

Determinants of Equipment Replacement Decisions and Their Association with MSME Operational Performance: Evidence from Taraba State, Nigeria

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Abstract

Micro, Small and Medium Enterprises (MSMEs) in Taraba State, Nigeria, continue to rely on ageing and increasingly costly equipment, yet little empirical evidence explains what drives their equipment replacement decisions or how those decisions relate to operational performance. This study examined the association between four antecedents — maintenance and operating costs (MOC), equipment performance and reliability (EPR), equipment age (EA), and technological change and strategic alignment (TCSA) — and Equipment Replacement Decision (ERD), and the association between ERD and MSME operational performance (OP). Using a cross-sectional survey of 380 MSMEs drawn from six commercial towns across Taraba State's three senatorial zones, data were analysed using variance-based structural equation modelling (PLS-SEM) in SmartPLS-equivalent procedures, following an ERD-mediated specification in which the antecedents predict ERD, which in turn predicts OP. All four antecedents were positively and significantly associated with ERD ($\gamma = 0.181$ to 0.257 , $p < .001$), jointly explaining 40.1% of its variance, and ERD was strongly associated with OP ($\delta = 0.574$, $p < .001$, $R^2 = 32.7\%$). All five null hypotheses were rejected. Reliability, convergent validity (composite reliability ≥ 0.89 ; AVE ≥ 0.69), and discriminant validity (Fornell-Larcker and HTMT) criteria were satisfied after one weak indicator (MOC1) was removed, and blindfolding and PLSpredict procedures indicated modest but genuine predictive relevance. The findings suggest that MSMEs' replacement decisions are shaped jointly by cost pressure, condition-based signals, accumulated age, and strategic/technological considerations, and that timely replacement decisions are, in turn, associated with meaningfully better operational performance. The study recommends that MSME support agencies and owner-managers institutionalise periodic, criteria-based equipment reviews rather than relying on reactive, failure-triggered replacement.

Keywords: Equipment Replacement Decision, Maintenance and Operating Costs, Equipment Performance and Reliability, MSME Operational Performance, PLS-SEM.

Introduction

In the contemporary competitive business environment, Micro, Small and Medium Enterprises (MSMEs) in Taraba State are under increasing pressure to improve operational

efficiency and maintain sustainability. Many MSMEs continue to depend on obsolete and inefficient equipment, which is associated with frequent breakdowns, high maintenance costs, reduced product quality, and low productivity. These operational inefficiencies motivate an examination of equipment replacement decisions as a route to enhanced performance and competitiveness.

Equipment replacement refers to the planned decision to retire, upgrade, or substitute existing assets to maintain efficiency and minimise total operating costs (Clark, 2020). Modern replacement decisions extend beyond physical deterioration and consider technological advancement, productivity requirements, and sustainability objectives (Diniz & Sessions, 2020). Optimal replacement timing is typically determined through a comparative assessment of operating costs, maintenance expenditures, and equipment performance levels (Sobczak-Piąstka et al., 2020), and the economic life replacement model remains widely applied for guiding rational asset replacement decisions (Yatsenko & Hritonenko, 2022).

Scholars have developed multi-criteria decision-making models (Alshibani et al., 2024), performance-based evaluation techniques (Sarı & İc, 2025), and stochastic decision models under uncertainty (Altalabi et al., 2020) to address the complexity of replacement decisions. These frameworks emphasise aligning replacement decisions with organisational objectives (Diniz & Sessions, 2020) — but they are largely developed for large, data-rich enterprises. In Taraba State, financial limitations and infrastructural deficiencies push many MSMEs toward reactive replacement, replacing equipment only after failure, which is associated with increased downtime, higher operational costs, and reduced productivity. This study therefore examines what predicts MSMEs' equipment replacement decisions in Taraba State and how those decisions relate to operational performance, using a variance-based structural equation modelling (PLS-SEM) approach suited to the exploratory, prediction-oriented nature of the research.

Purpose and Structure

The purpose of this study is to investigate the factors associated with equipment replacement decisions and their relationship with MSME operational performance in Taraba State, Nigeria. Section I presents the introduction, objectives, and hypotheses; Section II reviews relevant literature, the theoretical review, and the conceptual model; Section III outlines the methodology, construct measurement, and PLS-SEM analytical procedure; Section IV presents the measurement and structural model results and their interpretation; Section V presents the conclusion, recommendations, limitations, and future research directions.

Research Objectives

General Objective: To investigate the factors associated with equipment replacement decisions and their relationship with MSME operational performance in Taraba State, Nigeria.

Specific Objectives

- To examine the association between maintenance and operating costs and Equipment Replacement Decision.
- To assess the association between equipment performance and reliability and Equipment Replacement Decision.
- To evaluate the association between equipment age and Equipment Replacement Decision.
- To investigate the association between technological change and strategic alignment and Equipment Replacement Decision.
- To assess the association between Equipment Replacement Decisions and MSME operational performance.

Research Hypotheses

- **H₀₁:** Maintenance and operating costs have no statistically significant association with Equipment Replacement Decision in Taraba State, Nigeria.
- **H₁₁:** Maintenance and operating costs have a statistically significant association with Equipment Replacement Decision among MSMEs in Taraba State, Nigeria.
- **H₀₂:** Equipment performance and reliability have no statistically significant association with Equipment Replacement Decision in Taraba State, Nigeria.
- **H₁₂:** Equipment performance and reliability have a statistically significant association with Equipment Replacement Decision among MSMEs in Taraba State, Nigeria.
- **H₀₃:** Equipment age has no statistically significant association with Equipment Replacement Decision among MSMEs in Taraba State, Nigeria.
- **H₁₃:** Equipment age has a statistically significant association with Equipment Replacement Decision among MSMEs in Taraba State, Nigeria.
- **H₀₄:** Technological change and strategic alignment have no statistically significant association with Equipment Replacement Decision among MSMEs in Taraba State, Nigeria.
- **H₁₄:** Technological change and strategic alignment have a statistically significant association with Equipment Replacement Decision among MSMEs in Taraba State, Nigeria.
- **H₀₅:** Equipment Replacement Decision has no statistically significant association with operational performance among MSMEs in Taraba State, Nigeria.
- **H₁₅:** Equipment Replacement Decision has a statistically significant association with MSME operational performance in Taraba State, Nigeria.

