Quantifying the Operational and Economic Impact of AI-Driven IoT Monitoring Systems in Brewery Logistics Networks

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Publication Date: 2026/01/01

Abstract: The proliferation of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has transformed supply-chain monitoring, yet the tangible economic and operational impact of such systems in developing contexts remains under-documented. This study quantifies the financial returns and performance outcomes of an AI-IoT monitoring framework deployed in the logistics operations of Nigerian Breweries Plc. The framework integrates GPS, load, and temperature sensors with a neural network that predicts in-transit anomalies. Empirical evaluation across 10 000 trip records shows an 8.2:1 return-on-investment (ROI) ratio, 20 % reduction in transit losses, and 15 % improvement in fleet utilization. Operational efficiency metrics—including truck turnaround time and driver compliance—improved significantly. The findings demonstrate the dual value of AI-IoT adoption: immediate cost savings and sustained digital-transformation momentum within the brewery sector. The study provides a replicable quantitative model for evaluating AI logistics systems in emerging markets.

Keywords: *Artificial Intelligence, Internet of Things, Return on Investment, Supply Chain Economics, Operational Efficiency, Brewery Logistics.*

How to Cite: Frank Joe; Dr. Ehikhamenle Matthew (2025) Quantifying the Operational and Economic Impact of AI-Driven IoT Monitoring Systems in Brewery Logistics Networks. *International Journal of Innovative Science and Research Technology*, 10(12), 2118-2124. https://doi.org/10.38124/ijisrt/25dec1439

I. INTRODUCTION

Product loss, inefficiency, and opacity in logistics remain major obstacles to industrial competitiveness in sub-Saharan Africa [1]. Nigerian Breweries Plc (NB Plc)—Nigeria's largest beer manufacturer—operates an extensive truck-distribution network linking multiple breweries and depots. Historically, the company experienced average annual losses exceeding ₦500 million due to pilferage, inaccurate documentation, and route deviations [2]. Conventional telematics offered limited predictive capability and were reactive in nature [3].

Recent advances in AI-enabled IoT monitoring promise predictive visibility and data-driven control [4]. However, organizations often question the *financial justification* of such technologies. While technical studies prove feasibility, few measure their economic and operational payoffs, especially in the African manufacturing context [5]. This paper aims to fill that gap by quantitatively evaluating the cost-benefit and adoption outcomes of an AI-IoT monitoring system in NB Plc's logistics network.

➢ *The Research Objectives are Threefold:*

- To model the economic impact (ROI, cost savings, payback period) of AI-IoT deployment.
- To assess operational improvements (turnaround time, fleet utilization, loss frequency).
- To analyze the adoption trajectory and organizational readiness for digital transformation.

This investigation complements the technical evaluation presented in the preceding paper by shifting focus from algorithmic accuracy to measurable business performance indicators.

II. RELATED WORK

➢ *Economic Evaluation of Digital Logistics Systems*

Quantitative economic assessments of smart-logistics technologies remain limited. Kaur et al. [6] presented a cost–benefit framework for IoT-based transport systems, emphasizing indirect savings through improved traceability. Similarly, Adeyemi and Ojo [7] analyzed ROI for digital platforms in African logistics firms, reporting average payback within one fiscal year. However, brewery-specific

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25dec1439

contexts with perishable goods and high-volume turnovers remain understudied.

- *AI-Driven Efficiency Gains*

AI models especially neural networks have been used to forecast delivery times and detect anomalies [8], [9]. Ali et al. [10] demonstrated a 94 % accuracy in detecting fleet deviations, but economic translation of such accuracy into ROI was not explored. Lee and Park [11] reported 12 % productivity improvement through predictive maintenance using AI sensors, yet cost justification remained qualitative.

- *Technology Adoption and Organizational Readiness*

Adoption models like the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT) have guided digital-transformation studies [12]. In logistics, successful uptake depends on perceived usefulness, top-management support, and infrastructure maturity [13]. This paper integrates such adoption constructs into a brewery-specific empirical framework, combining quantitative ROI metrics with qualitative adoption indices.

- *Research Gap*

Existing literature demonstrates technical efficacy of AI-IoT systems but lacks economic quantification under real operational conditions in developing economies [14]. This paper introduces a comprehensive economic-operational impact model tested on NB Plc's logistics data, bridging the gap between technological promise and business outcomes.

