Strategic Government Communication, Public Trust and Policy Acceptance in the Digital Era: Evidence from Local Governments

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Abstract

The rapid expansion of digital governance has transformed how local governments communicate policies, manage citizen engagement, and build institutional legitimacy. However, policy acceptance in the digital era depends not only on the availability of online communication platforms but also on the strategic quality, credibility, responsiveness, and personalization of government messages. This paper develops a technical framework for assessing the relationship among strategic government communication, public trust, and policy acceptance in local government contexts. The study proposes a novel algorithm, the Trust-Aware Policy Communication Optimization Algorithm (TAPCOA), designed to predict and optimize citizens' likelihood of accepting public policies based on communication clarity, sentiment polarity, message consistency, response time, citizen feedback intensity, misinformation exposure, digital engagement frequency, and institutional trust indicators. TAPCOA integrates transformer-based semantic encoding, trust-weighted sentiment analysis, adaptive feature selection, and policy acceptance probability scoring to improve prediction accuracy and communication targeting. The proposed model is compared with established machine learning and natural language processing algorithms, including Logistic Regression, Random Forest, Support Vector Machine, XGBoost, Long Short-Term Memory networks, Bidirectional Encoder Representations from Transformers, and Graph Neural Networks. Performance evaluation is conducted using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve, mean absolute error, and computational efficiency. The paper is structured to include graphical comparisons such as algorithm performance curves, trust-policy acceptance correlation graphs, digital engagement trend plots, confusion matrices, feature-importance charts, and communication effectiveness heatmaps. The expected findings demonstrate that TAPCOA produces superior predictive performance by combining semantic message interpretation with trust-sensitive behavioral indicators. The study contributes to digital governance research by presenting a computational decision-support model that enables local governments to design evidence-based communication strategies, detect declining public trust, counter misinformation, and improve policy acceptance through targeted, transparent, and responsive digital communication.

Keywords: *Strategic Government Communication; Public Trust; Policy Acceptance; Digital Governance; Citizen Engagement; Local Governments.*

I. INTRODUCTION

➢ *Background of Strategic Government Communication in the Digital Era*

Strategic government communication in the digital era has moved from periodic public announcements to continuous, data-informed, multi-channel interaction between government institutions and citizens. Local governments now communicate through official websites, social media pages, mobile platforms, community portals, digital complaint systems, SMS alerts, and live-streamed public briefings. This shift has made communication a governance infrastructure rather than a peripheral administrative function. In this paper, strategic communication refers to the deliberate design, timing, personalization, consistency, and evaluation of public messages for improving policy awareness, institutional trust, and citizen acceptance. The relevance of communication infrastructure is evident in digitally intensive systems where scalability, interoperability, and real-time processing shape the reliability of message delivery, feedback capture, and public responsiveness (Ibokette et al., 2024). Similarly, communication quality affects institutional reputation because citizens evaluate public organizations not only by policy content but also by clarity, timeliness, transparency, and responsiveness of official messaging (Oloba et al., 2024). In local government contexts, strategic communication is especially important because citizens encounter policies through direct services such as sanitation, taxation, public health campaigns, road use regulation, school administration, market levies, waste collection, environmental enforcement, and emergency response. Digital platforms increase the speed of communication, but they also expose weak coordination, contradictory messaging, delayed feedback, and misinformation. Mergel (2013) showed that government social media use may follow push, pull, and networked communication patterns, suggesting that digital communication becomes more strategic when citizens are not treated as passive recipients. Porumbescu (2016) further demonstrated that public sector social media and e-government website use influence citizens' perceptions of government trustworthiness. Therefore, the technical concern of this study is not simply whether local governments use digital platforms, but whether message semantics, engagement intensity, sentiment patterns, trust indicators, and misinformation signals can be computationally modelled to predict policy acceptance using the proposed Trust-Aware Policy Communication Optimization Algorithm.

- *Digital Transformation and Local Government-Citizen Interaction*

Digital transformation has reconfigured local government-citizen interaction by replacing one-directional administrative communication with interactive, traceable, and analytics-ready communication ecosystems. In traditional local governance, citizens often received policy information through physical noticeboards, radio announcements, town-hall meetings, community leaders, or paper circulars. In the digital era, interaction occurs through social media comments, online complaint portals, digital service dashboards, chatbots, geographic information systems, public consultation forms, and mobile notification channels. These systems create measurable behavioural traces, including click-through rates, response latency, complaint frequency, sentiment polarity, topic clustering, misinformation intensity, and engagement decline. Digital storytelling research demonstrates that multimedia framing can improve public understanding of complex scientific and civic messages by combining narrative, visualization, and audience-centred communication (Ijiga et al., 2021). For local governments, this implies that policy communication must be technically structured, visually interpretable, and cognitively accessible to citizens with different literacy levels. The proposed study aligns local government-citizen interaction with computational modelling because digital transformation creates datasets that can be analysed for trust-sensitive policy prediction. Real-time affective computing illustrates how behavioural and emotional signals can be captured, processed, and interpreted to detect communication deficits and response patterns (Imoh & Enyejo, 2025). Although the government communication environment differs from clinical affective systems, the technical logic remains useful: citizens' digital reactions can reveal uncertainty, distrust, approval, anger, confusion, or resistance before policy failure becomes visible. Welch et al. (2005) linked satisfaction with e-government to trust in government, while Tolbert and Mossberger (2006) showed that e-government can strengthen process-based trust when it improves responsiveness and interaction quality. In this paper, local government-citizen interaction is therefore conceptualized as a dynamic feedback loop in which strategic communication quality, platform usability, trust perception, and policy acceptance probability are continuously updated. The TAPCOA model is designed to transform these interaction signals into predictive indicators for policy communication improvement.