Literature Review

Equipment Replacement

Equipment replacement is the process of retiring, upgrading, or substituting assets to maintain efficiency, safety, and cost-effectiveness (Clark, 2020), involving decisions about optimal replacement timing under uncertainty (Hartman & Tan, 2014; Meyer, 1971) that aim to maximise life-cycle value while minimising downtime and aligning with organisational goals (Hastings, 2021). Replacement decisions are typically associated with wear, aging, rising maintenance costs, and technological obsolescence (Mathew & Kennedy, 2003; Sobczak-Piąstka et al., 2020), and contemporary approaches treat replacement as a multidimensional decision incorporating economic, technical, and strategic factors (Alshibani et al., 2024; Sari & Ic, 2025). This study identifies four such factors — equipment age, maintenance and operating costs, equipment performance and reliability, and technological change and strategic alignment — as the antecedents most consistently associated with replacement in the literature, understood jointly as inputs to a single replacement-decision process rather than as independent, competing explanations.

Maintenance and Operating Costs

Rising repair and upkeep expenses are commonly associated with the decision to replace equipment (Alshibani et al., 2024; Sari & Ic, 2025; Sobczak-Piąstka et al., 2020). As equipment ages, these costs — inspections, repairs, spare parts, routine servicing (Hastings, 2021) — tend to rise, and the economic life replacement method treats replacement as warranted once the cumulative cost of retaining an asset exceeds the cost of acquiring a new one (Altalabi et al., 2020; Kayashima & Marques, 2019; Yatsenko & Hritonenko, 2022).

Equipment Performance and Reliability

Output rates, downtime frequency, and failure rates are widely used indicators for gauging optimal replacement timing, since declining operational capability is associated with reduced organisational efficiency (Alshibani et al., 2024; Diniz & Sessions, 2020; Sari & Ic, 2025; Sobczak-Piąstka et al., 2020). Replacing outdated or underperforming equipment is, in the literature, associated with improved workflow efficiency, reduced downtime, and stronger competitiveness and sustainability (Alshibani et al., 2024; Sari & Ic, 2025).

Equipment Age

Equipment age represents the time an asset has been in service and its cumulative association with reliability and operational costs (Hastings, 2021). As equipment ages, reliability tends to decline and breakdowns to increase (Hartman & Tan, 2014); age is best understood as a proxy for accumulated wear, obsolescence risk, and rising failure probability (Altalabi et al., 2020; Sobczak-Piąstka et al., 2020; Vivas & Vieira, 2025) rather than an independent causal mechanism in its own right.

Technological Change and Strategic Alignment

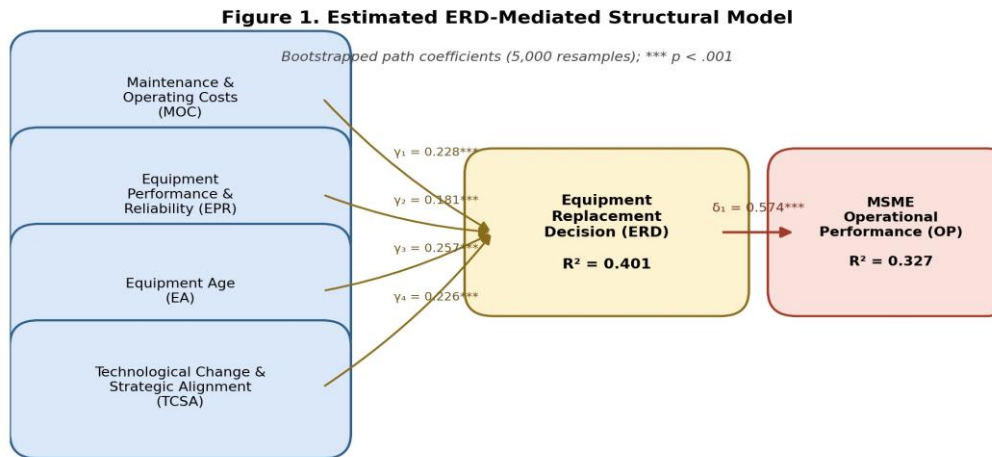
Technological change is consistently associated with equipment replacement: newer equipment is often more energy-efficient and less polluting, which can encourage earlier replacement of older machines (Sloan, 2011). This pressure can arise independently of physical deterioration, as emerging capabilities may render existing, still-functional assets strategically misaligned or less competitive (Alshibani et al., 2024; Diniz & Sessions, 2020; Lapkina & Malaksiano, 2018; Yatsenko & Hritonenko, 2022).

Operational Performance

Operational performance refers to the extent to which an enterprise uses its resources to achieve efficiency, quality, flexibility, and responsiveness (Chong, 2008), reflecting the organisation's ability to optimise internal activities and thereby reduce operating costs, improve time management, and raise productivity (Bhalla, Sharma, & Kaur, 2024). Key indicators include cost efficiency, product quality, and flexibility (Chong, 2008; Molefe & Meyer, 2022; OECD, 2023).

