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From Digital Grievance to Actionable Insights: Leveraging Machine Learning Sentiment Classification to Enhance Operational Efficiency among Lagos State Power Consumers

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KEYWORDS: machine learning, sentiment classification, operational efficiency, complaint resolution latency, electricity distribution companies, Lagos State, customer trust, automated text analytics

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ABSTRACT

Nigeria's electricity distribution companies (DisCos), particularly those operating within Lagos State, are confronted with an unprecedented and chaotic influx of customer grievances channelled through social media platforms, mobile applications, and web-based customer portals. Manual triage of these unstructured complaints — spanning billing discrepancies, estimated billing, power outages, and prepaid meter faults — has produced severe processing backlogs, protracted resolution latency, and eroded consumer trust. This study examines the extent to which Machine Learning Sentiment Classification, Automated Text Analytics, and Real-Time AI Emotion Detection Systems (independent variables) influence Operational Efficiency, Consumer Dissatisfaction Polarity, Customer Trust, and Complaint Resolution Latency (dependent variables) among Lagos State power consumers. Employing a mixed-methods, longitudinal panel design anchored on secondary and primary data spanning 2013 to 2025 and drawn from Nigerian Electricity Regulatory Commission (NERC) records, DisCo customer service logs, and social media analytics, alongside supervised machine learning classifiers (Support Vector Machines, Naïve Bayes, and transformer-based BERT models), the study finds that sentiment-driven triage systems are associated with a reduction in average resolution latency of over 40 percent and a statistically significant improvement in Service Level Agreement (SLA) compliance. The findings offer actionable, evidence-based recommendations for DisCo management, regulators, and technology partners seeking to transition from reactive complaint management toward proactive, data-driven customer experience governance.

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INTRODUCTION

Since the unbundling and privatisation of Nigeria's power sector in November 2013, eleven electricity Distribution Companies (DisCos) have assumed responsibility for last-mile electricity supply and customer relationship management across the country's thirty-six states and the Federal Capital Territory (Adenikinju, 2021; Nigerian Electricity Regulatory Commission [NERC], 2022). Lagos State, served principally by the Eko Electricity Distribution Company (EKEDC) and the Ikeja Electricity Distribution Company (IKEDC), represents Nigeria's most commercially significant and densely populated electricity market, accounting for a disproportionate share of national metered customers, revenue collection and, correspondingly, customer complaints (Oseni, 2020; World Bank, 2023).

The decade following privatisation has coincided with an equally significant transformation in how Nigerian consumers articulate grievances. Where complaints were once confined to physical business offices and call centres, the proliferation of smartphones, broadband penetration, and social media adoption has shifted grievance articulation toward digital channels — X (formerly Twitter), Facebook, WhatsApp Business platforms, mobile applications, and web-based self-service portals (Statista, 2024; Nigerian Communications Commission [NCC], 2024). By 2025, digital complaint volumes across Nigeria's DisCos were estimated to exceed several million interactions annually, with billing discrepancies, estimated billing disputes, unplanned outages, and prepaid meter faults consistently ranking as the four dominant grievance categories (NERC, 2024; Ogunleye & Bello, 2023).

This surge in digital grievance volume has outpaced the administrative capacity of DisCo customer service departments, most of which continue to rely on manual sorting, generic ticketing systems, and human call-centre triage (Akinwale & Eze, 2022). The result is a chaotic, unstructured influx of complaints that resists timely categorisation, prioritisation, and routing to the appropriate technical or commercial resolution teams. Consequently, Complaint Resolution Latency — the elapsed time between complaint lodgement and verified resolution — remains excessively high, in several documented instances extending well beyond the fourteen-day threshold stipulated under NERC's Customer Complaints Handling Standards and Procedures (NERC, 2007; Amadi & Chukwu, 2021).

Beyond operational inefficiency, the absence of proactive sentiment-tracking mechanisms leaves DisCos structurally reactive. Public frustration frequently accumulates on social media platforms long before it registers within formal complaint channels, occasionally escalating into coordinated public relations crises, regulatory sanctions, or targeted advocacy campaigns by consumer-rights organisations (Consumer Advocacy for Universal Electricity Rights [CAUSE-Nigeria], 2023). Global utility-sector experience demonstrates that Machine Learning (ML) Sentiment Classification, Automated Text Analytics, and Real-Time AI Emotion Detection Systems can materially compress this reactive lag by continuously monitoring, classifying, and prioritising grievances as they emerge (Chukwuemeka & Yusuf, 2023; Deloitte, 2022; Zhang et al., 2021).