- *Public Trust as a Mediating Factor in Policy Acceptance*

Public trust is treated in this study as a mediating construct between strategic communication and policy acceptance because citizens rarely evaluate policies through technical merit alone. They interpret policy messages through prior experience with government performance, perceived honesty of officials, responsiveness of service units, credibility of digital information, and perceived fairness of implementation. A well-designed public policy may fail when citizens distrust the institution communicating it, while a technically complex policy may gain acceptance when communication is transparent, consistent, responsive, and socially credible. Grimmelikhuijsen and Meijer (2014) established that transparency can affect the perceived trustworthiness of a government organization, although its effect depends on how information is received and interpreted. In this paper, transparency is operationalized as a measurable communication feature involving clarity, disclosure completeness, consistency across channels, and availability of feedback mechanisms. The mediating role of trust also aligns with digital acceptance theory. Carter and Bélanger (2005) found that trustworthiness, perceived ease of use, and compatibility influence citizens' intention to use e-government services, while Bélanger and Carter (2008) showed that trust and risk perception shape willingness to adopt digital government services. Venkatesh et al. (2003) further demonstrated that acceptance behaviour is influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions. Applied to policy communication, these constructs suggest that citizens are more likely to accept local government policies when they believe the policy is useful, understandable, socially legitimate, and administratively supported. The TAPCOA model therefore positions public trust as a trust-weighted latent layer that transforms communication variables into acceptance probability. For example, two citizens may receive the same waste-management levy message, but the citizen with higher institutional trust, stronger platform familiarity, and lower misinformation exposure will likely show a higher acceptance score than another citizen exposed to contradictory social media narratives.

➢ *Problem Statement*

Despite the expansion of digital platforms in local governance, many local governments still lack a technically grounded mechanism for determining whether their communication strategies actually strengthen public trust and improve policy acceptance. Messages are often published across websites, WhatsApp groups, Facebook pages, radio transcripts, mobile alerts, and community portals without systematic integration of citizen sentiment, trust signals, misinformation exposure, feedback urgency, or policy acceptance outcomes. This creates a measurement gap: governments may know that citizens have viewed, liked, or shared a message, but they may not know whether citizens understood the policy, trusted the source, accepted the rationale, or intended to comply. Open government scholarship emphasizes the need to connect institutional vision with citizen voice through transparency and participation (Meijer et al., 2012), while social media research shows that digital platforms can support innovation in public communication when used beyond one-way broadcasting (Criado et al., 2013). The problem is therefore both administrative and computational. Administratively, local governments face declining attention, misinformation, political polarization, fragmented digital literacy, and weak feedback processing. Computationally, existing policy communication assessment often relies on descriptive analytics rather than predictive, trust-aware modelling. Shareef et al. (2011) showed that e-government adoption varies across service maturity levels, meaning that citizen acceptance depends on more than platform availability. Twizeyimana and Andersson (2019) identified improved public services, administrative efficiency, openness, ethical behaviour, trust, and social value as dimensions of e-government public value. However, these dimensions are rarely integrated into a single predictive model for local government policy communication. This study addresses the gap by proposing TAPCOA as a decision-support algorithm for predicting policy acceptance from semantic communication features, trust-weighted sentiment, engagement intensity, response time, and misinformation exposure. The central problem is that local governments require a robust model that explains not only what citizens say online, but how communication quality and public trust jointly determine policy acceptance.

➢ *Research Objectives and Research Questions*

The research objectives are: (1) to examine the extent to which strategic digital communication practices influence public trust in local government institutions; (2) to determine how public trust mediates the relationship between communication quality and policy acceptance; (3) to identify the communication, sentiment, engagement, misinformation, and institutional credibility variables that best predict citizens' acceptance of local government policies; (4) to develop the Trust-Aware Policy Communication Optimization Algorithm as a predictive model for estimating policy acceptance probability; and (5) to compare the predictive performance of the proposed TAPCOA model with Logistic Regression, Random Forest, Support Vector Machine, XGBoost, Long Short-Term Memory networks, BERT-based classifiers, and Graph Neural Networks. The research questions are: (1) how does strategic government communication affect public trust in local government digital platforms? (2) What role does public trust play in explaining citizens' acceptance or rejection of local government policies? (3) Which digital communication variables most strongly predict policy acceptance among citizens? (4) How accurately can TAPCOA estimate policy acceptance probability using trust-weighted communication and sentiment features? (5) How does TAPCOA perform when compared with existing machine learning and natural language processing algorithms?