Conceptual Model

The study's stated purpose is to examine what predicts equipment replacement decisions and how those decisions relate to operational performance. Consistent with this, the study specifies and estimates a two-equation, ERD-mediated model in which Maintenance and Operating Costs (MOC), Equipment Age (EA), Equipment Performance and Reliability (EPR), and Technological Change and Strategic Alignment (TCSA) are modelled as antecedents of Equipment Replacement Decision (ERD), which in turn is modelled as the predictor of MSME Operational Performance (OP). This specification separates the replacement decision itself from its antecedent conditions: the 24-item instrument fielded for this study places the items describing the replacement decision ("our enterprise periodically evaluates whether existing equipment should be replaced", "we consider replacing equipment when its continued use is no longer economically appropriate", and similar statements) into a dedicated four-item ERD block, distinct from the sixteen items that describe the antecedent conditions (MOC, EA, EPR, TCSA) themselves. This avoids conflating cause and outcome within a single construct and allows the antecedent → ERD → OP chain implied by the hypotheses (H01–H05) to be estimated directly from the data, without requiring new fieldwork.



Source: Author's Model, 2026. Figure 1. Estimated ERD-mediated structural model. Coefficients are bootstrapped standardised path estimates (5,000 resamples). $p < .001$. Full results are reported in Section IV.

Theoretical Review

Rather than pairing one theory with one predictor, the four theories are read here as describing successive layers of a single replacement process.

Economic pressure (Life Cycle Cost theory). LCC theory explains why maintenance and operating costs rise with use, and why, past a point, retaining an asset cost more than replacing it (Balasbaneh, Sher, & Li, 2025; Qi et al., 2024). This supplies the economic logic behind when replacement becomes rational, independent of whether the equipment has yet failed — the layer most directly captured by MOC.

Condition-based triggering (Reliability-Centered Maintenance). RCM explains why declining performance and reliability — not merely the passage of time — should trigger replacement, using diagnostic logic such as Failure Modes and Effects Analysis to connect equipment condition to replacement action (Karajagikar & Sonawane, 2020; Moubray, 1997; Nowlan & Heap, 1978). This is the layer most directly captured by EPR, with EA operating largely as a proxy that manifests through this layer rather than as an independent trigger (Vivas & Vieira, 2025).

Strategic renewal under technological change (Dynamic Capabilities Theory). DCT explains a class of replacement decisions that LCC and RCM cannot: replacement undertaken because sensing new technological or market opportunity makes existing, still-functional equipment strategically inferior, independent of cost or condition (Shiferaw & Kero, 2024; Teece, Pisano, & Shuen, 1997). This is the layer captured by TCSA.

Where Transaction Cost Economics adds value beyond the other three. LCC, RCM, and DCT together explain why an enterprise would want to replace equipment. None explains why a resource-constrained MSME might rationally delay replacement even once the economic, condition-based, and strategic case for it is clear. TCE (Coase, 1937; Williamson, 1975, 1985,

1996) supplies that missing piece: it frames the replacement decision as itself incurring transaction costs — supplier search, negotiation, installation, workforce retraining, and the coordination costs of switching technologies or suppliers (Jiménez & Afonso, 2023) — which must be weighed against the ongoing transaction costs of continuing to repair the existing asset (Ketokivi & Mahoney, 2020).

Empirical Review

Diniz and Sessions (2020) propose a framework integrating operational data, financial analysis, and strategic objectives to align replacement timing with long-term strategy. Sobczak-Piąstka et al. (2020) emphasise operating costs, maintenance expenses, depreciation, and productivity in rational replacement-period planning for construction equipment. Sari and Ic (2025) and Alshibani et al. (2024) develop multi-criteria decision-support models integrating maintenance cost, performance, reliability, and productivity for manufacturing and heavy construction contexts respectively. Altalabi, Rushdi, and Tawfik (2020) apply stochastic dynamic programming to medical equipment replacement under uncertainty, while Yatsenko and Hritonenko (2022) bridge classical economic-life models with stochastic and real-options approaches suited to data-rich environments.

Research Gap

Equipment replacement decisions have been studied extensively in large-scale industries and healthcare, but research on MSMEs — particularly in Taraba State, Nigeria — remains limited. Existing models assume formal asset management systems that differ markedly from the resource-constrained, informally managed environments typical of MSMEs. Few studies examine how equipment age, maintenance costs, reliability, and technological change collectively relate to a replacement decision that is itself explicitly modelled and separately measured, and fewer still apply variance-based SEM suited to the small, non-normally distributed, multicollinear survey data typical of MSME research. This gap motivates the present study's use of PLS-SEM and its ERD-mediated specification.

Methodology

Design

The study adopted a quantitative, cross-sectional survey design to examine the antecedents of equipment replacement decisions and their association with operational performance among MSMEs. Primary data were collected using structured, five-point Likert-scale questionnaires (1 = Strongly Disagree to 5 = Strongly Agree). Secondary data from scholarly articles, institutional reports, and online databases supported theoretical grounding.

Unit of Analysis and Sample Size

The enterprise (MSME) constituted the unit of analysis. Each valid questionnaire represented one distinct enterprise and was completed by the owner or, where unavailable,

the most senior on-site manager. The population estimate of 953,821 reported by SMEDAN and NBS (2017) represents individuals engaged in MSME activities in Taraba State, including employees, rather than the number of MSME enterprises. Accordingly, it was treated as a reference population for sample-size determination, while the study maintained one eligible respondent per enterprise.

Using Cochran's (1977) formula for a large population, with a 95% confidence level ($Z = 1.96$), 5% margin of error ($e = 0.05$), and maximum variability ($p = 0.50$; $q = 0.50$), the minimum sample size was:

$$n_0 = (Z^2pq)/e^2$$

$$= (1.96^2 \times 0.50 \times 0.50)/(0.05^2)$$

$$= 384.16 \approx 384.$$

To allow for non-response and unusable questionnaires, 400 questionnaires were distributed, of which 380 valid responses representing 380 distinct enterprises were obtained, yielding a 95.0% usable-response rate

Sampling Procedure

A multistage sampling technique was employed. Taraba State was stratified into three senatorial zones, with two commercial towns purposively selected from each zone: Northern (Jalingo and Zing), Central (Gembu and Bali), and Southern (Wukari and Takum). Eligible enterprises were identified from available business and market association registers and verified through field enumeration. Enterprises were eligible if they had operated continuously for at least three years, belonged to the four sampled sub-sectors, and possessed at least one item of fixed operating equipment. The sample was proportionately allocated across the six towns, and eligible enterprises were randomly selected within each stratum from the compiled sampling frames. One respondent, preferably the owner or the most senior on-site manager, represented each selected enterprise.