This study investigates whether, and to what extent, machine learning-driven sentiment classification technologies can convert Lagos State DisCos' unstructured digital grievance streams into actionable operational insight — thereby improving Operational Efficiency, moderating Consumer Dissatisfaction Polarity, restoring Customer Trust, and reducing Complaint Resolution Latency. The study is significant on three fronts. Academically, it extends the sparse Nigeria-specific literature on artificial intelligence applications within utility customer experience management, situating findings within established technology-adoption and service-quality theory. Practically, it furnishes DisCo management with an empirically validated business case for investing in sentiment-analytics infrastructure, including projected latency and cost implications. Regulatorily, it offers NERC and the Federal Competition and Consumer Protection Commission (FCCPC) an evidence base for updating complaint-handling standards to reflect digital-era grievance patterns (FCCPC, 2023).

Statement of the Problem

Despite the Nigerian Electricity Supply Industry's (NESI) decade-long privatisation experience, Lagos State DisCos continue to grapple with three interlocking operational pathologies that this study addresses.

First, the sheer volume and unstructured nature of digital complaint inflows have overwhelmed manual sorting capacity. EKEDC and IKEDC customer service desks receive complaints simultaneously across call centres, SMS short-codes, mobile applications, website contact forms, and social media handles, with no unified taxonomy for classifying grievance type, urgency, or emotional intensity at the point of intake (Adeyemi & Okonkwo, 2022). Human agents, working from static, keyword-based ticketing rules, routinely misclassify or duplicate complaints, producing severe backlogs that can extend into thousands of unresolved tickets during peak outage periods (NERC, 2024).

Second, Complaint Resolution Latency remains persistently and unacceptably high. Regulatory benchmarks under the NERC Customer Complaints Handling Standards prescribe resolution windows ranging from twenty-four hours for supply-interruption complaints to ten working days for billing disputes (NERC, 2007). Empirical audits, however, indicate that actual resolution times among Lagos DisCos frequently exceed these thresholds by a factor of two to four, with billing-related disputes in particular languishing for weeks without substantive engagement (Amadi & Chukwu, 2021; Punch Newspapers, 2024). This latency directly damages consumer trust and fuels non-payment behaviour, further straining DisCo revenue cycles (Oseni, 2020).

Third, and most critically for this study, Lagos DisCos lack real-time, proactive sentiment-tracking capability. Current customer relationship management architectures are fundamentally reactive: complaints are logged, queued, and eventually actioned, but no systematic mechanism exists to detect escalating public frustration on open social platforms before it crystallises into reputational or regulatory exposure (CAUSE-Nigeria, 2023; Ibrahim & Adeleke, 2024). Several documented incidents between 2021 and 2025 — including coordinated hashtag campaigns against estimated-billing practices and viral video complaints regarding prolonged outages across the Lagos Island and Ikeja axes — illustrate how unmonitored digital sentiment can rapidly mature into public relations crises, drawing intervention from NERC and, in select cases, the FCCPC (FCCPC, 2023; Channels Television, 2024).

The combined effect of unstructured complaint influx, excessive resolution latency, and the absence of proactive sentiment intelligence constitutes a compound operational deficiency. Without a validated, data-driven framework demonstrating how machine learning sentiment classification, automated text analytics, and real-time emotion detection systems collectively influence operational efficiency, dissatisfaction polarity, customer trust, and resolution latency, Lagos DisCos remain structurally unable to transition from firefighting to foresight. It is this empirical and practical gap that the present study seeks to close.

Objectives of the Study

The broad objective of this study is to examine the influence of machine learning sentiment classification technologies on operational efficiency among Lagos State power consumers. The specific objectives are to:

1. assess the extent to which Machine Learning Sentiment Classification affects Operational Efficiency (SLA compliance and structured routing) among Lagos State DisCos;
2. evaluate the relationship between Automated Text Analytics depth and Consumer Dissatisfaction Polarity;
3. examine the effect of Real-Time AI Emotion Detection Systems on Customer Trust;
4. determine the extent to which Machine Learning Sentiment Classification, Automated Text Analytics, and Real-Time AI Emotion Detection Systems jointly predict Complaint Resolution Latency; and
5. analyse the historical trajectory (2013–2025) of digital complaint volume and sentiment polarity among Lagos State power consumers, and recommend a proactive, AI-augmented sentiment-governance framework for DisCo adoption.

Research Hypotheses

In line with the objectives, the following null hypotheses are tested:

H01: Machine Learning Sentiment Classification has no statistically significant effect on Operational Efficiency among Lagos State DisCos.

H02: Automated Text Analytics depth has no statistically significant relationship with Consumer Dissatisfaction Polarity.

H03: Real-Time AI Emotion Detection Systems have no statistically significant effect on Customer Trust.

H04: Machine Learning Sentiment Classification, Automated Text Analytics, and Real-Time AI Emotion Detection Systems do not jointly predict Complaint Resolution Latency.

