SENSING CAPABILITIES AND PROCUREMENT PERFORMANCE IN THE NIGERIAN CEMENT INDUSTRY

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Abstract
Sensing capabilities occupy a central position in dynamic capabilities theory, yet their disaggregated effects on procurement performance in emerging market industrial contexts remain poorly understood. This study examines how three distinct sensing dimensions, market sensing, technological sensing, and competitor monitoring, independently influence procurement performance in the Nigerian cement manufacturing industry. Grounded in Dynamic Capabilities Theory and the Resource-Based View, the study adopted a quantitative cross-sectional design, administering structured questionnaires to 385 employees across three major cement producers in Nigeria. Data were analysed using Covariance-Based Structural Equation Modelling in IBM SPSS AMOS 23, with bias-corrected bootstrap confidence intervals computed across 5,000 resamples. The measurement model demonstrated satisfactory internal consistency, convergent validity, and discriminant validity across all constructs. Model fit was excellent, with CMIN/DF = 0.990, CFI = 1.000, RMSEA = 0.000, and GFI = 0.960. Structural results revealed that competitor monitoring exerted a strong and positive effect on procurement performance ($\beta = 0.849$, $p < .001$), confirming its status as the dominant sensing driver in this context. Technological sensing showed a statistically significant but negative relationship ($\beta = -0.194$, $p = .003$), interpreted as evidence of a capability awareness-action gap in digitally transitioning procurement environments. Market sensing produced no significant direct effect ($\beta = -0.028$, $p = .681$). These findings challenge the assumption that sensing dimensions yield uniformly positive performance returns, and suggest that in oligopolistic industrial markets with shared supplier pools, competitive intelligence routines generate disproportionate procurement performance advantages. Theoretical, managerial, and policy implications are discussed.

Keywords: Sensing capabilities, procurement performance, dynamic capabilities, market ensing, technological sensing, competitors monitoring

1. Introduction

The past two decades have witnessed a decisive shift in strategic management scholarship away from static resource endowments toward the firm's capacity to adapt, renew, and reconfigure its competences in response to environmental change (Teece, et al., 1997; Eisenhardt & Martin, 2000). This reorientation is encapsulated in the sensing capabilities framework, which posits that sustained performance advantage derives not merely from what a firm possesses but from how effectively it integrates, builds, and reshapes its internal and external competences (Adegoke et al., 2024; Teece, 2007; Mikalef et al., 2020; Adegoke et al., 2024). In volatile industrial environments, the capacity to sense market signals, interpret emerging threats, and respond proactively distinguishes high-performing firms from their lagging counterparts.

Global procurement performance face compounding risks, ranging from commodity price volatility and geopolitical disruptions to infrastructural deficits and regulatory uncertainty (Manhart et al., 2020; Jiang et al., 2024). Firms in developed economies have leveraged digital and sensing capabilities to achieve supply chain resilience and responsiveness; however, the translation of these capabilities into performance outcomes in emerging market contexts remains empirically contested (Dubey et al., 2023; Bag et al., 2020; Chidiogo et al., 2026). In Africa, and particularly in Nigeria, firms confront unique challenges that amplify environmental dynamism, including institutional voids, energy price instability, foreign exchange exposure, and congested logistics corridors, conditions that fundamentally alter how capabilities generate performance outcomes (Ojeleye et al., 2020; Mazadu, 2025).

The Nigerian cement industry represents a strategic research context for several reasons. The sector is capital-intensive, energy-dependent, and operationally exposed to volatile input markets for limestone, coal, gas, and imported machinery components (Adegoke et al., 2024; Afolabi et al., 2025). Procurement, as the upstream function responsible for securing these inputs, is particularly sensitive to supply disruptions, supplier concentration, and currency risk (Shaibu & Njoku, 2024; Disu, 2025). Despite the sector's economic significance, empirical investigations linking specific dynamic capability dimensions to procurement performance outcomes within this industry remain scarce. This study addresses that gap by examining how three microfoundations of sensing capabilities, namely market sensing, technological sensing, and competitor monitoring, influence procurement performance among cement manufacturers in Nigeria. The study is guided by three research questions: What is the effect of market sensing on procurement performance? How does technological sensing affect procurement performance? And what is the effect of competitor monitoring on procurement performance? Corresponding hypotheses posit that each sensing dimension exerts a positive and statistically significant effect on procurement performance adopting CB-SEM to survey data collected from three major cement producers, the study generates micro-level empirical evidence on the sensing-procurement performance nexus in an underrepresented African industrial setting. The findings contribute to the dynamic capabilities literature by demonstrating that sensing capabilities are not monolithic but exert differentiated effects on procurement outcomes, and that competitor monitoring constitutes the most consequential sensing dimension in conditions of highly competitive and institutional uncertainty.