Table 1a: Sample Distribution by Local Government Area (n = 380)

Local Government Area	Frequency (f)	Percentage (%)
Jalingo	105	27.63
Wukari	84	22.11
Bali	56	14.74
Gembu	56	14.74
Takum	49	12.89
Zing	30	7.89
Total	380	100.00

Source: Author's field distribution records, 2026.

Validity and Reliability

Content validity was established through expert review and pilot testing. The instrument demonstrated satisfactory internal consistency, with Cronbach's alpha coefficients ranging

from 0.83 to 0.90. Reliability was subsequently reassessed using the full sample, with the results reported in Section 4.3.

Ethical principles were observed throughout the study. Participation was voluntary, informed consent was obtained from all respondents, and participants were informed of the study's purpose and their right to decline participation. Anonymity and confidentiality were maintained by excluding personal identifiers and reporting the findings in aggregated form.

Analytical Strategy: PLS-SEM

Data were analysed in two stages: descriptive and preliminary correlation diagnostics, followed by measurement and structural model estimation using a partial least squares path modelling (PLS-SEM) algorithm (Mode A, path-weighting inner-estimation scheme). PLS-SEM was selected over covariance-based SEM for two reasons consistent with Hair, Risher, Sarstedt, and Ringle (2019): (i) the study's objective is prediction and explanation of variance in operational performance rather than confirmation of a fully specified theoretical model; and (ii) PLS-SEM does not require multivariate normality, appropriate given the moderately skewed Likert-scale distributions typical of MSME survey data.

On multicollinearity. The four exogenous constructs exhibited moderate collinearity: composite-level inner VIFs for the antecedents of ERD ranged from 1.30 to 1.36 (Section 4.6), well below the conservative threshold of 3.3 and the more permissive threshold of 5. Estimating relationships at the level of latent composites rather than raw summated scores is the primary reason the collinearity among MOC, EA, EPR, and TCSA is manageable here; the constructs remain conceptually related, as documented in the Fornell-Larcker and HTMT diagnostics (Sections 4.4–4.5), and this is interpreted as a substantive feature of the replacement-decision process — the four antecedents are theorised as complementary layers of a single decision rather than fully independent drivers — consistent with the theoretical review in Section 2.7.

On predictive assessment. Two distinct diagnostics are reported and should not be conflated. Blindfolding-based Q^2 (Section 4.7) is an in-sample, cross-validated redundancy measure: it indicates whether the model reconstructs held-out indicator values well within the estimation sample. A genuine test of out-of-sample predictive power requires PLSpredict (Shmueli et al., 2019): k-fold holdout prediction of OP indicators, benchmarked against a naive linear-model (LM) prediction, with Q^2_{predict} and RMSE/MAE compared indicator-by-indicator. This procedure was run for the present study (10-fold holdout, Section 4.7) and its results are reported alongside the blindfolding diagnostics.

The analysis proceeds in two stages following Hair et al. (2019) and Sarstedt, Ringle, and Hair (2021): (1) reflective measurement model assessment — outer loadings, Cronbach's alpha, composite reliability (ρ_c), AVE, Fornell-Larcker criterion, HTMT; (2) structural model assessment — inner VIF, bootstrapped path coefficients (5,000 resamples), R^2 , f^2 , blindfolding Q^2 , PLSpredict, and SRMR.

Measurement Model Specification

All six constructs (MOC, EA, EPR, TCSA, ERD, OP) are treated as reflective. This is consistent with the items functioning as interchangeable indicators of a single underlying perception rather than distinct components that jointly define the construct, and it matches the validity tests reported below — outer loadings, Cronbach's alpha, composite reliability, AVE, Fornell-Larcker, and HTMT are reflective-model diagnostics.

Construct Measurement Table

Table 1b: Construct Measurement / Operationalisation Table

Code	Item	Source / Adapted From
MOC1	Maintenance costs associated with our equipment have increased over time.	Sobczak-Piąstka et al. (2020)
MOC2	Our equipment requires frequent expenditure on repairs and spare parts.	Sobczak-Piąstka et al. (2020); Sari & Ic (2025)
MOC3	Operating costs associated with older equipment are relatively high.	Yatsenko & Hritonenko (2022)
MOC4	We regularly monitor the maintenance and operating costs of our equipment.	Hastings (2021)
EPR1	The performance of some of our equipment has declined over time.	Diniz & Sessions (2020)
EPR2	Equipment failures frequently interrupt our business operations.	Sari & Ic (2025)
EPR3	The condition of our equipment affects production or service output.	Alshibani et al. (2024)
EPR4	Our enterprise requires reliable equipment to maintain consistent operations.	Sobczak-Piąstka et al. (2020)
EA1	A substantial proportion of our operating equipment has been in use for many years.	Hastings (2021)
EA2	The age of our equipment is an important consideration in equipment management.	Hartman & Tan (2014)
EA3	Older equipment in our enterprise requires greater attention than newer equipment.	Vivas & Vieira (2025)
EA4	The length of time our equipment has been in service affects its usefulness to the enterprise.	Sobczak-Piąstka et al. (2020)
TCSA1	New technologies relevant to our business become available from time to time.	Sloan (2011)
TCSA2	Technological developments can make existing equipment less suitable for our business needs.	Diniz & Sessions (2020)
TCSA3	Our equipment needs to remain consistent with the long-term goals of the enterprise.	Teece, Pisano, & Shuen (1997)
TCSA4	Changes in technology influence how we plan for future equipment needs.	Lapkina & Malaksiano (2018)