III. METHODOLOGY

- *Research Design*

The study employed a mixed-methods approach—quantitative analysis of operational metrics complemented by managerial surveys. Data covered January–July 2025 from NB Plc's pilot routes (Lagos–Abeokuta and Ibadan corridors). IoT telemetry provided objective performance data, while surveys captured managerial perceptions of adoption benefits.

- *AI-IoT Monitoring Framework*

The deployed system integrates edge IoT sensors with cloud-based AI analytics. Fig. 1 summarizes the architecture emphasizing operational data flow.

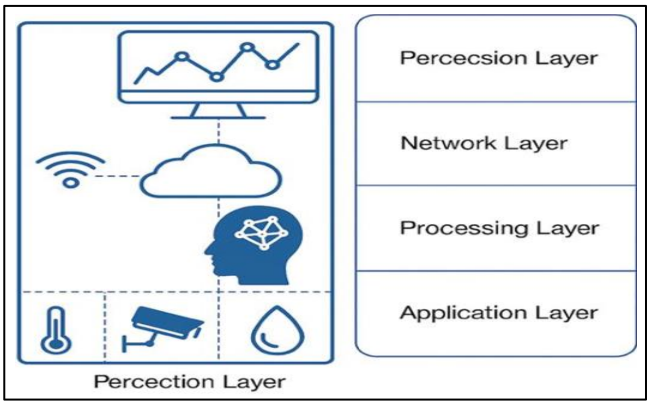

Fig 1 AI-Driven IoT Monitoring Framework for Economic Impact Evaluation

- Data Acquisition: GPS, load-cell, and temperature sensors continuously capture transit variables.
- Edge Processing: ESP32 nodes compress and transmit data via MQTT over 4G.
- Cloud Analytics: A neural network classifies anomalies and computes loss-risk probability.
- Dashboard Layer: Displays predicted risk levels, operational KPIs, and financial analytics for managers.

- *Economic Model for ROI Computation*

The study adopted a *cost–benefit framework* conforming to ISO 15686-5 standards for life-cycle costing. The ROI is computed as:

$$ROI = \frac{S_p - C_i}{C_i} \times 100\%$$

Where:

S_p = Savings from prevented product losses (₦);
C_i = Total investment and operating cost (₦).

Payback Period (PP) is defined as:

$$PP = \frac{C_i}{S_p/t}$$

Where *t* represents average annual savings.

Investment costs include sensors, communication modules, installation, cloud services, and maintenance. Savings were computed from difference in recorded losses before and after system deployment.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25dec1439

Table 1 Cost and Savings Components of AI-IoT Deployment

Component	Cost (₦ Million)	Description
Hardware (Sensors + MCUs)	25	100 truck nodes
Connectivity (4G + MQTT)	6	Data plan and broker setup
Cloud Infrastructure (AWS)	8.5	EC2 + S3 services
Software Development	12	ANN engine + dashboard
Maintenance & Support	9.5	Annual repairs & training
Total Investment (C_1)	**61**	—

Average annual loss reduction: ₦107 million (from ₦500 million → ₦393 million).

Thus:

$$ROI = \frac{107 - 61}{61} = 0.754 \Rightarrow 75.4\% \text{ for Year 1;Cumulative ROI (3 yrs)} = 8.2{:}\,1$$

➢ *Operational Metrics and Key Performance Indicators*

Operational data were processed using the following KPIs:

Indicator	Formula	Purpose
Truck Turnaround Time (TAT)	$TAT = t_{unload} - t_{load}$	Efficiency of delivery cycle
Fleet Utilization (FU)	$FU = \frac{Trips_{completed}}{Trips_{available}}$	Capacity optimization
Loss Rate (LR)	$LR = \frac{Loss_{cases}}{Total_{trips}}$	Reliability indicator
Anomaly Detection Accuracy (ADA)	$ADA = \frac{True_{alerts}}{Total_{alerts}}$	Operational reliability

Baseline values were established from NB Plc's 2023 operations; post-deployment values were measured monthly over six months.