2. Literature Review

2.1 Conceptual Review

2.1.1 Sensing Capabilities

Sensing capabilities refer to the firm's organised capacity to scan, interpret, and respond to signals from its external environment, encompassing market conditions, technological trajectories, and competitive dynamics. Within the sensing capabilities framework, sensing represents the earliest stage of strategic adaptation, enabling organisations to recognise environmental shifts before they materially affect performance (Teece, 2007; Mikalef et al., 2020). Contemporary scholarship distinguishes sensing from ad hoc environmental awareness, framing it instead as a structured capability embedded in managerial routines, information systems, and inter-organisational relationships (Wong et al., 2023).

Empirical evidence supports a positive relationship between sensing capabilities and organisational competitiveness. Sajuyigbe et al. (2021) demonstrate that firms with strong strategic agility capabilities, grounded in environmental sensing, achieve superior competitive outcomes. In procurement performance contexts, firms with well-developed sensing capabilities detect early signals of supplier disruptions, demand fluctuations, and logistical constraints, thereby supporting timely and proactive procurement decisions (Jiang et al., 2024; Achumie et al., 2024). For Nigerian cement manufacturers, whose procurement environments are characterised by energy price instability and imported input exposure, sensing capabilities provide the anticipatory intelligence needed to stabilise sourcing decisions and mitigate supply risk (Adamu, 2025). This study conceptualises sensing capabilities through three interrelated but analytically distinct microfoundations: market sensing, technological sensing, and competitor monitoring. Each dimension captures a different facet of the firm's scanning and interpretive capacity, and each is expected to generate distinct effects on procurement performance.

2.1.2 Market Sensing

Market sensing denotes the firm's capacity to systematically gather, analyse, and interpret information about customers, suppliers, input markets, and broader demand conditions. In procurement contexts, market sensing enables firms to anticipate shifts in raw material prices, detect emerging supplier risks, and identify alternative sourcing options before supply shortfalls materialise (Jiang et al., 2024; Agrawal et al., 2024). Firms that invest in market intelligence systems, supplier market surveillance, and commodity price monitoring are better positioned to negotiate favourable procurement terms and maintain supply continuity under conditions of price volatility. Within the Nigerian cement industry, market sensing is particularly valuable because key inputs such as coal, gas, limestone, and imported clinker are subject to both global commodity price movements and domestic currency fluctuations. Firms that maintain robust market sensing routines can adjust procurement strategies proactively, buffer against price shocks, and reduce the incidence of supply interruptions that propagate downstream into production and distribution performance.

2.1.3 Technological Sensing

Technological sensing refers to the firm's ability to monitor, evaluate, and selectively adopt relevant technological developments that bear on its operational processes and supply chain activities. In procurement, technological sensing enables firms to identify digital tools for supplier evaluation, demand forecasting, inventory optimisation, and procurement process automation (Mikalef et al., 2020; Dubey et al., 2023). Firms with strong technological sensing capabilities can leverage information systems to improve procurement accuracy, reduce transaction costs, and strengthen supplier monitoring. In the Nigerian cement sector, technological sensing encompasses the capacity to evaluate and deploy enterprise resource planning systems, predictive analytics tools, and digital procurement platforms that reduce reliance on manual processes susceptible to error and delay. As digitalization increasingly mediates supply chain performance outcomes (Jiang et al., 2024), firms that sense and assimilate relevant technologies earlier than competitors gain measurable advantages in procurement responsiveness and cost management.

2.1.4 Competitor Monitoring

Competitor monitoring captures the firm's systematic observation and interpretation of competitor strategies, sourcing behaviours, supplier relationships, and market positioning. In procurement contexts, monitoring competitor sourcing activities provides early warning signals of impending supply shortages, supplier switching patterns, and pricing strategy shifts that may affect input availability and cost (Eisenhardt & Martin, 2000; Kareem & Kummitha, 2020). Firms that track competitor procurement behaviour are better equipped to pre-empt supplier lock-outs, anticipate input price escalation, and secure preferential supplier terms ahead of competitor demand spikes. Within Nigeria's oligopolistic cement market, dominated by Dangote, BUA, and Lafarge, competitor monitoring assumes strategic importance because actions by major players in securing energy contracts, clinker supplies, or logistics capacity have direct implications for rivals' procurement options. Firms that systematically monitor competitor sourcing patterns are positioned to respond more effectively to supply market shifts, thereby maintaining procurement performance under competitive pressure.