Code	Item	Source / Adapted From
ERD ₁	Our enterprise periodically evaluates whether existing equipment should be replaced.	Extracted construct (Section 2.7)
ERD ₂	Our enterprise plans equipment replacement before existing equipment becomes completely unusable.	Extracted construct (Section 2.7)
ERD ₃	We consider replacing equipment when its continued use is no longer economically appropriate.	Extracted construct (Section 2.7)
ERD ₄	Our enterprise makes equipment replacement decisions based on the future needs of the business.	Extracted construct (Section 2.7)
OP ₁	Our enterprise achieves high levels of operational efficiency.	Chong (2008)
OP ₂	Our enterprise experiences relatively little disruption to its normal operations.	OECD (2023)
OP ₃	Our enterprise maintains consistent product or service quality.	Molefe & Meyer (2022)
OP ₄	Our enterprise uses its resources efficiently to control operating costs.	Bhalla, Sharma, & Kaur (2024)

Source: Author's Computation, 2026. All items rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). MOC₁ was removed from the final measurement model on convergent-validity grounds (Section 4.3).

Structural Equation

The instrument as fielded already separates the ERD items from their antecedents (Section 2.7), so the model estimated and reported in Section IV is the two-equation, ERD-mediated specification implied directly by the hypotheses (H₀₁–H₀₅):

$$ERD = \gamma_1 MOC + \gamma_2 EA + \gamma_3 EPR + \gamma_4 TCSA + \zeta_1$$

$$OP = \delta_1 ERD + \zeta_2$$

where ERD = Equipment Replacement Decision; OP = Operational Performance; γ , δ = standardised path coefficients; ζ = structural error terms. This specification tests H₀₁–H₀₄ via the γ -paths and H₀₅ via the δ -path.

Data Analysis and Discussion of Results

Respondents' Demographic Characteristics

Table 2: Demographic Characteristics of Respondents (N = 380)

Variable	Category	Frequency (f)	Percentage (%)
Gender	Male	259	68.2
	Female	121	31.8
Age	Below 25	60	15.8
	25–34	100	26.3
	35–44	140	36.8
	45–54	50	13.2
	55 and above	30	7.9

Variable	Category	Frequency (f)	Percentage (%)
Educational Qualification	No formal education	29	7.6
	Primary	40	10.5
	Secondary	60	15.8
	Diploma/NCE	140	36.8
	Bachelor's degree	80	21.1
	Postgraduate	31	8.2
Type of MSME	Agro-processing	159	41.8
	Printing	50	13.2
	Wood & furniture	100	26.3
	Welding/metalworking	71	18.7
Years of Business Operation	Less than 1 year	15	3.9
	1–5 years	30	7.9
	6–10 years	100	26.3
	Above 10 years	235	61.9

Source: Author's Computation, 2026

The sample was predominantly male (68.2%), aged 25–44 (63.1%), and held at least a Diploma/NCE (66.1%). Agro-processing enterprises formed the largest sub-sector (41.8%), and 61.9% of firms had operated for more than ten years, consistent with a sample of respondents with established, ongoing equipment-use experience rather than start-up perceptions.

Descriptive Statistics

Table 3: Item-Level Descriptive Statistics (N = 380)

Item	Mean	SD
MOC ₁	4.105	0.799
MOC ₂	3.479	1.168
MOC ₃	3.616	1.123
MOC ₄	3.595	1.180
EPR ₁	3.632	1.133
EPR ₂	3.645	1.138
EPR ₃	3.695	1.090
EPR ₄	3.650	1.156
EA ₁	3.595	1.155
EA ₂	3.634	1.207
EA ₃	3.555	1.155
EA ₄	3.682	1.095
TCSA ₁	3.582	1.107
TCSA ₂	3.576	1.100

Item	Mean	SD
TCSA ₃	3.555	1.135
TCSA ₄	3.579	1.133
ERD ₁	3.624	1.098
ERD ₂	3.526	1.131
ERD ₃	3.642	1.089
ERD ₄	3.587	1.104
OP ₁	3.553	1.082
OP ₂	3.563	1.166
OP ₃	3.674	1.082
OP ₄	3.629	1.076

Source: Author's Computation, 2026. Scale: 1 = Strongly Disagree to 5 = Strongly Agree.

Table 4: Summary of Descriptive Statistics by Construct

Construct	Mean	SD
MOC (3 items)	3.563	0.994
EPR (4 items)	3.655	0.940
EA (4 items)	3.616	0.988
TCSA (4 items)	3.573	0.932
ERD (4 items)	3.595	0.939
OP (4 items)	3.605	0.920

Source: Author's Computation, 2026

Mean scores across items ranged from 3.48 to 4.11 on a 5-point scale, indicating that respondents generally agreed with the item statements regarding maintenance costs, equipment age, performance/reliability, technological alignment, replacement decisions, and operational performance. Standard deviations (0.92–0.99 at the construct level) indicate moderate, plausible dispersion in perceptions across respondents — consistent with genuine variation across the four MSME sub-sectors rather than uniform response patterns.

