DRIVING ECO-INNOVATION THROUGH INTANGIBLES: INTELLECTUAL CAPITAL EFFICIENCY AND GREEN INVESTMENT IN NIGERIAN LOGISTICS COMPANIES

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ABSTRACT

Purpose: *This paper investigates the empirical relationship between intellectual capital efficiency components and physical corporate green capital investments within listed logistics and freight transport companies in Nigeria. Grounded in the Natural Resource-Based View (NRBV), the study examines whether intangible knowledge capabilities act evenly or generate resource trade-offs when driving direct monetary outlays into green assets.*

Design/methodology/approach: *The study operationalizes Pulic's Value Added Intellectual Coefficient framework across a strongly balanced panel of listed transport enterprises from 2020 through 2024 ($N = 7$, $T = 5$, $N \times T = 35$). Model specification tests establish the Fixed Effects (FE) panel estimator as the optimal specification, supplemented by panel Feasible Generalized Least Squares (FGLS) under an AR(1) autocorrelation structure for robustness.*

Capital Employed Efficiency (CEE) is not statistically significant in either revised fixed-effects specification. In the HCE model, its coefficient is -0.0785 ($t = -1.98$, $p = .056$), while in the SCE model it is 0.0353 ($t = 1.30$, $p = .202$). The change in sign across the alternative specifications reinforces the need for caution in assigning a stable substantive interpretation to CEE in this very small panel. The evidence does not establish a statistically significant association between CEE and green investment. H3 is therefore not supported.

Research limitations/implications: *The sample is restricted to listed logistics and transport firms in Nigeria, reflecting the formal corporate transport segment.*

Practical implications: *The findings demonstrate that expanding overhead can constrain green fleet modernization. To decarbonize operations, logistics firms must streamline structural overhead and prioritize technical workforce competence.*

Originality/value: *This study provides one of the first balance sheet grounded econometric evaluations of how audited intellectual capital components drive green CapEx in an emerging economy setting.*

Keywords: *Intellectual Capital; Value Added Intellectual Coefficient (VAIC); Human Capital Efficiency; Structural Capital; Corporate Green Investment; Natural Resource-Based View; Logistics*

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

In the current global economy, the imperative to decarbonize industrial operations and transition toward sustainable supply chains has shifted corporate priorities from traditional financial capital accumulation toward intangible resource management (Bontis et al., 2018; Chen, 2008). According to the MIT Climate Portal (2024), freight transportation and logistical infrastructure account for over one-third of global freight emissions and industrial fuel consumption. Consequently, logistics and transit enterprises operating within emerging economies face numerous institutional and economic pressures, ranging from navigating severe domestic infrastructure deficits to complying with sustainable development standards (Appah, 2026).

To achieve environmental performance, corporate entities must deploy discretionary capital expenditures directly into eco-friendly technologies, carbon-mitigation equipment, and fuel-efficient systems (Xu & Wang, 2022). However, physical capital allocation does not occur in a structural

vacuum. Drawing from the Resource-Based View (RBV) and its ecological extension, the Natural Resource-Based View (NRBV), a firm's capacity to execute environmental investments depends fundamentally on its stock and efficient utilization of intangible capabilities (Barney, 1991; Hart, 1995; Pulic, 2000). For emerging market logistics providers, failing to modernize fleets results in real financial penalties, including fuel consumption taxes, cross-border carbon border adjustment tariffs (CBAM), and an estimated 14% to 22% penalty on debt financing from international green climate funds (Connected Development et al., 2025).

Utilizing the Value Added Intellectual Coefficient (VAIC) framework (Pulic, 2000, 2004), intellectual capital efficiency (ICE) is divided into three dimensions: Human Capital Efficiency (HCE), representing the value added generated per unit of capital invested in human talent; Structural Capital Efficiency (SCE), capturing the systems, databases, processes, routines, and administrative arrangements that support execution; and Capital Employed Efficiency (CEE), reflecting the financial return generated from physical and financial capital assets.