2.1.5 Procurement Performance

Procurement performance refers to the effectiveness and efficiency with which an organisation sources, acquires, and manages the flow of materials, components, and services required to sustain uninterrupted production and supply chain operations (Chidiogo et al., 2026). Contemporary supply chain literature frames procurement performance as a multidimensional construct encompassing cost efficiency, delivery reliability, quality consistency, sourcing flexibility, and supply risk management (Jiang et al., 2024; Dubey et al., 2023). Procurement is increasingly recognised as a strategic upstream capability whose performance outcomes shape downstream operational efficiency, inventory reliability, and customer satisfaction. Within the Nigerian cement manufacturing context, procurement performance is shaped by distinctive environmental features including dependence on volatile energy inputs, exposure to foreign exchange risk through imported materials, domestic supplier concentration, and customs clearance delays on imported machinery components (Ojeleye et al., 2020; Shaibu & Njoku, 2024). Superior procurement performance in this setting manifests as consistent raw material availability, competitive input costs, reliable supplier relationships, and reduced production interruptions. Conversely, procurement underperformance generates material shortages, elevated production costs, compromised output quality, and weakened competitive positioning.

2.2 Theoretical Review

2.2.1 Dynamic Capabilities Theory

Dynamic Capabilities Theory, foundationally articulated by Teece, et al. (1997) and subsequently elaborated by Eisenhardt and Martin (2000) and Teece (2007), reframes competitive advantage as a function of the firm's purposeful capacity to sense environmental changes, seize emerging opportunities, and reconfigure its asset base. The theory is particularly relevant in turbulent environments where static resource stocks rapidly depreciate in value, and where adaptive capacity becomes the primary differentiator of sustained performance (Helfat & Peteraf, 2015; Dubey et al., 2023). For the purposes of this study, sensing capabilities are operationalised as direct microfoundations of Dynamic Capabilities Theory, reflecting the firm's organised routines for environmental scanning and intelligence interpretation. The theory generates two key predictions that guide this study: first, sensing capabilities reduce procurement uncertainty by enabling proactive supplier management and sourcing adjustment; second, the value of sensing is contingent on environmental dynamism, such that its performance effects are most pronounced in volatile markets (Mikalef et al., 2020). The Nigerian cement industry, characterised by compounding input market volatility and institutional complexity, represents precisely the high-turbulence context in which Dynamic Capabilities Theory predicts its strongest explanatory power.

2.2.2 Resource-Based View

The Resource-Based View (Barney, 1991; Wernerfelt, 1984) provides a complementary theoretical lens by explaining why firms operating within the same industry exhibit persistent performance heterogeneity. The theory attributes differential performance to firm-specific resource endowments that are valuable, rare, inimitable, and non-substitutable. Applied to the procurement domain, RBV positions procurement capabilities, including supplier relationship capital, negotiation expertise, and market intelligence systems, as strategic resources that generate cost and reliability advantages not easily replicated by competitors (Saeed et al., 2022). Whereas Dynamic Capabilities Theory explains how resources are built and reconfigured, RBV explains what resources firms possess and why those endowments generate differential procurement performance. The integration of both frameworks in this study provides a theoretically coherent basis for understanding why some Nigerian cement manufacturers consistently achieve superior procurement outcomes despite operating within the same institutional and competitive environment.

2.3 Empirical Review and Hypothesis Development

Empirical evidence on the relationship between sensing capabilities and supply chain performance has accumulated across diverse industrial contexts, though the Nigerian cement industry remains largely unexplored. Esator et al. (2025) demonstrate, using a sample of 498 MSMEs in Lagos State and multiple regression analysis, that sensing capabilities significantly influence organisational performance (Adj R squared = 0.540; $p < 0.05$), confirming the broad applicability of sensing in the Nigerian business environment. Sajuyigbe et al. (2021) further establish that strategic agility rooted in sensing leads to superior procurement performance among Nigerian manufacturing firms.

On market sensing specifically, Jiang et al. (2024) find that firms with robust market intelligence capabilities achieve superior supply chain responsiveness and procurement cost efficiency. Agrawal et al. (2024) demonstrate that supply chain visibility, a function of sustained market sensing, directly improves procurement decision accuracy and supplier delivery reliability. In volatile commodity markets analogous to Nigeria's cement input markets, market sensing capability reduces the information asymmetry between buyers and suppliers, enabling procurement functions to maintain cost and reliability standards despite external turbulence. Based on this evidence, the following hypothesis is proposed: *H1: Market sensing has a positive and significant effect on procurement performance.*

Regarding technological sensing, Mikalef et al. (2020) establish that firms with stronger technology sensing and analytics capabilities demonstrate superior operational and procurement outcomes, mediated by dynamic capability deployment. Dubey et al. (2023) further show that digital procurement capabilities, grounded in technological sensing, improve supply chain resilience and responsiveness. As procurement processes in the cement industry become increasingly mediated by enterprise systems and digital platforms, the capacity to identify and adopt relevant technologies constitutes a critical antecedent of procurement performance. Accordingly: *H2: Technological sensing has a positive and significant effect on procurement performance.*