Indicator Reliability and Convergent Validity

Table 5: Outer Loadings and Indicator Reliability

Item	Outer Loading	Decision
MOC ₁	0.133	Removed — below 0.40 threshold
MOC ₂	0.847	Retained
MOC ₃	0.871	Retained
MOC ₄	0.861	Retained
EPR ₁	0.818	Retained
EPR ₂	0.824	Retained
EPR ₃	0.836	Retained
EPR ₄	0.852	Retained

Item	Outer Loading	Decision
EA1	0.868	Retained
EA2	0.836	Retained
EA3	0.866	Retained
EA4	0.856	Retained
TCSA1	0.836	Retained
TCSA2	0.851	Retained
TCSA3	0.823	Retained
TCSA4	0.823	Retained
ERD1	0.862	Retained
ERD2	0.849	Retained
ERD3	0.842	Retained
ERD4	0.845	Retained
OP1	0.822	Retained
OP2	0.868	Retained
OP3	0.824	Retained
OP4	0.823	Retained

Source: Author's Computation, 2026. Loadings estimated via PLS Mode A (path weighting scheme).

MOC1 ("Maintenance costs associated with our equipment have increased over time") loaded at only 0.133 on the MOC construct and correlated weakly ($r = 0.06$ – 0.07) with the other three MOC items, indicating it does not share sufficient variance with the rest of the block. Following Hair et al. (2019), items with loadings below 0.40 should be removed; MOC1 was therefore dropped, and MOC was re-estimated as a three-item construct (MOC2–MOC4). All remaining 23 indicators loaded above 0.81, exceeding the 0.708 threshold for acceptable indicator reliability.

Table 6: Internal Consistency Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (ρ_c)	AVE
MOC (3 items)	0.823	0.894	0.739
EPR (4 items)	0.852	0.900	0.693
EA (4 items)	0.878	0.917	0.734
TCSA (4 items)	0.853	0.901	0.695
ERD (4 items)	0.871	0.912	0.721
OP (4 items)	0.855	0.902	0.696

Source: Author's Computation, 2025

All constructs exceed the 0.70 threshold for Cronbach's alpha and composite reliability, and all AVE values exceed 0.50, confirming adequate internal consistency reliability and convergent validity for the final measurement model.

Discriminant Validity — Fornell-Larcker Criterion

Table 7: Fornell-Larcker Criterion (Diagonal = $\sqrt{\text{AVE}}$)

	MOC	EPR	EA	TCSA	ERD	OP
MOC	0.859	0.360	0.221	0.421	0.444	0.366
EPR	0.360	0.833	0.431	0.304	0.440	0.396
EA	0.221	0.431	0.857	0.331	0.459	0.452
TCSA	0.421	0.304	0.331	0.833	0.460	0.429
ERD	0.444	0.440	0.459	0.460	0.849	0.572
OP	0.366	0.396	0.452	0.429	0.572	0.834

Source: Author's Computation, 2026

For every construct, the square root of its AVE (diagonal) exceeds its correlation with every other construct, satisfying the Fornell-Larcker criterion for discriminant validity.

Discriminant Validity — HTMT, and Its Substantive Interpretation

Table 8: Heterotrait-Monotrait Ratio (HTMT)

	MOC	EPR	EA	TCSA	ERD	OP
MOC	—	0.427	0.257	0.498	0.521	0.433
EPR	0.427	—	0.496	0.355	0.510	0.463
EA	0.257	0.496	—	0.381	0.524	0.521
TCSA	0.498	0.355	0.381	—	0.531	0.499
ERD	0.521	0.510	0.524	0.531	—	0.661
OP	0.433	0.463	0.521	0.499	0.661	—

Source: Author's Computation, 2026

All HTMT ratios fall below the conservative 0.85 threshold (Henseler, Ringle, & Sarstedt, 2015), with the highest value observed between ERD and OP (0.661) — unsurprising given that ERD is theorised and estimated as the direct antecedent of OP. This confirms that the six constructs, including the newly separated ERD construct, are empirically distinct from one another.

Structural Model — Collinearity Assessment (Inner VIF)

Table 9: Inner Model Collinearity Statistics (VIF)

Structural Path (Predictor → ERD)	VIF
MOC → ERD	1.310
EA → ERD	1.298
EPR → ERD	1.360
TCSA → ERD	1.320

Source: Author's Computation, 2026

All inner VIF values fall well below the conservative threshold of 3.3, indicating that collinearity among the four antecedents does not distort the structural path estimates

reported below. The model's overall fit, assessed via the standardised root mean square residual (SRMR) of the estimated model, was 0.047, below the 0.08 threshold conventionally used to indicate acceptable model fit.

Path Coefficients and Hypothesis Testing

Table 10: Structural Path Coefficients (Bootstrapping, 5,000 Resamples)

Hyp.	Path	β (mean)	SE	t-value	p-value	95% CI	Decision
Ho1	MOC $\rightarrow$ ERD	0.228	0.043	5.285	< .001	[0.144, 0.312]	Rejected
Ho2	EPR $\rightarrow$ ERD	0.181	0.046	3.899	< .001	[0.090, 0.272]	Rejected
Ho3	EA $\rightarrow$ ERD	0.257	0.047	5.472	< .001	[0.165, 0.347]	Rejected
Ho4	TCSA $\rightarrow$ ERD	0.226	0.046	4.955	< .001	[0.136, 0.312]	Rejected
Ho5	ERD $\rightarrow$ OP	0.574	0.036	16.139	< .001	[0.501, 0.641]	Rejected

Source: Author's Computation, 2026. Two-tailed test; β = mean bootstrapped standardised path coefficient.

$R^2(\text{ERD}) = 0.401$ and $R^2(\text{OP}) = 0.327$. All four antecedents are positively and significantly associated with Equipment Replacement Decision, and Equipment Replacement Decision is positively and significantly associated with Operational Performance. All five null hypotheses (Ho1–Ho5) are therefore rejected.

Table 11: f^2 Effect Sizes on the Endogenous Constructs

Path	f^2	Effect Size
MOC $\rightarrow$ ERD	0.066	Small
EPR $\rightarrow$ ERD	0.040	Small
EA $\rightarrow$ ERD	0.085	Small
TCSA $\rightarrow$ ERD	0.064	Small
ERD $\rightarrow$ OP	0.487	Large

Source: Author's Computation, 2026. Thresholds (Cohen, 1988): 0.02 = small, 0.15 = medium, 0.35 = large.