While accounting and management literature suggests that intellectual capital efficiency drives competitive advantage and general financial performance (Naseem et al., 2024; Pulic, 2000), emerging empirical evidence suggests that measures of intellectual capital may exert distinct and non-linear pressures when applied to discretionary eco-innovations and green capital commitments (Asiaei et al., 2023; Rehman et al., 2021).

1.2 Statement of the Problem

Despite the accelerating literature on corporate sustainability, prior research exhibits three critical empirical and theoretical limitations. First, the majority of existing empirical studies evaluate corporate environmental responses through subjective Likert-scale surveys (Asiaei et al., 2023; Chen, 2008; Rehman et al., 2021) or qualitative sustainability disclosure indexes (Yadiati et al., 2019). While qualitative disclosures signal corporate legitimization strategies, they frequently reflect greenwashing and do not measure actual monetary outlays committed to physical environmental capital assets.

Second, the dominant RBV narrative treats intellectual capital as a monolithic, uniformly positive driver of corporate eco-performance (Bontis et al., 2018). This oversimplification conceals potential internal resource rivalries. Specifically, while human technical expertise enables green project conceptualization, rigid procedures or heavy structural overhead may compete directly with physical capital projects for limited corporate funds, creating internal trade-offs (Xu & Wang, 2022).

Third, evidence linking VAIC-based intellectual capital efficiency to direct corporate green investment remains limited in the Nigerian logistics context. Existing studies have more commonly examined intellectual capital in relation to financial performance, environmental disclosure, or broader sustainability outcomes. The extent to which accounting-based intellectual capital efficiency is associated with actual green capital expenditure in listed Nigerian logistics firms therefore remains insufficiently documented.

1.3 Significance and Novel Contribution

This study makes three primary contributions to the international management and accounting literature:

Theoretical contribution: The findings provide qualified evidence that human-capital efficiency is positively associated with green investment in the sampled Nigerian logistics firms. The SCE result is weaker and should not be interpreted as an independently identified structural-capital mechanism because SCE is algebraically linked to HCE. The evidence therefore supports a narrower NRBV interpretation: workforce-related capability may be more closely associated with green capital allocation than the accounting-based structural component, although the small panel limits the strength of this inference.

Methodological Rigor via Balance Sheet Metrics: Moving beyond perception surveys, this study operationalizes audited financial metrics derived from standardized IFRS financial statements, pairing audited VAIC components with direct corporate green capital expenditure ratios to provide a replicable econometric framework for emerging market analysis.

Practical Policy and Managerial Insights: For logistics executives and policymakers in developing economies, the findings highlight that investing in human capital expertise and streamlining

structural overhead are prerequisites for executing physical fleet modernization and supply chain decarbonization.

CHAPTER 2: LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Theoretical Framework

2.1.1 Natural Resource-Based View (NRBV)

The theoretical foundation of this study is grounded in the Natural Resource-Based View (NRBV) formulated by Hart (1995), which extends Barney's (1991) classical Resource-Based View (RBV). Classical RBV posits that a firm achieves sustainable competitive advantage through the deployment of Valuable, Rare, Inimitable, and Non-substitutable (VRIN) resources. Hart (1995) argued that classical RBV ignores the explicit constraints of the natural environment and proposed three interconnected eco-strategic capabilities: pollution prevention (directing capabilities toward eliminating waste and emissions before they occur), product stewardship (integrating environmental considerations into the full lifecycle of corporate operations), and sustainable development (committing physical financial capital to long-term clean technologies).

In knowledge-intensive transit networks, physical decarbonization requires specialized internal knowledge assets. Applying NRBV, Intellectual Capital Efficiency is positioned as the underlying VRIN capability that enables a logistics firm to allocate physical capital toward green investments.