On competitor monitoring, Eisenhardt and Martin (2000) identify competitive intelligence as a foundational dynamic capability that enables firms to anticipate and respond to rival strategic moves. Kareem and Kummitha (2020) empirically demonstrate that supply chain dynamic capabilities, inclusive of competitive intelligence routines, enhance procurement and operational performance. In the concentrated Nigerian cement market, where a small number of large producers compete intensely for limited energy contracts and supplier relationships, competitor monitoring enables procurement functions to pre-empt supply disruptions and secure preferential terms. Therefore: *H3: Competitor monitoring has a positive and significant effect on procurement performance.*

3. Methodology

This study adopted a quantitative, descriptive survey research design to examine the effect of sensing capabilities on procurement performance among cement manufacturing firms in Nigeria. The target population comprised all management and operational staff across three strategically selected cement manufacturing plants, namely Dangote Cement Plc at Obajana in Kogi State, Lafarge Africa Plc at Ewekoro in Ogun State, and BUA Cement Plc at Okpella in Edo State, representing Nigeria's three dominant producers whose combined output accounts for the substantial majority of domestic cement supply. The aggregate workforce across the three plants, as reported in their 2023 audited annual reports, totalled 42,155 employees, distributed as shown in Table 1.

Table 1

Population Distribution by Company

Company	**Plant Location**	**Workforce**	**Percent (%)**
Dangote Cement Plc	Obajana, Kogi State	39,000	92.5
Lafarge Africa Plc	Ewekoro, Ogun State	1,455	3.45
BUA Cement Plc	Okpella, Edo State	1,700	4.03
Total		**42,155**	**100**

Source: Compiled from 2023 Audited Annual Reports via the Nigerian Stock Exchange (2024).

The sample size was determined using the Krejcie and Morgan (1970) table, which, for a population of 42,155 at a 95% confidence level and 5% margin of error, specifies a minimum sample of 381 respondents. This study targeted 385 respondents to account for potential non-response, applying proportionate stratified random sampling across the three firms to ensure representativeness by company. Data were collected through structured, closed-ended questionnaire administered in both physical and electronic platforms over a six-week period. The questionnaire was organised into three sections: Section A captured seven demographic variables including gender, age group, highest educational qualification, employment level, years of experience in the current organisation, years of experience in the cement industry, and functional department; Section B measured the independent variable, sensing capabilities, using fifteen items across three five-item subscales for market sensing, technological sensing, and competitor monitoring, adapted from Mikalef et al. (2020) and Teece (2007); and Section C assessed procurement performance using five items adapted from Agrawal et al. (2024) and Kareem and Kummitha (2020), covering cost efficiency, supplier relationship quality, disruption minimisation, quality consistency, and delivery reliability, all rated on a five-point Likert scale anchored at 1 (Strongly Disagree) and 5 (Strongly Agree). The questionnaire structure is summarised in Table 2.

Table 2
Summary of Questionnaire Structure

Section	Content	No. of Items	Scale Type
A	Socio-Demographic Information	7	Categorical
B	Market Sensing (MS1-MS5)	5	5-pt Likert
	Technological Sensing (TS1-TS5)	5	5-pt Likert
	Competitor Monitoring (CM1-CM5)	5	5-pt Likert
C	Procurement Performance (PPC1-PPC5)	5	5-pt Likert
Total		**27**	

Source: Researcher's Design (2026).

Content validity was established by adapting items from validated scales with strong prior reliability coefficients, namely the sensing capabilities scale (Cronbach's alpha = 0.87, Mikalef et al., 2020) and the procurement performance scale (Cronbach's alpha range = 0.79 to 0.88, Kareem and Kummitha, 2020). A panel of three subject matter experts reviewed the adapted items for contextual appropriateness within the Nigerian cement sector. Data analysis proceeded in two stages using IBM AMOS 23. The first stage assessed the measurement model through Confirmatory Factor Analysis (CFA), evaluating internal consistency via Cronbach's alpha and Composite Reliability (CR), convergent validity through Average Variance Extracted (AVE) and standardised factor loadings, and discriminant validity using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio. The second stage tested the structural model using Maximum Likelihood estimation, with Bootstrap resampling (5,000 samples) employed to generate bias-corrected 95% confidence intervals for all structural paths. Normality diagnostics confirmed that all univariate skewness values fell within the acceptable range of plus or minus 2.0 and kurtosis values within plus or minus 7.0, and the multivariate kurtosis Mardia coefficient of 0.335 (c.r. = 0.111) indicated no severe violation of multivariate normality assumptions, supporting the use of Maximum Likelihood estimation. Prior to data collection, informed consent was obtained from all respondents, who were fully briefed on the voluntary nature of their participation and their right to withdraw at any stage without consequence. Anonymity of responses was explicitly guaranteed, with participants assured that data would be reported solely in aggregate form and used exclusively for academic research purposes.