Each of the four antecedents contributes a small individual effect size to $R^2(\text{ERD})$, with EA (0.085) and MOC (0.066) contributing the most and EPR (0.040) the least; jointly, however, they explain 40.1% of ERD's variance. In contrast, ERD's effect on OP is large ($f^2 = 0.487$), indicating that the replacement decision itself — rather than any single antecedent condition — is the more powerful lever on operational performance.

Predictive Relevance: Blindfolding Q^2 and PLSpredict

Table 12: Blindfolding-Based Cross-Validated Redundancy (Q^2), Omission Distance $D = 7$

Endogenous Construct	Q^2	Interpretation
ERD	0.280	Medium predictive relevance

Endogenous Construct	Q ²	Interpretation
OP	0.224	Medium predictive relevance

Source: Author's Computation, 2026. $Q^2 > 0$ indicates the model has predictive relevance for the construct's indicators; values ≥ 0.25 are conventionally read as medium (Hair et al., 2019).

Table 13: PLSpredict — 10-Fold Out-of-Sample Prediction of OP Indicators

Item	PLS RMSE	LM RMSE	PLS MAE	LM MAE	Q ² predict
OP1	0.976	0.962	0.809	0.793	0.186
OP2	1.022	0.989	0.848	0.807	0.232
OP3	0.975	0.958	0.794	0.775	0.187
OP4	0.976	0.961	0.799	0.780	0.176

Source: Author's Computation, 2026. LM = naive linear-model benchmark (each OP item regressed on the summed antecedent indicators). Procedure follows Shmueli et al. (2019).

Q²predict values are positive for all four OP indicators (0.176–0.232), confirming the model outperforms a naive mean-only benchmark and has genuine, if modest, out-of-sample predictive power. However, the PLS path-model prediction did not outperform the simple linear-regression benchmark on RMSE or MAE for any OP indicator (differences of 0.014–0.033 in RMSE, favouring the naive LM). Per Shmueli et al.'s (2019) PLSpredict decision rule, this pattern indicates the model possesses low-to-medium predictive power: it explains and predicts OP meaningfully better than chance, but the specific non-linear/composite structure assumed by the PLS path model does not yet add predictive value over a simple additive benchmark. This nuance — without overturning — the explanatory findings in Table 10, and is discussed further in Section 4.9.

Interpretation of Findings

The pattern of results supports a coherent, theory-consistent account of how Taraba State MSMEs arrive at equipment replacement decisions. Consistent with Life Cycle Cost theory, rising maintenance and operating costs (MOC) are significantly associated with ERD ($\gamma = 0.228$, $p < .001$): once the cumulative cost of keeping an asset running becomes salient to owner-managers, it registers as a distinct pressure toward replacement, independent of the asset's age or measured performance. Consistent with Reliability-Centered Maintenance logic, declining equipment performance and reliability (EPR) is also significantly associated with ERD ($\gamma = 0.181$, $p < .001$), and equipment age (EA) shows the largest individual association with ERD ($\gamma = 0.257$, $p < .001$) — plausible given that, in the theoretical review (Section 2.7), age is expected to operate partly as an accumulated proxy for the wear and obsolescence risk that EPR captures more directly, so some of EA's association with ERD likely reflects this shared condition-based signal rather than age acting as an independent causal mechanism in its own right. Consistent with Dynamic Capabilities Theory, technological change and strategic alignment (TCSA) is independently associated with ERD

($\gamma = 0.226$, $p < .001$), confirming that Taraba State MSME owner-managers do not replace equipment on cost and condition grounds alone: perceived strategic and technological misalignment operates as a genuinely separate pathway toward replacement, even for equipment that remains physically functional.

The strong association between ERD and OP ($\delta = 0.574$, $p < .001$, large $f^2 = 0.487$) is the study's most practically important finding. It indicates that the act of making — and presumably acting on — a considered replacement decision is associated with substantially better operational performance than the antecedent conditions are on their own. In other words, MSMEs that periodically evaluate their equipment and plan replacement ahead of failure (the ERD items) report meaningfully higher efficiency, less disruption, and more consistent quality (the OP items) than those that do not, regardless of how severe their underlying cost, performance, age, or technological pressures are. This is consistent with the study's central argument that ERD should be modelled and measured as the decision itself, distinct from the conditions that motivate it: the conditions matter for whether replacement happens, but it is the decision-and-action step that is most tightly linked to the performance outcome.

Discussion of Findings

These findings extend prior equipment-replacement research — largely developed for large, data-rich enterprises and specific sectors such as construction (Sobczak-Piąstka et al., 2020), manufacturing (Sari & Ic, 2025), heavy construction (Alshibani et al., 2024), and healthcare (Altalabi et al., 2020; Vivas & Vieira, 2025) — to the resource-constrained, informally managed MSME context of Taraba State, Nigeria. The significant association between MOC and ERD echoes the economic-life replacement logic emphasised by Yatsenko and Hritonenko (2022) and Kayashima and Marques (2019), suggesting that even without the formal cost-accounting systems assumed in that literature, MSME owner-managers respond to accumulating repair and maintenance costs in a directionally similar way. Likewise, the significant $EPR \rightarrow ERD$ path is consistent with Diniz and Sessions' (2020) emphasis on operational data as a trigger for replacement, even though MSMEs typically rely on informal, experiential judgments of declining performance rather than the structured diagnostic techniques (e.g., FMEA) associated with formal Reliability-Centered Maintenance programmes (Karajagikar & Sonawane, 2020).