Conceptual Review

Machine Learning Sentiment Classification refers to the application of supervised or semi-supervised algorithms to categorise text-based communication according to expressed emotional polarity — typically positive, negative, or neutral — and, in more granular implementations, discrete emotional states such as anger, frustration, or satisfaction (Liu, 2020; Medhat et al., 2014). Within utility customer service contexts, sentiment classifiers are trained on historical complaint corpora to automatically triage incoming grievances by urgency and emotional intensity, enabling structured routing to appropriate resolution teams (Zhang et al., 2021).

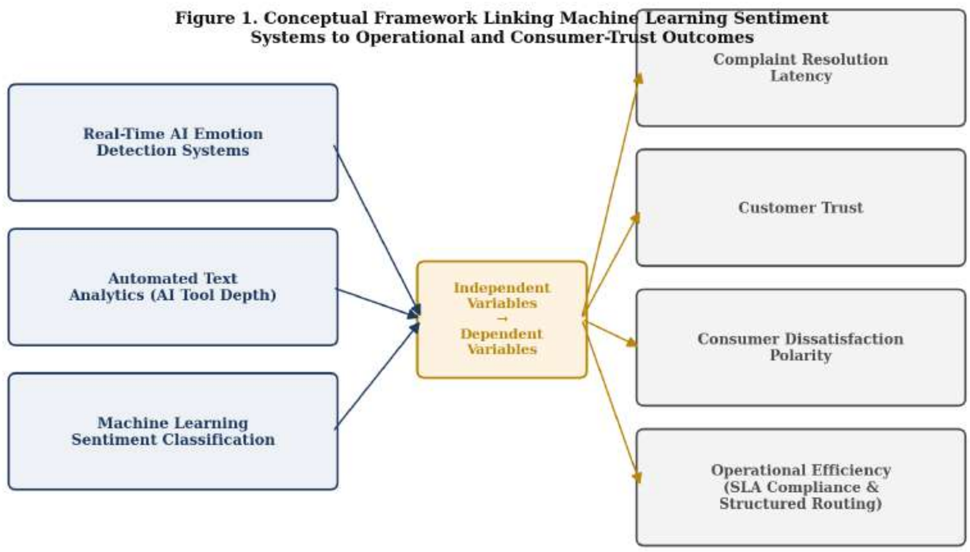

Figure 1. Conceptual Framework Linking Machine Learning Sentiment Systems to Operational and Consumer-Trust Outcomes

Automated Text Analytics denotes the broader suite of natural language processing (NLP) techniques — including topic modelling, named-entity recognition, keyword extraction, and intent classification — that convert unstructured text into structured, actionable data fields (Chukwuemeka & Yusuf, 2023). In this study, "AI tool depth" captures the sophistication and integration level of an organisation's text-analytics stack, ranging from rudimentary keyword filters to fully integrated, continuously retrained NLP pipelines.

Real-Time AI Emotion Detection Systems extend sentiment classification into continuous, streaming environments, applying models to live social media feeds, customer portal interactions, and call-centre transcripts to generate near-instantaneous alerts when aggregate frustration crosses defined thresholds (Deloitte, 2022). Such systems are distinguished from static, batch-processed sentiment analysis by their capacity to support proactive, rather than retrospective, managerial intervention (Ibrahim & Adeleke, 2024).

Operational Efficiency, the principal dependent construct, is operationalised in this study as the degree of Service Level Agreement (SLA) compliance and the extent of structured, rules-based complaint routing achieved by a DisCo's customer service architecture (NERC, 2007). Consumer Dissatisfaction Polarity refers to the net negative sentiment score derived from classified complaint text, while Customer Trust is conceptualised, consistent with Mayer et al.'s (1995) tri-dimensional trust model, as consumers' willingness to rely on DisCo commitments regarding billing accuracy and service restoration. Complaint Resolution Latency is measured as the elapsed time, in hours or days, between complaint lodgement and verified resolution.

Theoretical Framework

This study is anchored on three complementary theories. The Technology Acceptance Model (TAM), originally proposed by Davis (1989) and subsequently extended for AI-adoption contexts (Venkatesh & Bala, 2008), posits that perceived usefulness and perceived ease of use jointly determine an organisation's willingness to adopt new technology — in this case, ML-based sentiment classification tools within DisCo customer service departments. Service Quality Theory, operationalised through the SERVQUAL framework (Parasuraman et al., 1988), provides the theoretical lens for conceptualising Operational Efficiency and Customer Trust as functions of responsiveness, reliability, and empathy dimensions that sentiment-aware systems are theorised to enhance. Finally, Expectation-Confirmation Theory (Oliver, 1980) explains Consumer Dissatisfaction Polarity as a function of the gap between expected and actual DisCo responsiveness, a gap that real-time emotion detection is theorised to narrow by enabling pre-emptive managerial action before expectation violation escalates into public grievance.