2.1.2 Value Added Intellectual Coefficient (VAIC) Model

To quantify intangible resource efficiency, this study adopts Pulic's (2000, 2004) VAIC model, which measures the net value added (VA) created by a firm relative to its capital employed and human capital resources. While extended frameworks such as Modified VAIC (MVAIC) incorporate Relational Capital or Innovation Capital through subjective scoring or proxy allocations, this study adheres to Pulic's (2000, 2004) baseline three-component framework. The VAIC framework derives strictly from audited, standardized financial statement lines under International Financial Reporting Standards (IFRS). This avoids arbitrary indicator weighting, eliminates surveyor perception bias, and provides a replicable balance-sheet-grounded measurement of intangible efficiency in emerging capital markets.

2.2 Literature Review and Hypothesis Development

2.2.1 Human Capital Efficiency and Green Investment

Human capital includes the tacit knowledge, technical skills, problem-solving abilities, and managerial expertise embedded within an organization's workforce (Bontis et al., 2018; Pulic, 2000). In logistics and freight transportation, evaluating eco-efficient routing software, managing alternative-fuel vehicle adoption, and maintaining environmental compliance require specialized technical knowledge (Davenport & Harris, 2020).

Empirical studies by Chen (2008) and Rehman et al. (2021) demonstrate that green human capital directly fuels process eco-innovations. When personnel generate high value added relative to their wage cost, corporate management possesses the cognitive capability and confidence required to approve capital-intensive green investments. Conversely, low human capital efficiency restricts a firm's capacity to identify or execute complex decarbonization projects (Asiaei et al., 2023). Thus, it is hypothesized:

H1: Human Capital Efficiency has a statistically significant positive effect on corporate green investment.

2.2.2 Structural Capital Efficiency and Green Investment

Structural capital includes databases, patents, processes, internal control systems, and corporate culture (Pulic, 2000). While mainstream literature assumes that structural efficiency universally supports corporate performance (Bontis et al., 2018), institutional and trade-off literature suggests a more complex relationship in emerging markets (Xu & Wang, 2022). High SCE indicates that a firm's internal processes and systems absorb a substantial share of value added relative to human labor. In

knowledge-intensive logistics companies operating under severe capital constraints, highly formalized administrative systems or high structural retention can create internal inertia and resource competition (Xu & Wang, 2022). Capital earmarked for administrative and software systems competes directly with discretionary physical capital expenditure on green fleet assets (Hart, 1995; Xu & Wang, 2022). Therefore, under capital constraints, high structural absorption applies a friction effect on physical eco-investments:

H2: Structural Capital Efficiency has a statistically significant negative effect on corporate green investment.

2.2.3 Capital Employed Efficiency and Green Investment

Capital Employed Efficiency reflects the financial value added generated per unit of physical and financial capital invested in the business (Pulic, 2000, 2004). While physical financial efficiency drives conventional profitability and market valuation (Naseem et al., 2024), its direct relationship with discretionary, long-gestation green capital outlays remains disputed. In emerging economies, highly efficient deployment of physical assets is frequently achieved by maximizing fleet utilization and preserving short-term liquidity rather than committing funds to unproven or long-payback green technologies (Appah, 2026). Without explicit regulatory mandates or high human capital direction, financial efficiency alone does not automatically translate into green capital expenditure (Yadiati et al., 2019). We test this empirical relationship:

H3: Capital Employed Efficiency has a statistically significant association with corporate green investment.

2.2.4 Control Variables

To prevent omitted variable bias, the model incorporates two foundational corporate finance controls. Firm Size (f_size) is measured as the natural logarithm of total assets. Larger firms possess greater slack resources, face higher public legitimization pressure, and enjoy economies of scale when funding major green outlays (Appah, 2026; Davenport & Harris, 2020). Financial Leverage (lev) is measured as total debt divided by total equity. High debt burdens increase fixed interest obligations and financial distress risks, restricting discretionary capital allocation toward long-term environmental projects (Xu & Wang, 2022).

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design and Model Specification

Panel data modeling is used because it permits estimation from repeated firm-year observations while accounting for time-invariant firm-specific heterogeneity (Hsiao, 2014). Given the small cross-sectional dimension of the present panel, the resulting estimates are interpreted as within-sample associations rather than as broadly generalizable causal effects.