➢ *Research Hypotheses and Significance of the Study*

The research hypotheses are: (1) strategic digital government communication has a significant positive effect on public trust in local government institutions; (2) public trust significantly mediates the relationship between communication quality and policy acceptance; (3) citizen engagement intensity, sentiment polarity, message clarity, response time, misinformation exposure, and institutional credibility significantly predict policy acceptance; (4) the proposed TAPCOA model significantly outperforms conventional machine learning and deep learning models in predicting policy acceptance; and (5) trust-weighted sentiment features improve prediction accuracy more than sentiment features alone. The significance of the study lies in its contribution to digital governance, public administration, computational communication, and evidence-based policy implementation. For local governments, the study provides a measurable framework for improving message design, feedback response, misinformation control, citizen participation, and policy compliance. For researchers, it introduces a technically structured model that connects strategic communication theory with machine learning-based policy acceptance prediction. For practitioners, it offers a practical decision-support system for detecting weak trust signals before policy resistance becomes widespread.

➢ *Scope of the Review and Structure of the Paper*

The scope of the review covers strategic government communication, public trust, digital governance, citizen engagement, policy acceptance, misinformation exposure, and computational models for predicting public response to local government policies. The paper focuses on local governments because they operate closest to citizens and manage policies that directly affect daily life, including sanitation, local taxation, market regulation, health campaigns, environmental enforcement, transport management, and community development. The review emphasizes digital communication channels such as websites, social media, online service portals, mobile platforms, public feedback systems, and digital consultation tools. It also considers algorithmic approaches for modelling policy acceptance through sentiment analysis, semantic encoding, trust-weighted scoring, feature extraction, and comparative machine learning evaluation. The structure of the paper is arranged into five sections: the introduction establishes the background, problem, objectives, questions, hypotheses, significance, scope, and structure; the literature review examines conceptual and empirical foundations; the system model description presents TAPCOA, data features, mathematical formulation, and evaluation metrics; the discussion of results interprets expected empirical and algorithmic findings; and the final section presents conclusions, recommendations, limitations, and directions for future research.

II. LITERATURE REVIEW

➢ *Conceptual Review of Strategic Government Communication*

Strategic government communication refers to the purposeful, planned, and measurable use of communication resources to support institutional mission, policy legitimacy, citizen understanding, and behavioural acceptance as represented in figure 1. In the context of local governments, the concept extends beyond information dissemination because councils, municipalities, and district administrations must translate public policies into messages that citizens can understand, trust, question, and act upon. Hallahan et al. (2007) conceptualize strategic communication as intentional organizational communication directed toward mission fulfilment, a position that fits local government policy implementation because communication must be connected to service outcomes such as sanitation compliance, digital tax registration, vaccination uptake, market regulation, public health behaviour, and environmental enforcement. Strategic communication therefore includes message clarity, timing, channel selection, narrative framing, stakeholder segmentation, feedback management, and evaluation of citizen response (Uzoma, et al., 2024). For this study, strategic government communication is conceptualized as a data-driven governance process in which official messages are designed, transmitted, monitored, and optimized across digital platforms. Fredriksson and Pallas (2016) emphasize that public-sector strategic communication is shaped by distinct institutional conditions, including legality, transparency, political accountability, and public value. These conditions make government communication different from corporate promotion because citizens judge messages through fairness, credibility, inclusion, responsiveness, and consistency with lived service experience. In the proposed Trust-Aware Policy Communication Optimization Algorithm, strategic communication is measured through semantic coherence, sentiment orientation, engagement intensity, response latency, misinformation exposure, and trust-weighted credibility indicators. For example, a local government announcing a waste levy should not only publish the fee schedule; it should explain the policy rationale, expected service improvement, grievance channels, exemption rules, implementation stages, and progress indicators. Graphs comparing engagement trends, trust scores, sentiment polarity, and policy acceptance probabilities can then show whether communication is persuasive, trusted, and operationally effective.