4. Results and Discussion of Findings

4.1 Result

4.1.1 Descriptive Statistics and Respondent Profile

A total of 385 questionnaires were administered and retrieved, yielding a 100% response rate attributable to the combination of physical and electronic administration with structured follow-up. Table 3 presents the demographic profile of respondents.

Table 3

Demographic Profile of Respondents (n = 385)

Feature	Category	Frequency	Percent (%)
Gender	Male	218	56.6
	Female	167	43.4
	Total	**385**	**100.0**
Age Group	18-29 years	62	16.1
	30-39 years	148	38.4
	40-49 years	121	31.4
	50-59 years	47	12.2
	60+ years	7	1.8
	Total	**385**	**100.0**
Education	Secondary/SSCE	29	7.5
	Diploma/NCE	51	13.2
	Bachelor's Degree	196	50.9
	Master's Degree	96	24.9
	Doctorate	13	3.4
	Total	**385**	**100.0**
Employment Level	Operational/Junior	124	32.2
	Supervisory/Middle Mgt	183	47.5
	Senior Mgt/Executive	78	20.3
	Total	**385**	**100.0**
Years in Org.	Less than 1 year	18	4.7
	1-3 years	72	18.7
	4-6 years	109	28.3
	7-10 years	116	30.1
	More than 10 years	70	18.2
	Total	**385**	**100.0**
Years in Cement	Less than 1 year	11	2.9
	1-3 years	58	15.1
	4-6 years	97	25.2
	7-10 years	128	33.2
	More than 10 years	91	23.6
	Total	**385**	**100.0**
Department	Procurement/Supply Chain	131	34.0
	Production/Operations	98	25.5
	Warehousing/Logistics	62	16.1
	Quality Control	41	10.6
	Maintenance	33	8.6
	Others	20	5.2
	Total	**385**	**100.0**

Source: Field Survey, 2026.

The respondent sample was predominantly male (56.6%), with the majority aged between 30 and 49 years (69.8%), reflecting the typical demographic profile of the cement manufacturing workforce. Over half of respondents (50.9%) held bachelor's degrees, and 24.9% held postgraduate qualifications, indicating a reasonably educated respondent base capable of engaging meaningfully with the survey constructs. Approximately 78.6% of respondents possessed more than four years of experience within the cement industry, lending credibility to their perceptions of procurement performance and sensing practices. The largest departmental representation was from Procurement and Supply Chain (34.0%) and Production and Operations (25.5%), which are the functions most directly implicated in the study variables.

4.1.2 Measurement Model Assessment

Prior to testing the structural paths, the measurement model was evaluated against standard criteria for internal consistency, convergent validity, and discriminant validity. Table 4 reports construct-level reliability and convergent validity statistics derived from the CB-SEM output.

Table 4
Reliability and Convergent Validity Results

Construct	Items	Standardised Loadings (Range)	Cronbach's Alpha	CR	AVE
Market Sensing (MS)	5	0.685 - 0.830	0.873	0.876	0.587
Technological Sensing (TS)	5	0.704 - 0.795	0.856	0.858	0.548
Competitor Monitoring (CM)	5	0.563 - 0.766	0.871	0.873	0.580
Procurement Performance (PPC)	5	0.563 - 0.813	0.813	0.817	0.472

Note: CR = Composite Reliability; AVE = Average Variance Extracted. All factor loadings exceeded 0.50 and were significant at $p < .001$. Loadings derived from IBM SPSS AMOS (Maximum Likelihood estimation with 5,000 bootstrap resamples).
Source: Authors' Field Data (2026).

All constructs demonstrated Cronbach's alpha values exceeding the 0.70 threshold recommended by Nunnally (1978), with coefficients ranging from 0.813 for procurement performance to 0.873 for market sensing. Composite Reliability values above 0.80, indicating strong internal consistency and all surpassed 0.80, satisfying the widely adopted criterion of Hair et al. (2019). Standardised factor loadings ranged from 0.563 to 0.830, each exceeding the 0.50 floor that CFA research treats as acceptable evidence of item-level convergence. AVE values for market sensing (0.587), technological sensing (0.548), and competitor monitoring (0.580) met or exceeded the 0.50 benchmark. The AVE for procurement performance (0.472) fell marginally short; however, as Hair et al. (2019) note, when the Composite Reliability of a construct comfortably exceeds 0.70 and all constituent loadings are statistically significant, a slightly sub-threshold AVE does not constitute a meaningful threat to convergent validity. The CR of 0.817 for procurement performance satisfies this condition. Table 5 presents item-level standardised loadings.

