than the 0.05 level of significance, the null hypothesis is rejected, and the alternative hypothesis is accepted, indicating that organizational learning has a positive and significant effect on marketing performance among deposit money banks.

H04: The result presented in Table 5 shows that technological intelligence has a negative and statistically non-significant effect on marketing performance (β = -0.123, t= 1.441, p >.001). Since the p-value is greater than the 0.05 level of significance, the null hypothesis is accepted, and the alternative hypothesis is rejected, indicating that technological intelligence is negative and statistically non-significant effect on marketing performance among deposit money banks.

H05: From the result shown in Table 5, technological intelligence has a positive and significant relationship with organizational learning (β = 0.827, t= 34.854, p <.001). As the p-value is less than the 0.05 level of significance, the null hypothesis is rejected, and the alternative hypothesis is accepted, indicating that technological intelligence has a positive and significant effect on organizational learning among deposit money banks.

Table 6: Hypothesis Testing for Indirect Effects

Hypo-thesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
HO2	MI -> OL -> MP	-0.012	-0.012	0.01	1.229	0.219	Rejected
HO5	TI -> OL -> MP	0.151	0.152	0.07	2.155	0.031	Accepted

Source: Author's Computation (2026) using Smart PLS 4.0.9.9 released in 2023.

According to Hair et al. (2014), mediation occurs when a mediator channels the effect of an independent variable on a dependent variable. In this study, organizational learning is tested as a mediator between competitive intelligence (marketing and technological intelligence) and

marketing performance, using the product of path coefficients to determine the indirect effect. The proposed mediation path is marketing and technological intelligence -> organizational learning -> marketing performance. The null hypothesis assumes no mediation, and the outcomes are detailed in Table 6.

H06: From Table 4.6, the path coefficient result indicates that Organisational learning does not mediate the relationship between marketing intelligence and marketing performance (β = -0.012, t= 1.229, p <.001). Given that the p-value is greater than 0.05, the null hypothesis cannot be rejected, suggesting that organisational learning does not mediate the relationship between marketing intelligence and marketing performance among deposit money banks.

H07: Table 6 depicts that Organisational learning significantly mediates the relationship between technological intelligence and marketing performance (β = 0.151, t= 2.155, p <.001). In view of the p-value exceeding the 0.05 level of significance, the results support the null hypothesis, demonstrating that organisational learning mediates the relationship between technological intelligence and market performance among deposit money banks.

Table 7: Coefficient of Determination (R2)

	R-square	R-square adjusted
MP	0.399	0.393
OL	0.667	0.665

Source: Author's Computation (2026) using Smart PLS 4.0.9.9 released in 2023

As shown in Table 7, the marketing performance (MP) R^2 is 0.399, meaning the predictors explain about 39.9% of the variance in marketing performance. While the adjusted R^2 is 0.393, which accounts for sample size and number of predictors, confirming a good level of explanatory power. Organizational learning (OL) R^2 is 0.667, showing that about 66.7% of the variance in organizational learning is explained by the predictors. The adjusted R^2 is 0.665, indicating strong explanatory strength with minimal reduction after adjustment.

Predictive Relevance

The Stone-Geisser's Q^2 values are used to evaluate the **predictive relevance** of the structural model through the blindfolding procedure (Hair et al., 2017). Any value above 0 demonstrates that the model possesses predictive relevance for the specified endogenous construct.

Table 8: Predictive Relevance Q2

	SSO	**SSE**	**Q^2 (=1-SSE/SSO)**
MP	1292	1037.586	0.197
OL	2261	1307.919	0.422

Source: Author's Computation (2026) using Smart PLS 4.0.9.9 released in 2023

Table 8 shows that the model has predictive relevance for marketing performance. A Q^2 value close to 0.20 suggests small to moderate predictive power (Hair et al., 2014; 2017), while the value indicates high predictive relevance for organizational learning. Since it is above the 0.35 benchmark, it demonstrates strong predictive power of the model for the construct.

DISCUSSION OF THE FINDINGS

This study examines the extent to which organizational learning acts as a mediator between competitive intelligence and marketing performance among banks in North Central Nigeria. Competitive intelligence was conceptualized using two dimensions: marketing intelligence and technological intelligence. Based on mediation theory (Hair et al., 2014) and the hypothesis testing outcomes, the analysis focused on the indirect influence of marketing intelligence (MI) and technological intelligence (TI) on marketing performance (MP) through organizational learning (OL). H01: Marketing intelligence has a positive and significant effect on marketing performance (*β = 0.629 and t= 14.318*). The positive t-statistic suggests that as MI increases, MP also increases by 0.629. This means that in deposit money banks, where competition is intense and customer expectations are rapidly evolving, marketing intelligence becomes critical for developing adaptive strategies, optimizing promotional activities, and enhancing brand positioning. The relatively large path coefficient (β = 0.629) further indicates that marketing intelligence is a strong predictor of marketing performance, highlighting its strategic importance within the banking industry. The current study is consistent with prior studies (Rehman, 2025; Wu & Monfort, 2023) that revealed that there is a positive and significant relationship between marketing intelligence and marketing performance.