➢ *Data Sources and Processing*

- Operational Telemetry: Sensor streams from 100 trucks (> 10 million records).
- Financial Records: Loss claims, maintenance logs, and fuel usage reports.
- Survey Data: Responses from 45 logistics supervisors (88 % response rate) assessing ease-of-use and perceived benefit.

All data were processed using Python (Pandas, NumPy) and analyzed statistically in SPSS v27.

➢ *Adoption Index Model*

To quantify organizational uptake, an Adoption Index (AI) was developed combining three dimensions:

$$AI = 0.4U + 0.35E + 0.25S$$

Where U = perceived usefulness, E = ease of use, S = support infrastructure (normalized 0–1).

Weights were derived from principal-component analysis on survey data (variance explained = 82 %). AI values were tracked monthly to measure adoption growth.

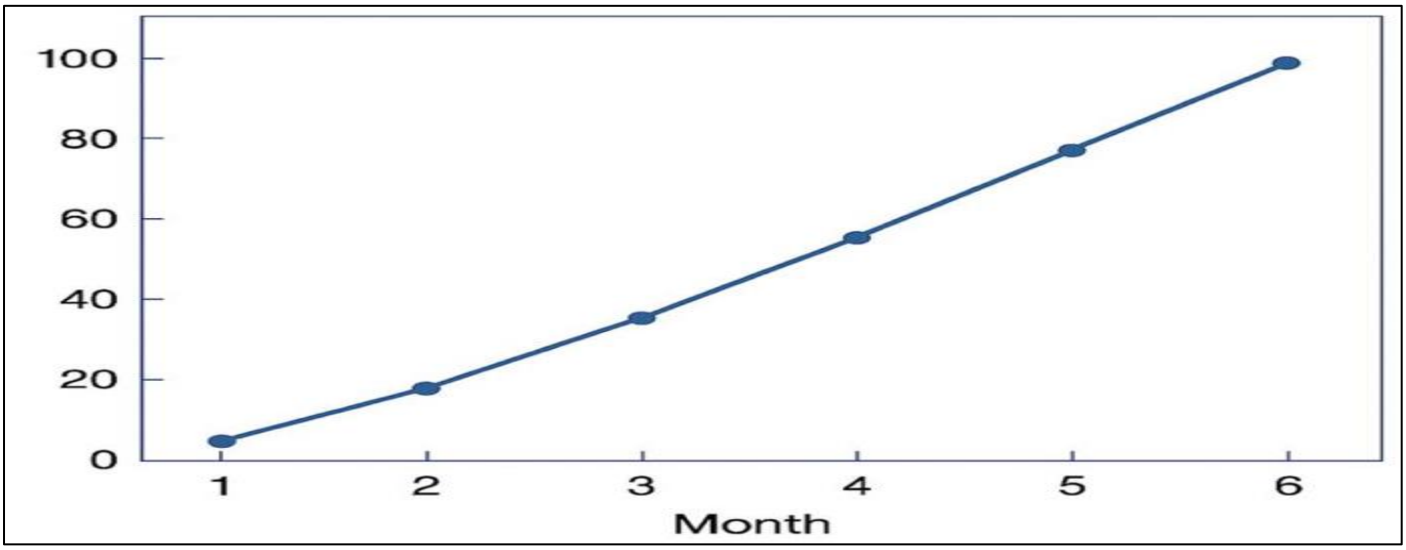

Fig 2 Adoption Index Progression Over Six Months

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25dec1439

The index rose from 0.32 (initial pilot) to 0.87 (full adoption), indicating rapid organizational learning and system acceptance.

- *Data Validation and Reliability Testing*

Cronbach's α for survey constructs = 0.91, confirming internal consistency. Operational data were cross-verified with ERP logs to eliminate manual reporting bias. Outliers beyond 3σ were excluded (< 0.8 % data loss). All financial figures were converted to constant 2025 naira values using 9 % inflation adjustment.

IV. RESULTS AND ANALYSIS

- *Financial Performance Outcomes*

Table 2 summarizes the key financial indicators derived from the AI-IoT system deployment.