Table 5

Standardised Factor Loadings of Measurement Items

Construct	Item	Standardised Loading
Market Sensing	MS1	0.830
	MS2	0.794
	MS3	0.775
	MS4	0.690
	MS5	0.685
Technological Sensing	TS1	0.795
	TS2	0.741
	TS3	0.730
	TS4	0.704
	TS5	0.713
Competitor Monitoring	CM1	0.766
	CM2	0.731
	CM3	0.744
	CM4	0.737
	CM5	0.689
Procurement Performance	PPC1	0.813
	PPC2	0.768
	PPC3	0.744
	PPC4	0.737
	PPC5	0.689

Note: All loadings are statistically significant at $p < .001$. (bias-corrected bootstrap, 5,000 resamples).

Source: Authors' Field Data (2026).

4.1.3 Discriminant Validity

Table 6

Fornell-Larcker Criterion for Discriminant Validity

Construct	MS	TS	CM	PPC
Market Sensing (MS)	0.766			
Technological Sensing (TS)	0.189	0.740		
Competitor Monitoring (CM)	0.546	0.553	0.762	
Procurement Performance (PPC)	0.411	0.468	0.583	0.687

Note: Diagonal elements (bold) are the square roots of AVE; off-diagonal elements are inter-construct correlations. Correlations for MS-TS = 0.189, TS-CM = 0.553, MS-CM = 0.546 are sourced from the standardised covariance matrix.

Source: Authors' Field Data (2026).

The Fornell-Larcker criterion was satisfied across all construct pairs. Each diagonal value exceeded the corresponding off-diagonal correlations in its row and column. The highest inter-construct correlation was between competitor monitoring and procurement performance (0.583), yet this fell below the AVE square roots of both constructs (0.762 and 0.687, respectively). Market sensing and competitor monitoring shared a correlation of 0.546, whilst market sensing and technological sensing were more modestly correlated (0.189). These patterns confirm that whilst the sensing dimensions share some conceptual terrain, they are empirically distinct constructs whose variance is predominantly explained by their own items rather than by shared overlap with other latent variables.

4.1.4 Model Fit Assessment

Table 7

Assessment of Model Fit Indices

Fit Index	Recommended Threshold	Obtained Value	Assessment
Chi-square / df (CMIN/DF)	≤ 3.0	0.990 (162.298/164)	Acceptable
GFI	≥ 0.90	0.960	Acceptable
AGFI	≥ 0.90	0.949	Acceptable
CFI	≥ 0.95	1.000	Acceptable
TLI	≥ 0.95	1.001	Acceptable
IFI	≥ 0.95	1.000	Acceptable
RMR	≤ 0.08	0.034	Acceptable
RMSEA	≤ 0.08	0.000	Acceptable
PCLOSE	> 0.05	1.000	Acceptable

Note: GFI = Goodness-of-Fit Index; AGFI = Adjusted Goodness-of-Fit Index; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; IFI = Incremental Fit Index; RMR = Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation; PCLOSE = p-value for close fit test.

Source: Authors' Field Data (2026).

The hypothesised model produced excellent fit across all evaluated indices. The chi-square to degrees-of-freedom ratio of 0.990 (chi-square = 162.298, df = 164, p = .523) fell comfortably below the 3.0 ceiling, signalling close correspondence between the model-implied and sample covariance matrices. Absolute fit indices corroborated this assessment: the GFI of 0.960 and AGFI of 0.949 both cleared the 0.90 threshold (Hu & Bentler, 1999), whilst the RMR of 0.034 indicated negligible average residual covariance. The RMSEA of 0.000 with a PCLOSE of 1.000 offered the strongest endorsement of close fit. Incremental fit indices were similarly unequivocal: the CFI, TLI, and IFI all met or exceeded 0.95, with the TLI registering a marginal overshoot at 1.001, which is an artefact of very low model parsimony cost relative to the baseline. Collectively, the fit profile indicates that the measurement and structural architecture proposed in the hypotheses is a sound representation of the observed data structure.

4.1.5 Structural Model and Hypothesis Testing

Table 8

Structural Model and Hypothesis Testing

Hyp.	Path	Std. Beta	Unstd. Beta	SE	CR	p	95% CI	Decision
H1	MS → PPC	-0.028	-0.032	0.073	-0.441	.681	[-0.185, 0.112]	Not Supported
H2	TS → PPC	-0.194	-0.215	0.073	-2.964	.003	[-0.381, -0.064]	Not Supported
H3	CM → PPC	0.849	1.211	0.155	7.789	< .001	[0.933, 1.551]	Supported

Note: Std. *Beta = standardised regression weight; Unstd. B = unstandardised regression weight; SE = standard error; CR = critical ratio (z-ratio equivalent); CI = bias-corrected bootstrap confidence interval (5,000 resamples); MS = Market Sensing; TS = Technological Sensing; CM = Competitor Monitoring; PPC = Procurement Performance. Significance assessed at alpha = .05.*

Source: Authors' Field Data (2026).