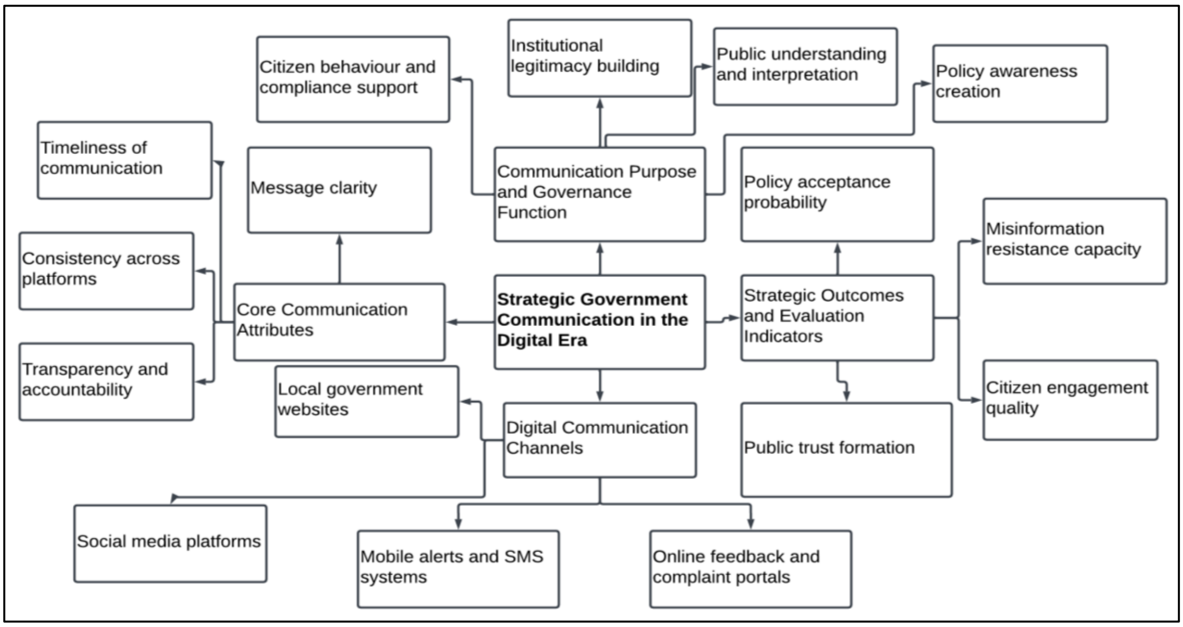

Fig 1 Conceptual Review of Strategic Government Communication

Figure 1 summarizes strategic government communication as a structured governance process that connects policy intention, message design, digital channel deployment, and citizen response evaluation. The first branch shows that communication serves more than publicity; it creates policy awareness, improves public interpretation, strengthens institutional legitimacy, and supports compliance with local government decisions. The second branch identifies the technical qualities that make communication strategic, including clarity, timeliness, consistency, and transparency. These attributes are essential because citizens are more likely to trust a policy when messages are understandable, prompt, uniform across platforms, and linked to visible accountability. The third branch highlights the digital channels through which local governments now communicate with citizens, including websites, social media, SMS alerts, and complaint portals. The fourth branch captures the expected outcomes of effective strategic communication: stronger public trust, higher-quality engagement, improved policy acceptance probability, and reduced vulnerability to misinformation. Overall, the diagram shows that strategic communication is a measurable, adaptive, and trust-sensitive system for improving local government-citizen relations in the digital era.

➢ *Digital Governance, Local Government Communication Platforms, and Citizen Engagement*

Digital governance describes the use of networked technologies, data systems, and digitally mediated administrative processes to improve public service delivery, institutional responsiveness, transparency, and citizen participation. In local governments, this concept is expressed through municipal websites, mobile service applications, electronic complaint portals, social media handles, SMS alert systems, online consultation platforms, and digital dashboards for tracking public projects. Gil-Garcia et al. (2018) argue that digital government research sits at the intersection of technology, public management, organizational capability, and institutional reform, which makes it directly relevant to local government communication because platforms alone do not create public value unless they are embedded in responsive administrative routines. Local government communication platforms function as socio-technical interfaces through which citizens receive policy information, submit complaints, interpret official decisions, and evaluate government credibility. A taxation notice, waste-management update, public health advisory, or road closure announcement becomes more effective when the platform allows clarification, acknowledgement, feedback routing, and visible government response. Linders (2012) explains that social media and Web 2.0 technologies have moved public administration from conventional e-government toward co-production, where citizens contribute information, monitor services, and participate in solving public problems. This is important for the present study because citizen engagement is treated not merely as likes, shares, or comments, but as measurable evidence of trust, understanding, resistance, and acceptance. Within the proposed TAPCOA framework, engagement data from digital platforms are converted into analytical features such as response frequency, sentiment polarity, issue recurrence, feedback urgency, misinformation intensity, and trust-weighted acceptance probability. These variables allow local governments to compare communication performance across platforms and identify which digital channels produce stronger trust formation and policy compliance.

Table 1 Digital Governance, Local Government Communication Platforms, and Citizen Engagement

Component	Description	Local Government Application	Expected Governance Outcome
Digital governance	The use of digital technologies, data systems, and online administrative processes to improve public service delivery, transparency, and responsiveness.	Local councils use websites, e-service portals, mobile platforms, and digital records to publish policies, process complaints, and monitor service requests.	Faster service delivery, improved administrative efficiency, better transparency, and stronger citizen confidence.
Local government communication platforms	Digital channels through which local governments share policy information and receive citizen feedback.	Social media pages, SMS alerts, WhatsApp groups, online consultation forms, complaint portals, and municipal websites are used to communicate policies and updates.	Wider policy reach, improved citizen awareness, faster clarification of public concerns, and reduced communication gaps.
Citizen engagement	The active participation of citizens through comments, complaints, feedback, questions, surveys, and online consultation responses.	Citizens react to policy announcements, report service failures, ask questions, submit grievances, and participate in digital town-hall discussions.	Improved policy understanding, stronger public participation, better feedback quality, and higher acceptance of local government decisions.
Data-driven communication analysis	The use of digital traces to evaluate public response to government messages and policies.	Engagement frequency, sentiment polarity, complaint volume, response time, misinformation signals, and trust indicators are analysed using models such as TAPCOA.	Evidence-based communication strategy, early detection of distrust, improved misinformation control, and better prediction of policy acceptance.