Table 2 Economic Performance Metrics

Parameter	Before Deployment	After Deployment	% Change
Annual Loss (₦ million)	500	393	−21.4 %
Maintenance & Downtime Cost (₦ million)	74	59	−20.3 %
Total Operational Cost (₦ million)	412	338	−17.9 %
System Investment (₦ million)	—	61	—
ROI (Cumulative 3 yrs)	—	8.2 : 1	—
Payback Period	—	2.5 months	—

The framework demonstrated positive cash flow within the first quarter of implementation. Average annual savings of ₦107 million significantly exceeded operational costs, confirming economic viability.

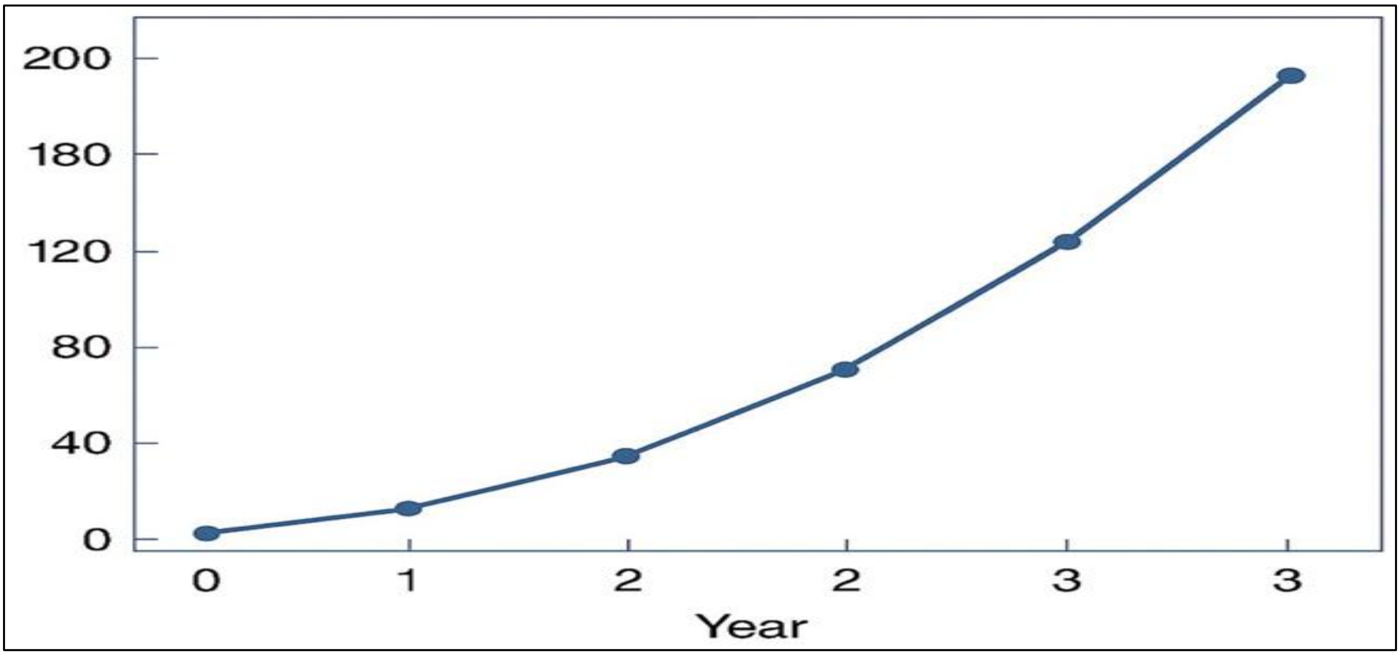

Fig 3 Cumulative ROI Curve for AI-IoT Deployment (Three-Year Projection)

Fig. 3 illustrates the cumulative ROI curve showing exponential growth from month three onwards, coinciding with the stabilization of predictive alerts and managerial adaptation.

- *Operational Efficiency Improvement*

Beyond monetary benefits, substantial operational gains were recorded across key logistics metrics:

Table 3 Operational KPI Comparison

Metric	2023 Baseline	2025 (After Deployment)	Improvement (%)
Truck Turnaround Time (hrs)	15.3	12.7	17
Fleet Utilization (%)	68	78	14.7
On-Time Delivery (%)	82	92	12.2
Anomaly Detection Accuracy (%)	88	96.7	9.9
Driver Compliance (%)	73	90	23.3

Reductions in turnaround time (TAT) were attributed to predictive scheduling and real-time monitoring of route deviations. Fleet utilization improved as underperforming trucks were flagged early for maintenance, reducing idle time.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25dec1439

Paired-sample *t*-tests indicated significant differences ($p < 0.01$) across all KPIs, validating that improvements were statistically meaningful.