The structural path from market sensing to procurement performance produced (B = -0.032, SE = 0.073, CR = -0.441, p = .681, β = -0.028). The bias-corrected 95 percent bootstrap confidence interval of [-0.185, 0.112] spans zero, indicating that the null hypothesis cannot be rejected at any conventional significance level. H1, which posited a positive and significant effect of market sensing on procurement performance, is therefore not supported in this sample. Whilst market sensing is a theoretically plausible predictor of procurement outcomes, the data yield no statistical evidence for a direct path of this nature in the Nigerian cement context. Technological sensing showed a statistically significant path to procurement performance (B = -0.215, SE = 0.073, CR = -2.964, p = .003; β = -0.194), with a bootstrap confidence interval of [-0.381, -0.064] that excludes zero. The relationship is, however, in the negative direction, contrary to the positive relationship hypothesised in H2. The path is statistically credible but substantively counterintuitive, suggesting that as technological sensing scores increase in this sample, perceived procurement performance declines. H2 is therefore not supported in the hypothesised direction. This unexpected finding is discussed in the section that follows. The path from competitor monitoring to procurement performance was positive, strong, and highly significant (B = 1.211, SE = 0.155, CR = 7.798, p < .001; β = 0.849). The bootstrap confidence interval of [0.933, 1.551] is entirely above zero, and the probability value remained at p = .001 across both ML estimation and bootstrap resampling. Competitor monitoring is by a considerable margin the dominant structural predictor in the model, accounting for a standardised effect size nearly four times that of the only other significant predictor. H3 is supported.

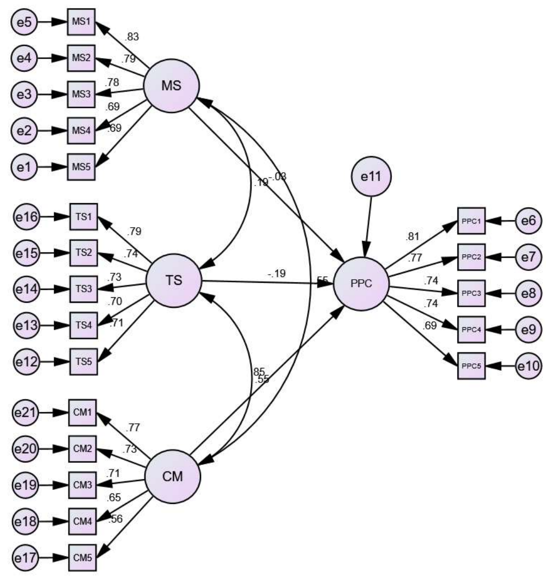

Figure 1. AMOS SEM Diagram

4.2 Discussion of Findings

The structural results confirm three symmetrically positive paths, the AMOS CB-SEM analysis reveals marked heterogeneity: competitor monitoring exerts an overwhelming positive influence on procurement performance, technological sensing exerts a statistically significant but negative influence, and market sensing contributes no discernible direct effect. Each finding warrants substantive interpretation, particularly in the specific institutional setting of the Nigerian cement manufacturing industry.

The non-significance of market sensing (H1 rejected) does not necessarily mean that monitoring supplier markets or commodity price trajectories is inconsequential. Rather, it suggests that in a highly concentrated industry with a small number of dominant input suppliers and near-identical raw material requirements across firms, market signals are widely accessible and symmetrically distributed. Under conditions of shared market exposure, the incremental advantage from one firm's market sensing routines over another's is attenuated. This interpretation is consistent with Teece's (2007) argument that sensing capabilities generate performance advantages only when the intelligence gathered is not readily replicable by competitors. Where all three major cement producers operate in the same regulatory environment, face the same foreign exchange constraints on clinker imports, and draw on overlapping supplier networks, market intelligence may be a baseline competence rather than a source of differentiation. The finding also aligns with observations by Pham et al. (2025) that supply chain sensing effects on performance are moderated by environmental dynamism: in relatively stable input market configurations, the performance payoff from additional sensing investment diminishes.