To test the hypothesized relationships, the baseline linear panel regression model is specified as follows:

The original joint specification was: $green_inv_{it} = \beta_0 + \beta_1 HCE_{it} + \beta_2 SCE_{it} + \beta_3 CEE_{it} + \beta_4 f_size_{it} + \beta_5 lev_{it} + \mu_i + \varepsilon_{it}$. Because $SCE = 1 - 1/HCE$ under the VAIC construction, the joint specification is not suitable for interpreting HCE and SCE as independent regressors. The revised analysis therefore estimates two alternative fixed-effects equations. Model 1 includes HCE, CEE, firm size, and leverage; Model 2 replaces HCE with SCE while retaining the same controls. Firm fixed effects are included in both models.

where $green_inv_{it}$ denotes green capital expenditure intensity for firm i in year t; HCE_{it}, SCE_{it}, and CEE_{it} represent Human Capital Efficiency, Structural Capital Efficiency, and Capital Employed Efficiency, respectively; f_size_{it} is firm size; lev_{it} is financial leverage; μ_i captures unobserved firm-specific fixed effects; and ε_{it} is the idiosyncratic error term.

3.2 Sample Selection and Data Sources

The target population comprises listed freight, supply chain, and logistics companies in Nigeria over the five-year period spanning 2020 through 2024. Financial data and capital expenditure disclosures were extracted from audited annual reports and financial statements published in accordance

with International Financial Reporting Standards (IFRS). A strongly balanced panel formation was enforced to eliminate attrition bias and ensure balanced observation weights across time. The final dataset yields N = 7 companies observed over T = 5 years, producing an empirical sample of N × T = 35 firm-year observations.

The study uses an exhaustive census of the eligible listed logistics and freight firms that operated continuously and published audited annual reports from 2020 to 2024. Census coverage reduces researcher discretion in firm selection, but it does not remove the statistical limitations associated with the small number of firms.

3.3 Econometric Estimation Strategy

To select the appropriate panel estimator, a sequential diagnostic routine is applied:

Pooled Ordinary Least Squares (OLS): Assumes no firm-specific unobserved heterogeneity ($\mu_i = 0$). OLS yields biased and inconsistent estimates if firm-level attributes correlate with explanatory variables.

Fixed Effects (FE) Estimator: Allows firm-specific intercept μ_i to correlate freely with explanatory variables. Within-group transformations remove time-invariant firm characteristics, isolating pure within-firm variation over time.

Random Effects (RE) Estimator: Assumes μ_i is distributed independently of the explanatory variables. RE is evaluated using Feasible Generalized Least Squares (FGLS).

Hausman Specification Test: Evaluates the null hypothesis (H_0) that random effects yields consistent estimates versus the alternative hypothesis (H_1) that fixed effects is required due to endogeneity between μ_i and the regressors.

Small-Cluster and Asymptotic Corrections: With only seven firms, neither conventional cluster-robust inference nor asymptotic specification tests can be assumed to provide reliable finite-sample inference. FGLS is therefore presented as a supplementary estimator rather than as a correction that guarantees valid small-sample significance levels. The revised interpretation emphasizes coefficient direction and magnitude, while statistical significance is treated as conditional on the limitations of the very small cross-sectional dimension.

Robustness and Diagnostics: Potential heteroskedasticity and serial correlation are examined through alternative FE and FGLS specifications. Because the panel contains only seven firms, these estimators are used for sensitivity analysis rather than as definitive solutions to finite-sample inference problems.

3.4 Revised Treatment of the HCE–SCE Dependency

A central feature of the VAIC construction is the deterministic relationship between HCE and SCE. HCE is defined as VA/HC, whereas SCE is defined as (VA − HC)/VA. Therefore, SCE = 1 − 1/HCE. This identity means that HCE and SCE cannot be treated as statistically independent dimensions in a joint regression. The revised analysis consequently estimates HCE and SCE in separate fixed-effects specifications, with CEE, firm size, and leverage retained as controls. This removes the definitional collinearity from the principal estimates. The two coefficients are interpreted as associations from alternative parameterizations of the VAIC labor-related component, not as independent causal mechanisms.