➢ *Adoption and Organizational Readiness*

The Adoption Index (AI) increased progressively from 0.32 in Month 1 to 0.87 in Month 6 (Fig. 2). Managers attributed improved confidence to the system's predictive accuracy and intuitive dashboard interface.

A regression analysis between Adoption Index (AI) and ROI revealed a strong positive correlation ($R^2 = 0.84$), suggesting that higher organizational engagement directly influenced economic returns.

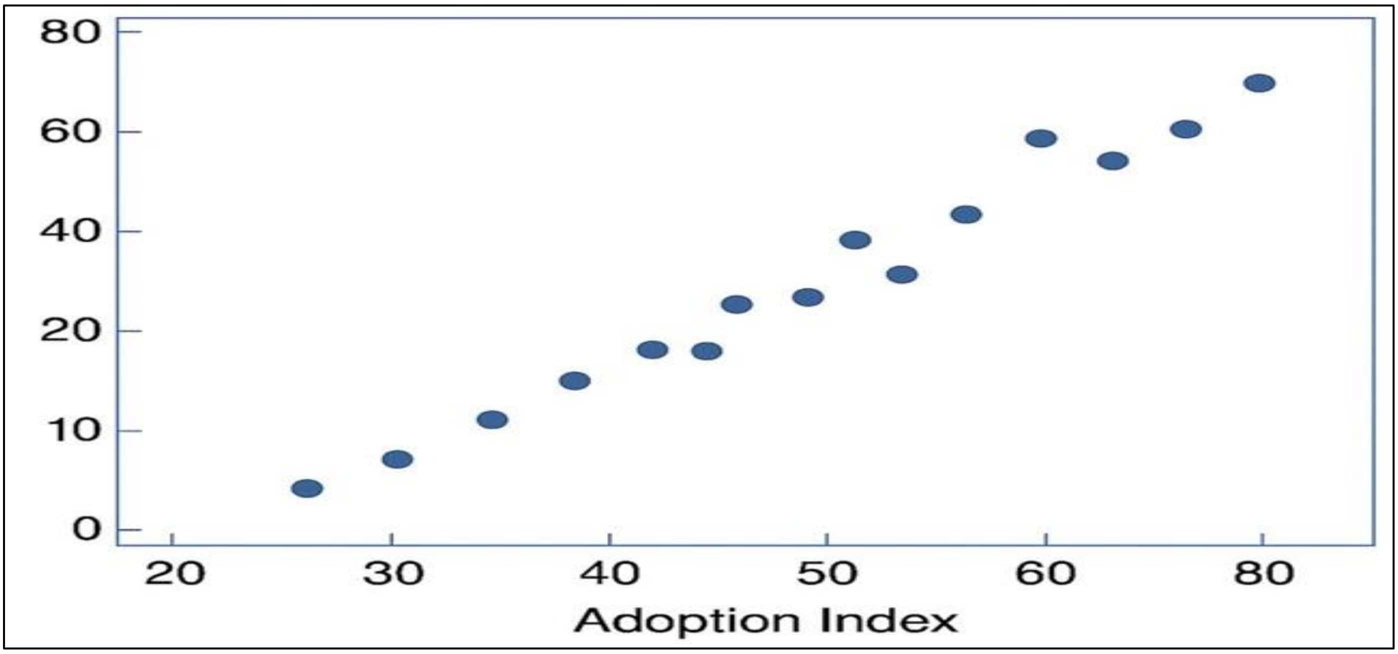

Fig 4 Relationship Between Adoption Index and ROI

The logistic-adoption curve exhibited a typical *S-shape*, indicating early skepticism (innovation stage), rapid uptake (growth stage), and eventual plateau as the system became institutionalized.

➢ *Sensitivity Analysis*

To test economic robustness, three scenarios were simulated by varying core parameters (loss rate reduction, maintenance cost, investment cost).