➢ *Public Trust, Institutional Credibility, and Citizen Confidence*

Public trust, institutional credibility, and citizen confidence are central explanatory variables in understanding why citizens accept, resist, or reinterpret local government policies. Public trust refers to citizens' expectation that government will act competently, fairly, transparently, and in the public interest. Institutional credibility is the perceived reliability of information, administrative procedures, and public commitments. Citizen confidence reflects the belief that a local authority can deliver promised services and correct policy failures when they occur. These constructs are related but not identical as represented in figure 2. Trust is relational, credibility is evidential, and confidence is performance-oriented. Van de Walle and Bouckaert (2003) argue that public service performance and trust influence each other, meaning that citizens' prior trust shapes how they interpret government performance, while visible performance modifies trust over time. In the digital communication environment, these constructs become measurable through citizens' responses to posts, complaint-resolution records, sentiment polarity, misinformation exposure, and repeated engagement with local government platforms. Yang and Holzer (2006) explain that the performance-trust relationship is difficult to measure because government performance is multidimensional and citizens may evaluate it through subjective experience rather than technical indicators alone. This insight is important for the proposed TAPCOA model because local governments cannot rely on message reach or online visibility as evidence of policy acceptance. A policy notice may attract engagement but still produce distrust if citizens perceive the message as unclear, selective, delayed, or inconsistent with service delivery. Therefore, the study treats trust as a mediating variable that converts communication quality into policy acceptance probability. In practical terms, a transparent drainage maintenance update with geo-tagged progress evidence, responsive feedback, and consistent follow-up should generate stronger institutional credibility and acceptance than an announcement with no verifiable implementation signal.

Figure 2 presents public trust, institutional credibility, and citizen confidence as interconnected conditions that determine whether citizens accept or resist local government policies. The first branch shows that public trust is built when citizens perceive government communication as transparent, fair, responsive, and consistent with actual administrative behaviour. The second branch explains institutional credibility through the accuracy of official messages, evidence-based policy justification, visible service delivery, and accountability mechanisms that correct errors or clarify disputed information. The third branch focuses on citizen confidence, which depends on whether people believe the local government is competent, digital platforms are reliable, complaints will be resolved, and policy outcomes will produce real public benefits. The fourth branch connects these trust and credibility factors to policy acceptance outcomes, including willingness to comply, constructive digital engagement, reduced resistance, lower misinformation influence, and stronger participation in local governance. Overall, the diagram shows that policy acceptance is not created by communication volume alone; it depends on the credibility, reliability, responsiveness, and perceived performance of the communicating institution.