CHAPTER 4: DATA ANALYSIS, EMPIRICAL RESULTS, AND DISCUSSION

4.1 Descriptive Statistics and Diagnostic Tests

Table 1 summarizes the descriptive properties for all regression variables across the 35 firm-year observations spanning 2020 through 2024.

Table 1

Descriptive Statistics of Model Variables (2020–2024)

Variable	*M*	*SD*	Min	Max	Skewness	Kurtosis
green_inv	0.0123	0.0093	0.0010	0.0350	0.7792	2.8028
HCE	1.5746	0.4177	0.7200	2.5400	0.2131	2.6870
SCE	0.3137	0.2096	−0.3900	0.6100	−1.3635	5.3354
CEE	0.2591	0.0855	0.0900	0.4400	0.1575	2.4124
f_size	9.9817	0.6506	8.6500	10.9500	−0.5129	2.6636
lev	1.0654	0.7600	0.2500	2.4500	0.5224	1.5716

Note. N = 35 (7 firms × 5 years). green_inv = green capital expenditure ratio; HCE = Human Capital Efficiency; SCE = Structural Capital Efficiency; CEE = Capital Employed Efficiency; f_size = natural logarithm of total assets; lev = total debt to total equity.

Structural Capital Efficiency (SCE) has a mean of 0.3137 and ranges from −0.39 to 0.61. Negative SCE values are mechanically possible when HCE is below one because SCE = 1 − 1/HCE. They should therefore not be interpreted automatically as evidence of negative structural-capital accumulation or administrative failure.

The negative minimum value observed for Structural Capital Efficiency (−0.3900) indicates that in certain underperforming years, total employee compensation exceeded net value added (HC > VA), thereby creating negative structural capital accumulation and highlighting substantial labor overhead burden in specific transit operations.

4.2 Pairwise Pearson Correlation Matrix

Table 2 reports the pairwise Pearson correlation coefficients among the variables.

Table 2

Pairwise Pearson Correlation Matrix

Variable	1	2	3	4	5	6
1. green_inv	1.000					
2. HCE	.759*	1.000				
3. SCE	.629*	.932*	1.000			
4. CEE	.740*	.976*	.910*	1.000		
5. f_size	.623*	.295	.300	.286	1.000	
6. lev	.176	−.209	−.155	−.140	.760*	1.000

Note. N = 35. * p < .05.

Bivariate correlation vectors indicate strong positive relationships between intellectual capital metrics and green investment outlays. Because high pairwise correlations between VAIC components can introduce variance inflation in pooled models, fixed effects within transformations are essential to isolate unique partial regression coefficients.

4.3 Panel Regression Analysis and Model Testing

Table 3 presents the empirical results across Pooled OLS, Fixed Effects (FE), Random Effects (RE), Robust Clustered FE, and Panel FGLS estimations.

Table 3

Panel Regression Estimations for Corporate Green Investment

Variable	HCE-only FE	SCE-only FE
HCE	0.0206** (2.23)	—
SCE	—	−0.0114 (−1.19)
CEE	−0.0785 (−1.98)	0.0353 (1.30)
Firm size	0.0558*** (6.14)	0.0512*** (4.37)
Leverage	−0.0148** (−2.37)	−0.0117 (−1.47)
Firm fixed effects	Yes	Yes
Observations	35	35
Residual df	24	24
Within R^2	0.832	0.814
F-statistic	38.48	33.91

Note. Dependent variable = green_inv. Conventional t-statistics in parentheses. Wild-cluster bootstrap p-values for the principal HCE and SCE coefficients are .099 and .176, respectively (9,999 Rademacher replications, seven firm clusters). * p < .10, ** p < .05, *** p < .01 under conventional FE inference. The separate specifications are estimated because SCE = 1 − 1/HCE under the VAIC construction.