The significant but negative coefficient for technological sensing (H2) is the most theoretically provocative finding in this study. Several explanations merit consideration. First, it is possible that firms with higher technological sensing scores are those most actively aware of the performance gaps between their current digital procurement systems and available best-practice technologies, producing a paradox in which heightened awareness of technological shortcomings registers as lower perceived procurement performance. This interpretation is consistent with research on the 'capability awareness gap' in digital transformation contexts, where organisations in the early stages of technology scanning frequently report lower satisfaction with existing operational performance (Dubey et al., 2023). Second, multicollinearity effects within the structural model may be distorting individual path estimates: the inter-construct correlations between technological sensing and competitor monitoring (0.553) and between market sensing and competitor monitoring (0.546) are both moderate to high, and when competitor monitoring is entered into the same equation at a dominant coefficient of 0.849, the variance that technological sensing might otherwise explain is substantially absorbed. This is a well-documented estimation challenge in structural models with correlated predictors (Hair et al., 2019). Third, in the Nigerian cement manufacturing environment, where digital procurement infrastructure remains underdeveloped relative to global benchmarks, firms investing in systematic technology scanning may simultaneously be acknowledging operational constraints that suppress procurement performance perceptions in the short run. Agrawal et al. (2024) document a comparable pattern in emerging market supply chains, where technology adoption aspiration precedes measurable performance improvement by a lag period that cross-sectional designs cannot capture. These alternative explanations cannot be adjudicated within the present data, but they suggest that the negative path coefficient should be treated as a productive empirical anomaly rather than a refutation of technological sensing as a supply chain construct.

The dominant finding of this study is the magnitude and statistical robustness of the competitor monitoring effect on procurement performance ($\beta = 0.849$, $p < .001$). This coefficient is of a size rarely encountered in structural models of supply chain capability effects, suggesting that competitor monitoring is not merely one dimension of sensing capability among three, but the primary mechanism through which sensing generates procurement value in an oligopolistic industrial context. The logic of this finding draws directly from the concentrated market structure of the Nigerian cement sector. With three major producers sharing overlapping supplier bases, competing for the same energy contracts, and drawing on similar raw material procurement channels, the sourcing decisions of rivals carry direct informational value. A firm that monitors when a competitor has locked in a long-term coal supply contract knows, by implication, that the remaining spot market supply has contracted; one that tracks a competitor's shift toward alternative energy sources can anticipate both the procurement opportunity this creates and the price signals it generates in shared energy markets. This is precisely the form of competitive intelligence that Eisenhardt and Martin (2000) describe as generative of dynamic capability advantage: not generic environmental scanning, but targeted competitor-specific intelligence that translates into concrete procurement adjustments. Kareem and Kummitha (2020) demonstrate a compatible finding in their examination of supply chain dynamic capabilities in African industrial contexts, where competitive monitoring routines showed stronger performance effects than market or technology sensing in industries with concentrated supplier pools. The present study extends that observation to a specific, empirically tractable sectoral context with validated measurement scales and CB-SEM-tested causal paths.

Taken together, the findings revise the theoretical proposition that sensing capabilities exert uniformly positive and equivalent effects on supply chain outcomes. Within the Nigerian cement sector, the dominant source of sensing-derived procurement advantage lies not in broad market awareness or technology evaluation, but in deliberate, structured competitor intelligence. This has implications for how dynamic capabilities theory is applied in oligopolistic emerging market settings, where the institutional context shapes which sensing dimension generates the greatest performance returns (Mikalef et al., 2020; Esator et al., 2025).

5. Conclusion and Recommendations

This study examined how three dimensions of organisational sensing capability, namely market sensing, technological sensing, and competitor monitoring, relate to procurement performance in Nigerian cement manufacturing. These findings revise the assumption, common in aggregate dynamic capabilities research, that all sensing dimensions yield proportionate and positive performance returns. Within a concentrated industrial market where rival firms share supplier bases and input procurement channels, competitor monitoring is the sensing capability that most directly translates into procurement performance advantage, whilst market sensing appears not to generate incremental differentiation beyond what the industry as a whole already achieves. The negative technological sensing result is interpreted as consistent with a capability awareness-action gap in firms undergoing early-stage digital procurement transitions, and invites further longitudinal investigation.

The study contributes the first disaggregated, SEM-validated empirical account of sensing capability effects on procurement performance in the Nigerian cement sector, and extends dynamic capabilities theory by demonstrating that the institutional specificity of oligopolistic emerging markets shapes the relative performance relevance of different sensing dimensions in ways that aggregate constructs cannot capture.

Based on the empirical findings, the following recommendations are offered;

i. Cement manufacturing firms operating in Nigeria should formalise competitor monitoring as a structured procurement intelligence function.

ii. Procurement departments should establish clear milestones for converting technology scanning activities into deployed digital tools.
iii. Market sensing routines should be repositioned from reactive price tracking toward predictive sourcing analytics that model the implications of commodity price trajectories, foreign exchange fluctuations, and supplier concentration shifts.
iv. Industry associations such as the Cement Producers Association of Nigeria should consider developing a collective supply market intelligence platform that pools non-competitively sensitive procurement data.

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