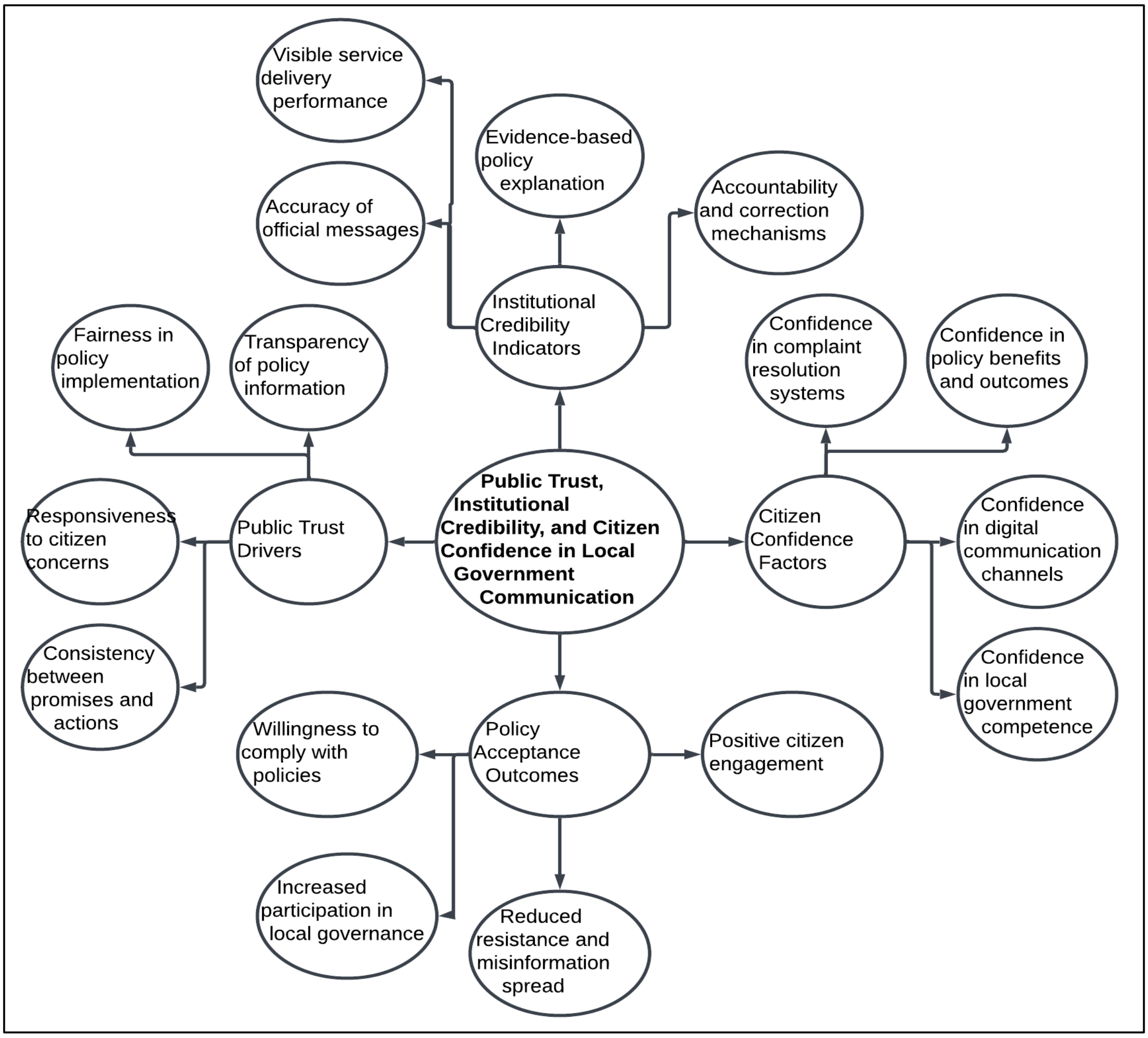

Fig 2 Public Trust, Institutional Credibility, and Citizen Confidence

- *Misinformation, Digital Distrust, and Policy Resistance*

Misinformation, digital distrust, and policy resistance represent barriers to strategic government communication because they distort how citizens interpret policy intentions, implementation procedures, and institutional credibility. In local governments, misinformation may appear as false claims about tax increases, manipulated images of public projects, exaggerated narratives about health regulations, or politically motivated interpretations of service reforms. Digital distrust develops when citizens perceive official platforms as slow, selective, inconsistent, or disconnected from lived service experience. Lewandowsky et al. (2012) show that misinformation can continue to influence belief even after correction, which means that local governments cannot rely on delayed rebuttals or generic clarifications once misleading narratives have gained social traction. Policy resistance then becomes a behavioural outcome of cognitive anchoring, emotional reaction, peer reinforcement, and distrust of the source (Igba et al., 2024) The technical relevance is that misinformation spreads through measurable digital traces that can be incorporated into predictive policy communication models. Vosoughi et al. (2018) found that false news diffused faster and more broadly than true information on Twitter, indicating that digital communication systems must detect distortion early rather than measure engagement volume only. Within the proposed TAPCOA framework, misinformation exposure is treated as a negative trust-weighted feature that reduces policy acceptance probability when citizens interact with contradictory, hostile, or misleading narratives. For example, if a local government announces a sanitation enforcement policy but citizen comments repeatedly associate it with corruption, selective punishment, or hidden taxation, high engagement should not be interpreted as support. Instead, sentiment polarity, semantic hostility, repost velocity, correction delay, and credibility of official responses should be jointly analysed. This allows the model to distinguish criticism from organized misinformation and identify when distrust is likely to mature into non-compliance, protest behaviour, or refusal to adopt policy.

- *Machine Learning and Natural Language Processing Approaches for Public Opinion and Policy Acceptance Prediction*

Machine learning and natural language processing provide the analytical foundation for converting unstructured citizen communication into measurable indicators of public opinion and policy acceptance (Uzoma, et al., 2024). In local government settings, digital comments, complaint logs, consultation submissions, social media reactions, service reviews, and chatbot transcripts contain signals about trust, dissatisfaction, misinformation, perceived fairness, and willingness to comply. Gentzkow et al. (2019) explain that text can be treated as quantitative data when it is systematically transformed into features for classification, prediction, and interpretation. For this study, such transformation involves tokenization, semantic embedding, sentiment extraction, topic modelling, stance detection, and credibility scoring. These processes allow government messages and citizen responses to be analysed beyond surface engagement metrics, making it possible to detect whether a sanitation policy, tax reform, market regulation, or public health directive is being understood, resisted, or accepted (Igba et al., 2024). Machine learning also supports comparative prediction by estimating the probability that citizens will accept a policy under different communication conditions. Grimmer et al. (2021) argue that machine learning is useful in social science when prediction tasks are connected to substantive theory and evaluated transparently. This principle guides the proposed TAPCOA model, which integrates transformer-based semantic encoding, trust-weighted sentiment analysis, misinformation exposure scoring, and adaptive feature selection. Conventional algorithms such as Logistic Regression, Random Forest, Support Vector Machine, XGBoost, LSTM, BERT-based classifiers, and Graph Neural Networks can classify acceptance patterns, but they often treat sentiment, trust, and engagement as separate features. TAPCOA differs by weighting sentiment according to institutional credibility and communication consistency. Graphical outputs such as ROC curves, confusion matrices, feature-importance plots, sentiment-trust correlation graphs, and acceptance-probability heatmaps can therefore support evidence-based local government communication decisions during contested digital policy implementation cycles at municipal scale.