The correlation matrix reports a high HCE–SCE correlation (.932), but this should not be treated as ordinary empirical multicollinearity. The relationship is definitional: SCE = 1 − 1/HCE. The high correlations among HCE, SCE, and CEE therefore reflect their common construction from value added and related inputs. The revised regression strategy avoids the HCE–SCE joint specification rather than relying on VIF or fixed-effects demeaning to resolve the dependency.

The Hausman specification test reports $\chi^2(5) = 14.80$ (p = .0112). This result is consistent with the use of fixed effects, but it is not treated as decisive because the test relies on an asymptotic reference distribution and the panel contains only seven firms. Fixed effects are retained as the principal within-firm specification on substantive grounds, while alternative estimates are used to assess sensitivity.

4.4 Discussion of Empirical Findings

4.4.1 Human Capital Capability as an Eco-Investment Catalyst

The revised HCE-only fixed-effects specification produces a positive coefficient for HCE of 0.0206 (t = 2.23, conventional p = .033). The estimate indicates a positive within-firm association between HCE and green investment after controlling for CEE, firm size, leverage, and firm-specific fixed effects. However, the small number of clusters materially affects inference: a wild-cluster bootstrap test gives p = .099 (9,999 Rademacher replications). Thus, the conventional FE result is suggestive rather than sufficiently strong to support a 5% significance claim. H1 is therefore described as receiving limited or suggestive support, not definitive confirmation.

This result aligns with the core premises of the Natural Resource-Based View (Chen, 2008; Hart, 1995), confirming that high value generating human capital provides the technical problem solving expertise required to evaluate, select, and manage complex green infrastructure investments. In transit and logistics networks, specialized workforce capabilities directly overcome technical uncertainties associated with fleet modernization and fuel efficiency investments (Davenport & Harris, 2020; Rehman et al., 2021). Consequently, human capital efficiency functions as a driver of physical decarbonization outlays rather than merely enhancing short-term financial liquidity.

4.4.2 Structural Capital Friction and Administrative Bottlenecks

The SCE-only fixed-effects specification gives a coefficient of −0.0114 (t = −1.19, conventional p = .244), while the wild-cluster bootstrap p-value is .176. The negative point estimate is therefore not statistically distinguishable from zero in the revised specification. More importantly, SCE is mechanically related to HCE through SCE = 1 − 1/HCE. The estimate should consequently not be presented as evidence that structural capital independently crowds out green investment. H2 is not supported by the revised evidence.

4.4.3 Capital Employed Neutrality and Firm Size Dynamics

Capital Employed Efficiency (CEE) displays a negative but statistically insignificant coefficient in the reported FE specification ($\beta = -0.0642$, $t = -1.58$, $p = .128$). Thus, the evidence does not support a statistically distinguishable association between CEE and green investment in this sample. The negative point estimate is not interpreted as evidence of a substantive negative effect.

Among control variables, Firm Size (f_size) exhibits a positive and statistically significant relationship with green investment ($\beta = 0.0330$, $t = 2.61$, $p = .016$; FGLS $\beta = 0.0084$, $z = 2.97$, $p = .003$). Larger logistics enterprises possess larger capital budgets and face greater institutional exposure, enabling them to absorb the upfront capital costs of green transport setup (Appah, 2026). Financial Leverage (lev) shows no statistically significant impact ($\beta = 0.0002$, $t = 0.03$, $p = .978$), indicating that debt composition does not directly drive green capital allocation decisions in this setting.

4.4.4 Robustness: Endogeneity and Lagged Specification

As a temporal robustness check, one-year lagged specifications were estimated separately for HCE and SCE. The lagged sample contains 28 firm-year observations, representing four usable years for each of the seven firms. In the HCE-lag model, the coefficient is 0.0156 ($t = 1.42$, conventional $p = .168$; wild-cluster bootstrap $p = .293$). In the SCE-lag model, the coefficient is −0.0139 ($t = -1.71$, conventional $p = .099$; wild-cluster bootstrap $p = .157$). The lagged results therefore do not provide statistically strong evidence that prior-year HCE or SCE predicts subsequent green investment. Lagging improves temporal ordering but does not eliminate omitted-variable bias or establish causality.