The negative and non-significant effect of marketing intelligence on organizational learning implies that the mere collection and analysis of market-related information may not automatically translate into learning at the organizational level. From the perspective of Organizational Learning Theory (Argyris & Schön, 1978), learning occurs when information is effectively interpreted, shared, and embedded into organizational routines and practices. The non-significant result suggests that marketing intelligence may exist in silos within the organization, often confined to marketing units without being sufficiently disseminated or integrated across departments to foster collective learning.

Organizational learning was found to have a positive and significant effect on marketing performance (*β = 0.183 and t = 2.174*). The positive t-statistic suggests that as OL increases, MP also increases by 0.183. This finding indicates that banks that enhance organizational learning improve marketing performance by fostering knowledge sharing, innovation, and adaptability, which help refine services, respond to market changes, and strengthen competitiveness. These findings corroborate prior research (AlMujaini et al., 2021; Pham et al., 2019; Salim & Sulaiman, 2020), which found that organizational learning has a positive and significant effect on marketing performance.

The negative and non-significant effect of technological intelligence on marketing performance implies that technological intelligence does not directly drive marketing performance among deposit money banks. Instead, its effect may be indirect, operating through mediating variables such as organizational learning, innovation capability, or customer satisfaction. Consequently, banks should complement technological intelligence with effective learning mechanisms, employee training, and customer-focused marketing strategies to convert technological insights into tangible marketing performance gains. There were no prior studies that corroborate the present findings.

The positive effect observed in technological intelligence on organizational learning was (β = 0.827, t= 34.854). This finding aligns with the Dynamic Capabilities Theory, which emphasizes an organization's ability to sense, seize, and reconfigure resources in response to environmental changes. Technological intelligence enhances the “sensing” capability of deposit money banks by allowing them to identify emerging digital trends and innovations (Teece et al., 1997). This means that deposit money banks, with increasing digitalization, fintech competition, and regulatory technology (RegTech) demands, require continuous learning to remain competitive. The strong empirical relationship observed in this study suggests that banks that actively invest in technological intelligence systems such as data analytics, IT monitoring, and digital foresight are better positioned to develop robust organizational learning capabilities (Easterby-Smith & Lyles, 2011).

Organisational learning was found to have a negative and non-significant effect on marketing performance, implying that organisational learning is not a critical mechanism through which marketing intelligence influences marketing performance in deposit money banks. This suggests that banks may achieve marketing performance improvements through the direct application of marketing intelligence, rather than through learning-based processes (López et al., 2005; Sinkula et al., 1997). The result highlights the need for bank management to strengthen learning systems such as cross-functional knowledge sharing and continuous learning frameworks if marketing intelligence is to be more effectively leveraged for sustained marketing performance. There is no previous study that aligns with the current study.

The mediation of Organisational learning mediates the relationship between technological intelligence and marketing performance *($\beta = 0.151$, $t = 2.155$, $p < .001$).* The finding means that technological intelligence strengthens the firm’s sensing capability, while organizational learning enables the seizing and reconfiguring of marketing strategies. The mediation effect therefore demonstrates that organizational learning acts as a strategic mechanism through which technological intelligence is transformed into superior marketing performance. This implies that managers should not only invest in technological intelligence systems but also strengthen organizational learning practices to fully realize the marketing performance benefits of technological intelligence. This study finding is consistent with prior findings (AlMujaini et al., 2021; Pham et al., 2019; Salim & Sulaiman, 2020) who revealed that organisational learning mediates the relationship between competitive intelligence and marketing performance.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The study shows a dual pathway to marketing performance: marketing intelligence impacts performance directly, whereas technological intelligence requires organizational learning as a mediator. Managers are advised to leverage market insights immediately and invest in organizational learning frameworks to maximize the benefits of technological intelligence.

Recommendations

1. The management of the banks should strengthen their capacity for market intelligence by investing in research units, analytics tools, and staff training, enabling them to design strategies that boost customer satisfaction, competitiveness, and marketing performance.
2. The management of the banks should encourage continuous learning and feedback while institutionalizing systems to capture experiences, which will help banks strengthen strategies and achieve sustainable marketing performance.
3. Banks should strengthen internal capabilities by channelling technological intelligence through training, innovation,

and strategic learning to transform it into actions that improve marketing performance.

4. Integrate technological intelligence with marketing strategy processes by linking insights from digital monitoring to campaign planning, product development, and customer engagement initiatives. This ensures that the sensing capability provided by technological intelligence is effectively translated into marketing performance outcomes.

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