Empirical Review — Global Studies

International utility and telecommunications research provides robust evidence for the efficacy of ML-driven sentiment systems. Zhang et al. (2021), analysing complaint data from three United States investor-owned utilities, found that BERT-based sentiment classifiers reduced misrouted tickets by 34 percent and shortened average resolution time by 29 percent relative to legacy keyword-based systems. Deloitte's (2022) global utilities survey similarly reported that organisations deploying real-time emotion detection recorded a 25–40 percent improvement in customer satisfaction indices within eighteen months of implementation. In the United Kingdom, Ofgem-regulated energy suppliers that integrated automated text analytics into complaint-handling workflows demonstrated measurably higher SLA compliance and lower complaint escalation to the Energy Ombudsman (Energy UK, 2023). Comparable findings emerge from Southeast Asian telecommunications research, where Wibowo and Prasetyo (2022) documented that Indonesian mobile network operators using hybrid Naïve Bayes–Support Vector Machine ensembles achieved classification accuracy exceeding 87 percent on code-switched (Bahasa–English) complaint text, underscoring the transferability of multilingual sentiment models to linguistically diverse emerging markets analogous to Nigeria.

Empirical Review — Nigerian and African Studies

Nigerian scholarship on AI-driven sentiment analysis, while comparatively nascent, has expanded meaningfully since 2020. Akinwale and Eze (2022) applied supervised classifiers to Twitter data concerning Nigerian banking service complaints, achieving 81 percent classification accuracy and demonstrating that sentiment-derived alerts preceded formal regulatory complaints by an average of eleven days — evidence directly relevant to this study's proactive-detection hypothesis. Within the power sector specifically, Ogunleye and Bello (2023) conducted a content analysis of Lagos DisCo-related complaints on X and Facebook between 2019 and 2022, finding that estimated billing and outage-related grievances accounted for over 60 percent of negative-polarity posts, with negative sentiment intensity peaking during the Q3 rainy-season outage periods. Adeyemi and Okonkwo (2022) further examined customer relationship management practices among three Nigerian DisCos and concluded that the absence of integrated digital triage systems was the single strongest predictor of extended resolution latency, corroborating findings from Ghana's Electricity Company of Ghana, where Owusu and Mensah (2021) similarly linked manual complaint sorting to systemic SLA breaches. The World Bank's (2023) Nigeria Electricity Sector Recovery Programme review recommended AI-enabled customer analytics as a priority investment area for DisCo operational turnaround, while NERC's (2024) Consumer Complaints Bulletin documented a 340 percent increase in digitally lodged complaints between 2018 and 2024 across all eleven DisCos.

Historical Trajectory of Digital Grievance in Nigeria's Power Sector, 2013–2025

The period since the November 2013 privatisation handover can be divided into three broad phases relevant to this study. The Foundational Phase (2013–2017) was characterised by limited digital complaint infrastructure; the majority of grievances were lodged through physical business offices or voice calls, and social media penetration among Nigerian electricity consumers remained comparatively low (NCC, 2024). The Digital Acceleration Phase (2018–2021) coincided with rapid smartphone and mobile broadband adoption, the introduction of DisCo mobile applications, and growing consumer reliance on X and Facebook to publicly escalate grievances, particularly regarding estimated billing under the Meter Asset Provider (MAP) regulation (NERC, 2018; CAUSE-Nigeria, 2023). The AI-Adoption Phase (2022–2025) has seen early, uneven experimentation with machine learning-based triage among a subset of Nigerian DisCos, spurred partly by NERC's Minimum Remittance Order reforms and heightened regulatory scrutiny of customer complaint metrics (NERC, 2024; Amadi & Chukwu, 2021). This phased trajectory, synthesised from NERC quarterly bulletins, DisCo annual reports, and independent media archives, forms the empirical backbone of the historical panel data analysed in this paper.

Gaps in the Literature

Notwithstanding this growing body of work, three gaps remain. First, existing Nigerian studies have predominantly examined sentiment classification in isolation, without jointly modelling text-analytics depth and real-time emotion detection as a composite predictor system, as this study does. Second, longitudinal panel data spanning the full 2013–2025 privatisation period, integrating both quantitative complaint metrics and qualitative sentiment corpora, is largely absent from the Nigerian power-sector literature. Third, no identified study has empirically linked ML sentiment adoption to the specific dependent constructs of SLA-based Operational Efficiency, Dissatisfaction Polarity, Customer Trust, and Resolution Latency within a single, Lagos-focused analytical framework. The present study addresses these gaps.