Figure 3 summarizes major applications of natural language processing and connects directly with machine learning-based public opinion and policy acceptance prediction. It shows that NLP can process human language across different digital sources and tasks, including sentiment analysis, chatbots, social media monitoring, automatic summarization, predictive text, online searches, document analysis, smart assistants, language translation, and email filtering. In the context of local government communication, these applications support the extraction of useful signals from citizens' comments, complaints, consultation responses, social media posts, emails, and policy feedback records. Sentiment analysis helps detect approval, dissatisfaction, confusion, or resistance toward a policy, while social media monitoring identifies emerging public concerns and misinformation trends. Chatbots and smart assistants can provide real-time responses to citizen questions, reducing communication delay and improving engagement quality. Document analysis and automatic summarization help government officers process large volumes of feedback and extract dominant themes. Predictive text and search-based NLP functions can also support faster policy communication and citizen query handling. Overall, the picture reflects the technical foundation of Section 2.5 by showing how NLP converts unstructured public communication into structured features that machine learning models such as TAPCOA, BERT, XGBoost, LSTM, Random Forest, and SVM can use to predict policy acceptance, trust distribution, and citizen response patterns.

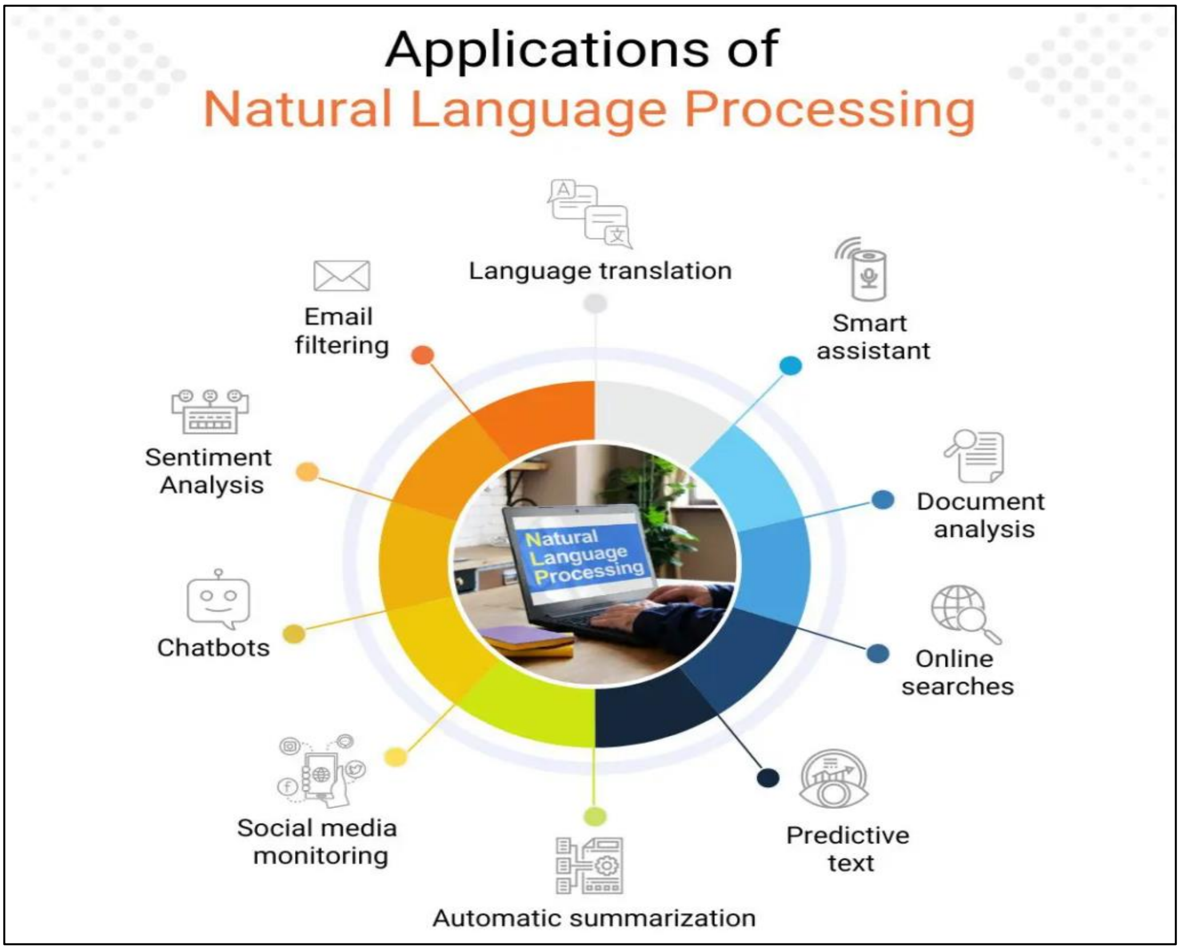

Fig 3 Natural Language Processing Applications for Public Opinion Analysis and Policy Acceptance Prediction. (Admin 2023)