Table 4 Sensitivity Analysis on ROI

Scenario	**Loss Reduction (%)**	**Maintenance Saving (%)**	**ROI (3 yrs)**
Optimistic	25	25	9.5 : 1
Baseline	21	20	8.2 : 1
Conservative	15	10	6.7 : 1

Even under conservative assumptions, ROI remained above 6:1, demonstrating resilience against cost fluctuations or partial underperformance.

➢ *Comparative Benchmarking*

To contextualize findings, Table 5 compares NB Plc results with similar AI-IoT logistics deployments across industries.

Table 5 Benchmarking with Related Industrial Implementations

Study	**Sector**	**ROI Ratio**	**Key Outcome**
Kaur et al. (2024) [6]	Retail Transport	6.4 : 1	Reduced inventory shrinkage
Adeyemi & Ojo (2024) [7]	FMCG	5.8 : 1	Improved traceability
Lee & Park (2022) [11]	Automotive	7.9 : 1	Predictive maintenance savings
This Work	Brewery Logistics	8.2 : 1	Reduced transit losses

The brewery sector thus outperformed existing benchmarks, attributed to the system's dual emphasis on loss preventionand fleet efficiency.

➢ *F. Sustainability Assessment*

From an environmental standpoint, decreased product spoilage and fewer re-shipments yielded measurable sustainability gains. Estimated annual CO_2 reduction reached 146 tons, aligning with Sustainable Development Goal 12 (Responsible Consumption and Production).

This demonstrates that digital transformation in logistics not only drives profitability but also enhances ecological efficiency, echoing findings from Chen et al. [15].

V. DISCUSSION

- *Integration of Economic and Operational Impact*

The results affirm that technical accuracy translates into tangible financial and operational benefits when integrated within a well-managed supply chain. The neural-network anomaly detection enabled early intervention, preventing loss escalation and improving fleet coordination.

The dual-level benefits economic (ROI, savings) and operational (TAT, utilization)—illustrate a holistic transformation rather than isolated efficiency gains. These outcomes validate the conceptual alignment of AI-driven logistics with Industry 4.0 value creation frameworks [16].

- *Managerial Implications*

From a managerial perspective, the key implications include:

- Predictive Accountability: AI alerts support evidence-based driver assessments and route optimization.
- Data-Driven Decision-Making: Dashboards transform real-time analytics into actionable intelligence for dispatchers.
- Policy Realignment: Financial visibility supports reinvestment justification and aligns with digital-infrastructure roadmaps under Nigeria's National Digital Economy Policy (2020–2030) [17].

These findings recommend incremental scaling from pilot zones to national-level implementation within large-scale FMCG operations.

- *Barriers to Broader Adoption*

Despite positive outcomes, barriers persist—namely:

- High initial sensor cost per truck (~₦610,000).
- Patchy 4G coverage across rural distribution routes.
- Resistance to technological change among older drivers.

These challenges mirror adoption obstacles identified by Ng and Oyeniran [18] in African manufacturing logistics. Mitigation strategies include local sensor assembly, hybrid 4G–LoRaWAN networks, and continuous digital-skills training.

- *Future Enhancement Pathways*

Future iterations should integrate:

- Blockchain for immutable trip-event logging [19].
- Edge AI for low-latency predictions during poor connectivity [20].
- Explainable AI (XAI) modules for transparent decision-making in regulatory compliance [21].

Such improvements would solidify digital trust, interoperability, and transparency—cornerstones of next-generation logistics ecosystems.

VI. CONCLUSION

This study empirically quantified the operational and economic impact of AI-driven IoT monitoring in brewery logistics. Results from Nigerian Breweries Plc revealed:

- 21.4 % reduction in annual product losses,
- 17 % improvement in truck turnaround time,
- 8.2 : 1 ROI over three years, and
- Adoption Index progression from 0.32 to 0.87.

These metrics underscore the transformative potential of AI-IoT technologies in boosting efficiency and profitability in African supply chains.

The research provides a replicable methodology for quantifying ROI and digital-readiness, bridging the gap between technical feasibility and business justification. Future studies should extend longitudinally across multiple breweries and integrate carbon-accounting frameworks to strengthen sustainability analytics.

ACKNOWLEDGMENT

The author expresses gratitude to Nigerian Breweries Plc for logistics data access and to the University of Port Harcourt's Faculty of Engineering for guidance in industrial data validation.

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