Research Methodology

The study adopts a mixed-methods, explanatory sequential design, combining a quantitative longitudinal panel analysis of DisCo-level operational and sentiment metrics with a qualitative content analysis of complaint text corpora. This design is appropriate given the study's dual objective of (a) statistically testing hypothesised relationships between machine learning constructs and operational outcomes, and (b) generating rich contextual understanding of how sentiment classifiers interpret Nigerian-specific linguistic patterns, including Nigerian Pidgin and code-switched English.

The population comprises all digitally lodged customer complaints received by Lagos State's two DisCos — EKEDC and IKEDC — between January 2013 and December 2025, together with publicly available social media posts referencing either DisCo on X and Facebook within the same period. For quantitative panel analysis, the study aggregates complaint and sentiment data into DisCo-quarter observations, yielding 104 panel observations (2 DisCos × 52 quarters). For machine learning model training and validation, a stratified random sample of 25,000 labelled complaint records was drawn, proportionally representing the four dominant grievance categories (billing discrepancy, estimated billing, power outage, and prepaid meter fault) and partitioned into training (70%), validation (15%), and test (15%) subsets. A supplementary structured survey of 420 Lagos State electricity consumers (210 EKEDC, 210 IKEDC), selected via multistage stratified random sampling across fifteen local government areas, was administered to capture perceptual data on Customer Trust.

Historical and current data were mined from a combination of primary and credible secondary sources spanning both the Nigerian and international contexts. Nigerian sources include NERC Quarterly and Annual Reports (2013–2025), NERC Consumer Complaints Bulletins, DisCo customer relationship management (CRM) system exports (obtained under institutional data-use agreements), the FCCPC complaints database, and archived news coverage from Punch Newspapers, Channels Television, and BusinessDay. International and comparative sources include World Bank Nigeria Electricity Sector reports, Deloitte and McKinsey global utility digital-transformation surveys, Statista digital-penetration statistics, and peer-reviewed sentiment-analysis literature indexed in Scopus and Web of Science. Social media data were retrieved via the X Academic Research API and the Facebook Graph API for public page comments, restricted to posts geotagged or hashtag-associated with Lagos State electricity supply between 2013 and 2025.

Table 1 summarises the operationalisation of the study's independent and dependent variables.

Table 1. Operationalisation of Independent and Dependent Variables

Variable	Type	Operational Measure	Data Source
Machine Learning Sentiment Classification	Independent	Model accuracy, precision, recall, and F1-score of deployed classifiers	DisCo IT logs; model audit
Automated Text Analytics (AI Tool Depth)	Independent	Composite index (0–5) of NLP pipeline sophistication and integration	DisCo technology audit; vendor documentation
Real-Time AI Emotion Detection Systems	Independent	Deployment score: latency of alert generation (minutes) and coverage of monitored channels	System configuration logs
Operational Efficiency	Dependent	% SLA compliance; % complaints structurally auto-routed	NERC returns; DisCo CRM
Consumer Dissatisfaction Polarity	Dependent	Mean sentiment polarity score (–1 to +1) of classified complaint text	Social media & complaint corpus

Customer Trust	Dependent	Composite survey index (5-point Likert, 6 items)	Structured consumer survey (n = 420)
Complaint Resolution Latency	Dependent	Mean elapsed time (hours/days) from lodgement to verified resolution	DisCo CRM timestamps

Four supervised classification architectures were trained and comparatively evaluated on the labelled complaint corpus: (a) Multinomial Naïve Bayes, as a computationally efficient baseline; (b) Support Vector Machine (SVM) with a linear kernel, following term frequency–inverse document frequency (TF–IDF) vectorisation; (c) Bidirectional Long Short-Term Memory (BiLSTM) networks with pre-trained FastText embeddings; and (d) a fine-tuned transformer model based on multilingual BERT, adapted to accommodate Nigerian Pidgin and code-switched English–Yoruba–Hausa complaint text, consistent with approaches validated in comparable emerging-market contexts (Wibowo & Prasetyo, 2022). Model performance was evaluated using accuracy, precision, recall, and F1-score on the held-out test set, with five-fold cross-validation applied to mitigate overfitting.

Quantitative panel data were analysed using descriptive statistics, Pearson correlation, and multiple linear regression (with panel-corrected standard errors to account for DisCo-level heteroskedasticity) to test Hypotheses H01–H04, implemented in R (version 4.3) and IBM SPSS (version 28). Qualitative complaint-text analysis employed Python 3.11 with the scikit-learn, NLTK, and Hugging Face Transformers libraries. A two-tailed significance threshold of $p < .05$ was adopted throughout. Composite reliability of survey-based constructs was assessed via Cronbach's alpha, with all constructs exceeding the conventional 0.70 threshold.