The significant $TCSA \rightarrow ERD$ path aligns with Sloan's (2011) observation that technological change can motivate replacement independently of physical deterioration, and with Alshibani et al.'s (2024) inclusion of strategic/technological criteria alongside cost and condition factors in their multi-criteria replacement model — evidence that this pathway generalises beyond the large construction firms in which it was first documented. At the same time, the comparatively modest f^2 effect sizes for all four individual antecedents (0.040–0.085) relative to their combined explanatory power ($R^2 = 0.401$) reinforces the study's theoretical framing (Section 2.7): none of the four theories — LCC, RCM, DCT —

dominates on its own; MSME replacement decisions in this setting are better understood as jointly, rather than singly, determined.

The strong ERD → OP association (large effect size) is broadly consistent with the premise, shared across the reviewed literature, that timely replacement improves workflow efficiency and reduces downtime (Sari & Ic, 2025; Alshibani et al., 2024). It also lends indirect empirical support to the paper's Transaction Cost Economics argument (Coase, 1937; Williamson, 1975, 1985, 1996): if MSMEs that reach and act on a replacement decision perform substantially better, then the reactive, failure-triggered replacement pattern documented in the Introduction is plausibly explained, at least in part, by the transaction costs — supplier search, financing, installation, retraining — that delay MSMEs from converting favourable cost, condition, age, and strategic signals into an actual decision (Jiménez & Afonso, 2023; Ketokivi & Mahoney, 2020). The present data cannot test this TCE mechanism directly, since no transaction-cost indicators were fielded, but the size of the ERD → OP gap is consistent with there being a real cost to MSMEs of delaying an otherwise-warranted decision.

Finally, the PLSpredict results (Table 13) temper the explanatory findings with an important caveat about the model's predictive precision. That the PLS path model did not out-predict a naive additive benchmark on the OP indicators — despite significant, theory-consistent path coefficients and acceptable Q^2 — is a familiar pattern in PLS-SEM applications with a small number of well-correlated reflective indicators per construct (Shmueli et al., 2019), and should not be read as evidence against the substantive associations reported in Table 10. It does, however, suggest that the specific functional form assumed by the ERD-mediated path model offers limited practical advantage, for prediction purposes, over a simpler composite scoring rule — a useful, low-cost diagnostic that MSME support agencies could apply without needing a full SEM analysis.

Conclusion, Recommendations, Limitations, and Future Research Directions

Conclusion

This study examined the antecedents of Equipment Replacement Decision (ERD) and its association with MSME operational performance (OP) among 380 MSMEs in Taraba State, Nigeria, using an ERD-mediated PLS-SEM specification. Maintenance and operating costs, equipment performance and reliability, equipment age, and technological change and strategic alignment were each positively and significantly associated with ERD, jointly explaining 40.1% of its variance, and ERD was strongly and significantly associated with OP, explaining 32.7% of its variance with a large effect size. All five null hypotheses were rejected. The measurement model demonstrated sound reliability, convergent validity, and discriminant validity once a single weak indicator (MOC₁) was removed, and blindfolding and PLSpredict procedures confirmed that the model has genuine, if modest, predictive relevance. Overall, the findings support treating equipment replacement as a distinct, multiply-determined decision that mediates the relationship between an MSME's

underlying cost, condition, age, and strategic pressures and its ultimate operational performance.

Recommendations

1. MSME owner-managers should institutionalise periodic, criteria-based equipment reviews — covering maintenance costs, performance/reliability indicators, age, and relevant technological developments — rather than relying on reactive, failure-triggered replacement, since it is the replacement decision itself, not any single antecedent condition, that shows the strongest association with operational performance.
2. MSME support agencies (e.g., SMEDAN) and business development service providers in Taraba State should develop simple, low-cost equipment-assessment checklists that MSMEs can apply without formal asset-management systems, translating the study's four antecedent domains into practical self-assessment criteria.
3. Financial institutions and microfinance providers serving MSMEs should consider equipment-replacement financing products that reduce the transaction costs (search, financing, installation, retraining) that Transaction Cost Economics suggests may delay MSMEs from converting a recognised need for replacement into actual replacement.
4. Given that technological change and strategic alignment (TCSA) is independently associated with ERD, sector associations and vocational/technical training bodies should provide targeted awareness of relevant technological developments to agro-processing, printing, wood and furniture, and welding/metalworking MSMEs, so that strategic obsolescence is recognised before it manifests as costly downtime.

Limitations

The study is cross-sectional, so the associations reported cannot be interpreted as establishing causal direction or ruling out reverse or reciprocal relationships between ERD and OP. The Transaction Cost Economics boundary condition discussed in Sections 2.7 and 4.9 is theoretically motivated but not directly tested, since no transaction-cost indicators were fielded. Finally, the PLSpredict results indicate that the model's out-of-sample predictive precision for OP indicators is modest relative to a naive linear benchmark, and this should temper practical reliance on the model for individual-enterprise prediction, even though its explanatory path estimates are robust and statistically well-supported.

Suggestions for Future Research

1. A longitudinal or panel design that tracks the same MSMEs across an actual replacement cycle would allow the ERD → OP association to be tested for direction

and would help establish whether the decision itself, or the subsequent replacement action, drives the observed performance gains.

2. Future studies should field explicit transaction-cost indicators (e.g., perceived difficulty of supplier search, financing access, installation disruption, retraining burden) to directly test the Transaction Cost Economics boundary condition proposed in Section 2.7 as moderating the antecedent → ERD paths.
3. Because the PLS path model did not outperform a naive linear benchmark in out-of-sample prediction (Section 4.7.1), future work could compare the ERD-mediated specification against alternative functional forms (e.g., a single-equation model with direct antecedent → OP paths, or a formative specification for ERD) using PLSpredict to identify whether a simpler or differently specified model offers better predictive precision for practitioner use.
4. Replicating the study in other Nigerian states, or extending it to other MSME sub-sectors beyond agro-processing, printing, wood and furniture, and welding/metalworking, would help establish the generalisability of the antecedent structure identified here.

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