Table 4

One-Year-Lagged Fixed-Effects Specifications

Variable	Lagged HCE FE	Lagged SCE FE
HCE(t−1)	0.0156 (1.42)	—
SCE(t−1)	—	−0.0139* (−1.71)
CEE(t−1)	−0.0572 (−1.19)	0.0468* (1.89)
Firm size(t−1)	0.0780*** (6.90)	0.0598*** (4.59)
Leverage(t−1)	−0.0164* (−1.98)	−0.0047 (−0.49)
Firm fixed effects	Yes	Yes
Observations	28	28
Residual df	17	17

Notes: 28 observations remain because the first year of each of the seven firms has no prior-year value. Conventional t-statistics are in parentheses. Wild-cluster bootstrap p-values are .293 for lagged HCE and .157 for lagged SCE.

Several limitations qualify the empirical interpretation. First, the balanced panel contains seven firms over five years (35 observations). The revised HCE-only and SCE-only FE models contain four slope regressors and firm fixed effects, leaving 24 residual degrees of freedom; the lagged models contain 28 observations and leave 17 residual degrees of freedom after accounting for four slope regressors and firm effects. These small degrees of freedom constrain statistical power. Second, conventional cluster-robust inference is unreliable with only seven clusters, so wild-cluster bootstrap p-values are reported for the principal HCE and SCE coefficients. Third, HCE and SCE are algebraically dependent under VAIC and are therefore estimated separately. Fourth, the lagged models do not resolve omitted-variable bias or reverse causality. The findings should accordingly be interpreted as sample-specific associations rather than causal estimates.

CHAPTER 5: CONCLUSION AND IMPLICATIONS

5.1 Summary of Findings

This study evaluated the impact of intellectual capital efficiency on physical green capital investments across listed Nigerian logistics companies from 2020 to 2024. Utilizing revised separate Fixed Effects panel specifications, the findings indicate that human capital efficiency displays a positive within-firm association with corporate green investment ($\beta = 0.0206$), though wild-cluster bootstrap inference indicates this relationship is suggestive rather than definitive. In contrast, structural capital efficiency exhibits no statistically significant independent relationship with green investment outlays

($\beta = -0.0114$) once separated from its algebraic dependency on HCE.**5.2 Theoretical and Managerial Implications**

The results suggest that the relationship between accounting-based intellectual-capital efficiency and green investment may not be uniform across VAIC components. The positive HCE association is consistent with the argument that workforce capability can support the evaluation and implementation of green investments. The SCE result, however, should not be presented as proof of a distinct structural-capital friction because of its algebraic dependence on HCE. The evidence is therefore better viewed as exploratory and specific to the observed listed logistics firms.

Managerial Strategy: Logistics executives must avoid treating intellectual capital as a monolithic asset. While investments in human technical expertise directly enhance decarbonization capabilities, expanding overhead can crowd out physical capital outlays required for green fleet modernization.

Actionable Policy and Institutional Directives:

For Chief Financial Officers (CFOs): Ring-fence green capital budgets from generic IT and overhead lines to prevent SCE-driven capital diversion.

For Transport Fleet Managers: Tie human capital training expenditures directly to alternative-fuel certifications and telematics optimization rather than static process mapping.

For Financial Regulators (SEC Nigeria / NGX): Mandate standardized, balance-sheet-level reporting of direct physical environmental CapEx to eliminate subjective corporate sustainability greenwashing.

Managerial implications should be stated without fixed numerical thresholds. The results suggest that logistics firms may benefit from strengthening workforce capability relevant to fleet modernization, environmental compliance, data use, and operational redesign. However, the estimates do not justify a universal HCE or SCE cutoff for investment decisions. Managers should therefore treat the reported coefficients as evidence for attention to human-capital capability, not as a mechanical investment rule.

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