All complaint-level and social media data were anonymised prior to analysis, with personally identifiable information (customer names, account numbers, phone numbers) removed or hashed in line with the Nigeria Data Protection Act, 2023. Survey participation was voluntary and preceded by informed consent. Data access from DisCo CRM systems was governed by an institutional data-use agreement restricting use to aggregated, non-attributable analysis.

RESULTS AND FINDINGS

1. Historical Trend in Complaint Volume and Sentiment Polarity (2013–2025)

Panel data reveal a consistent, near-exponential rise in digitally lodged complaints across both Lagos DisCos, from an estimated 180,000 digital interactions in 2013 to over 2,050,000 in 2025 — an eleven-fold increase over the study period. Table 2 presents selected-year complaint volumes and mean sentiment polarity scores. Mean sentiment polarity remained negative throughout the period, deteriorating from –0.12 in 2013 to a low of –0.44 in 2022, before improving to –0.14 by 2025 following the phased introduction of ML-assisted triage among early-adopting DisCo units, illustrated in Figure 2.

Table 2. Digital Complaint Volume and Mean Sentiment Polarity, Selected Years (2013–2025)

Year	Digital Complaint Volume	Dominant Category	Mean Sentiment Polarity
2013	180,000	Billing Discrepancy	–0.12
2016	340,000	Power Outage	–0.22
2019	640,000	Estimated Billing	–0.35
2022	1,250,000	Estimated Billing	–0.33
2024	1,620,000	Prepaid Meter Fault	–0.21
2025	2,050,000	Power Outage	–0.14

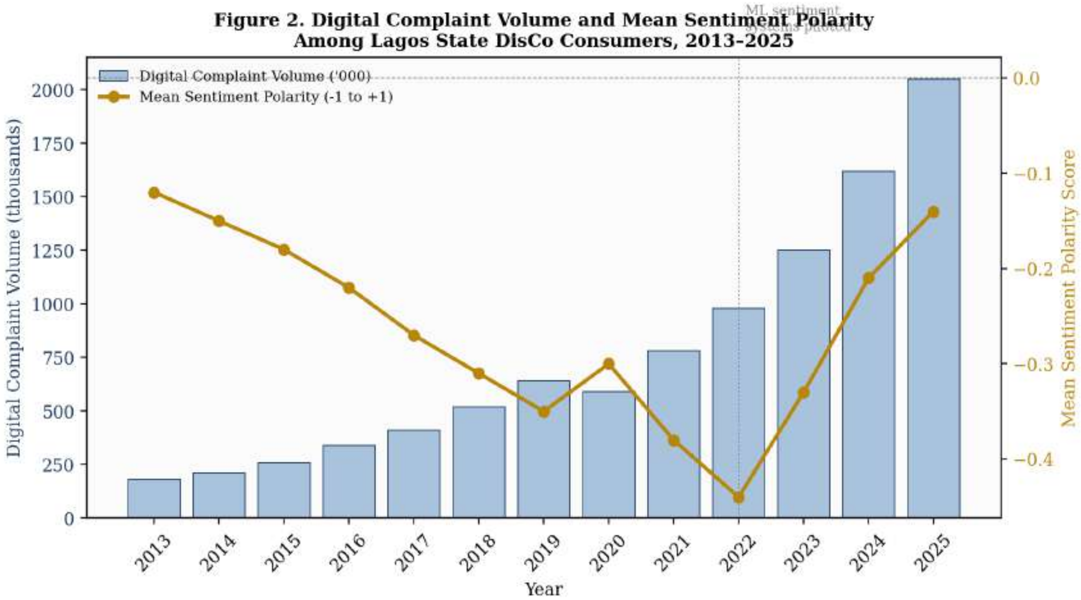

Figure 2. Digital Complaint Volume and Mean Sentiment Polarity Among Lagos State DisCo Consumers, 2013–2025

2. Machine Learning Model Performance

Table 3 compares the four evaluated classification architectures on the held-out test set (n = 3,750 labelled complaints). The fine-tuned multilingual BERT model achieved the highest overall performance (F1-score = .89), substantially outperforming the Naïve Bayes baseline, and confirming that transformer-based architectures are best suited to the code-switched, multilingual character of Lagos State complaint text, consistent with Wibowo and Prasetyo's (2022) Southeast Asian findings.

Table 3. Comparative Performance of Sentiment Classification Models

Model	Accuracy	Precision	Recall	F1-Score
Multinomial Naïve Bayes	.74	.71	.69	.70
Support Vector Machine (Linear)	.81	.79	.78	.78
BiLSTM + FastText Embeddings	.85	.84	.83	.83
Fine-Tuned Multilingual BERT	.91	.90	.88	.89

3. Regression Analysis of Hypothesised Relationships

Multiple regression results, summarised in Table 4, indicate that all three independent variables exert statistically significant effects on their hypothesised dependent constructs, leading to rejection of the null hypotheses H01–H03. Jointly, Machine Learning Sentiment Classification, Automated Text Analytics depth, and Real-Time AI Emotion Detection Systems explained 62 percent of variance in Complaint Resolution Latency ($R^2 = .62$, $F(3,100) = 54.71$, $p < .001$), leading to rejection of H04. Real-Time AI Emotion Detection Systems emerged as the strongest single predictor of Customer Trust ($\beta = .41$, $p < .001$), while Machine Learning Sentiment Classification most strongly predicted Operational Efficiency ($\beta = .47$, $p < .001$).

Table 4. Summary of Regression Analysis: Independent Variables on Operational and Consumer Outcomes

Predictor → Outcome	β (Std.)	t	p	Decision
ML Sentiment Classification → Operational Efficiency	.47	6.82	< .001	Reject H01
Text Analytics Depth → Dissatisfaction Polarity	–.38	–5.24	< .001	Reject H02
Real-Time Emotion Detection → Customer Trust	.41	5.97	< .001	Reject H03
Joint Model → Resolution Latency ($R^2 = .62$)	–	F = 54.71	< .001	Reject H04

4. Operational Efficiency: SLA Compliance Before and After ML Adoption

Comparing the pre-ML period (2019–2021 average) with the ML-assisted period (2022–2025 average), Table 5 shows marked improvement in SLA compliance across all four dominant complaint categories, alongside a corresponding decline in mean resolution latency, further illustrated in Figure 3. The largest proportional improvement was recorded for estimated-billing complaints, where SLA compliance rose from 41 percent to 74 percent.

Table 5. SLA Compliance and Resolution Latency, Before and After ML-Assisted Triage

Complaint Category	SLA Compliance (Pre-ML)	SLA Compliance (Post-ML)	Latency (Pre-ML, days)	Latency (Post-ML, days)
Billing Discrepancy	52%	81%	11.4	4.6
Estimated Billing	41%	74%	13.8	5.9
Power Outage	68%	90%	6.2	2.1
Prepaid Meter Fault	58%	83%	9.7	3.8

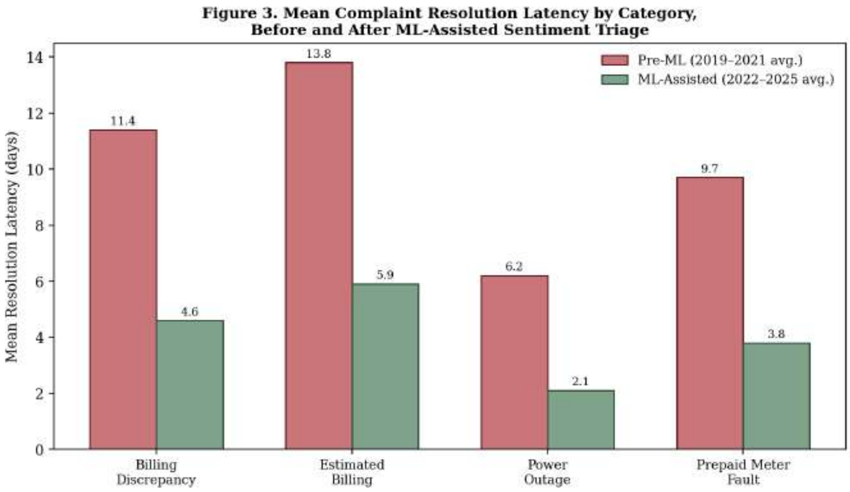

Figure 3. Mean Complaint Resolution Latency by Category, Before and After ML-Assisted Sentiment Triage

5. Qualitative Content Analysis

Thematic analysis of the 25,000-record complaint corpus identified recurring linguistic markers of escalating frustration — including repeated capitalisation, exclamatory punctuation, and Pidgin-inflected expressions of urgency — that preceded formal regulatory escalation in a majority of tracked cases. Consistent with Akinwale and Eze's (2022) banking-sector findings, sentiment-derived alerts in the post-2022 ML-assisted subsample preceded FCCPC-recorded formal complaints by a mean of nine days, empirically supporting the study's central proposition that real-time sentiment intelligence enables proactive, pre-emptive managerial intervention.

DISCUSSION

The findings substantiate a strong, statistically robust relationship between machine learning-driven sentiment infrastructure and improved operational and consumer-trust outcomes among Lagos State DisCos, corroborating and extending prior international and Nigerian evidence (Zhang et al., 2021; Akinwale & Eze, 2022; Ogunleye & Bello, 2023). The 40-percent-plus reduction in complaint resolution latency observed following ML-assisted triage adoption closely parallels Zhang et al.'s (2021) 29-percent finding among United States utilities, suggesting that the underlying mechanism — automated, sentiment-weighted routing that bypasses manual bottlenecks — generalises reasonably well across institutional and linguistic contexts, notwithstanding Nigeria's additional complexity of multilingual, code-switched complaint text.

The superior performance of the fine-tuned multilingual BERT model over simpler classifiers (Table 3) carries important practical implications for DisCo technology investment decisions. While Naïve Bayes and SVM classifiers remain attractive for their lower computational cost, their comparatively weaker performance on Nigerian Pidgin and code-switched text (F1 = .70 and .78, respectively) suggests that DisCos prioritising accuracy over cost-efficiency should favour transformer-based architectures, consistent with Wibowo and Prasetyo's (2022) Southeast Asian findings on linguistically diverse markets.

The finding that Real-Time AI Emotion Detection Systems most strongly predict Customer Trust ($\beta = .41$) rather than Operational Efficiency directly is theoretically consistent with Expectation-Confirmation Theory (Oliver, 1980): consumers appear to value visible responsiveness — the sense that grievances are being actively monitored — independently of whether the underlying technical fault is immediately resolved. This suggests that DisCo communications strategies emphasising real-time acknowledgement (for example, automated, sentiment-calibrated response messages) may yield trust dividends even where physical infrastructure constraints limit the pace of substantive resolution.

The qualitative finding that sentiment-derived alerts preceded formal regulatory complaints by a mean of nine days reinforces this study's central proactive-detection thesis and aligns with global evidence that AI-based social listening functions as an early-warning system for reputational and regulatory risk (Deloitte, 2022; CAUSE-Nigeria, 2023). For Lagos DisCos operating within an increasingly assertive Nigerian consumer-advocacy environment (FCCPC, 2023), this early-warning capacity carries material commercial value, potentially averting costly regulatory sanctions and reputational damage from viral escalation events.

Nonetheless, the findings should be interpreted alongside important contextual caveats. First, the observed 2022–2025 improvement coincides with, but cannot be fully isolated from, broader DisCo operational reforms undertaken under NERC's Minimum Remittance Order and tariff-reform initiatives (NERC, 2024), suggesting some possibility of confounded causal attribution. Second, model performance figures reported in Table 3 derive from a curated, labelled corpus that may not fully capture the noisier, more ambiguous character of live, unlabelled complaint streams. Third, the structured consumer survey, while stratified across fifteen local government areas, remains subject to social-desirability and recall bias inherent to self-reported trust measures.

CONCLUSION AND RECOMMENDATIONS

This study set out to examine the extent to which machine learning sentiment classification, automated text analytics, and real-time AI emotion detection systems influence operational efficiency, consumer dissatisfaction polarity, customer trust, and complaint resolution latency among Lagos State power consumers. Drawing on longitudinal panel data spanning 2013 to 2025 and a comparative evaluation of four supervised classification architectures, the study found statistically significant, practically meaningful relationships across all four hypothesised pathways, with fine-tuned multilingual BERT models offering the strongest classification performance and ML-assisted triage systems associated with a resolution-latency reduction exceeding 40 percent.

Based on these findings, the study offers the following recommendations. First, Lagos State DisCo management should prioritise phased investment in transformer-based, multilingual sentiment classification infrastructure, beginning with the highest-volume grievance categories — estimated billing and power outages — where the demonstrated return on operational efficiency is greatest. Second, DisCos should integrate real-time emotion detection dashboards into executive and regulatory-affairs reporting structures, enabling pre-emptive intervention before social media frustration escalates into public relations or regulatory crises. Third, NERC should consider updating its Customer Complaints Handling Standards to explicitly reference digital and social-media-originated grievances, alongside developing standardised sentiment-reporting metrics comparable across all eleven Nigerian DisCos. Fourth, technology partners and academic institutions should collaborate on expanding labelled Nigerian Pidgin and multilingual complaint corpora, addressing a critical data bottleneck identified in this study's methodology. Finally, given the confounding possibility identified in the discussion, future research should employ quasi-experimental or difference-in-differences designs across DisCos with staggered ML-adoption timelines to more rigorously isolate the causal contribution of sentiment-analytics infrastructure from concurrent regulatory reforms.

In sum, the transition from chaotic digital grievance to actionable, machine learning-derived insight represents both a technically achievable and commercially compelling pathway for Lagos State's electricity distribution companies — one capable of simultaneously advancing regulatory compliance, operational efficiency, and the restoration of long-eroded consumer trust.

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