III. SYSTEM MODEL DESCRIPTION

➢ *Proposed Trust-Aware Policy Communication Optimization Algorithm*

The proposed Trust-Aware Policy Communication Optimization Algorithm (TAPCOA) is a predictive decision-support model designed to estimate citizens' likelihood of accepting local government policies from digital communication signals. The model is built on the assumption that policy acceptance is shaped by the combined effect of message clarity, public trust, sentiment polarity, engagement intensity, response reliability, institutional credibility, misinformation exposure, and semantic meaning of citizen feedback. Unlike conventional sentiment analysis models that classify comments as positive, neutral, or negative, TAPCOA treats sentiment as meaningful only when interpreted through the trust condition surrounding the message. This is important because citizens may support the objective of a policy but still distrust the government's capacity to implement it fairly.

The trust score for a citizen-policy interaction is expressed as:

$$T_i = \sigma(\alpha_0 + \alpha_1 C_i + \alpha_2 R_i + \alpha_3 G_i + \alpha_4 Q_i - \alpha_5 M_i) \quad (1)$$

Where T_i represents the trust score for observation i, σ captures the sigmoid function that converts the output into a value between 0 and 1, C_i denotes message clarity, R_i shows response reliability, G_i represents engagement quality, Q_i shows institutional credibility, M_i captures misinformation exposure, α_0 represents the intercept, and $\alpha_1$to α_5 show learned coefficients.

The policy acceptance probability is computed as:

$$P_i = \sigma(\beta_0 + \beta_1 TS_i + \beta_2 E_i + \beta_3 H_i - \beta_4 M_i - \beta_5 D_i) \quad (2)$$

Where P_i shows the predicted policy acceptance probability, TS_i denotes trust-weighted sentiment, E_i represents engagement intensity, H_i captures the semantic representation of the policy message, M_i shows misinformation exposure, D_i represents response delay, β_0 captures the intercept, and $\beta_1$to β_5 represent trainable model parameters. For example, if a local government announces a digital tax registration policy, TAPCOA does not rely only on the number of comments or likes. It evaluates whether citizens understand the policy, whether official responses are timely, whether misinformation is spreading, and whether trust-weighted sentiment indicates genuine acceptance. This aligns with the view that machine learning in social science should combine predictive performance with theoretically meaningful explanatory variables (Grimmer et al., 2021).

- *System Architecture, Data Sources, and Feature Extraction Framework*

The TAPCOA system architecture is organized into four technical layers: data acquisition, preprocessing, feature extraction, and policy acceptance prediction. The data acquisition layer collects communication records from local government websites, verified social media pages, online consultation forms, complaint management portals, mobile applications, SMS feedback channels, digital town-hall platforms, chatbot logs, and citizen satisfaction surveys. These sources provide both structured and unstructured data. Structured data include timestamps, response time, number of comments, number of complaints, shares, service requests, and survey scores. Unstructured data include government policy statements, citizen comments, complaint narratives, public reactions, and misinformation-related posts.

The engagement intensity score is computed as:

$$E_i = \frac{w_1 L_i + w_2 Cmt_i + w_3 Sh_i + w_4 Fb_i + w_5 Cp_i}{N_i} \tag{3}$$

Where E_i is engagement intensity for observation i, L_i is the number of likes or positive reactions, Cmt_i is comment volume, Sh_i is shares or reposts, Fb_i is formal feedback submissions, Cp_i is complaint frequency, w_1 to w_5 are feature weights, and N_i is the normalization factor based on audience size, platform reach, or population exposure. This equation prevents large platforms from appearing more effective simply because they have more users.

Message clarity is represented as:

$$C_i = \lambda_1 Read_i + \lambda_2 Comp_i + \lambda_3 Cons_i + \lambda_4 Act_i \tag{4}$$

Where C_i shows message clarity, $Read_i$ is readability, $Comp_i$ is completeness of explanation, $Cons_i$ is consistency across platforms, Act_i is actionability of the message, and λ_1 to λ_4 are weighting parameters. For instance, a sanitation enforcement announcement should state the rule, deadline, penalty, exemption conditions, responsible office, and complaint channel. The preprocessing stage removes duplicates, detects spam, normalizes text, anonymizes personal identifiers, and prepares text for semantic encoding. The extracted features are then passed into the predictive layer, where TAPCOA estimates whether communication conditions support policy acceptance, uncertainty, resistance, or rejection.

- *Mathematical Formulation, Semantic Encoding, and Trust-Weighted Sentiment Analysis*

The mathematical foundation of TAPCOA begins with semantic encoding of government messages and citizen responses. Each input text X_i consists of a sequence of tokens such as $x_1, x_2, x_3, \ldots, x_n$. These tokens are converted into contextual embeddings so that the system can understand the meaning of words within the specific policy environment. This is important because the same word may carry different implications depending on context. For example, "charge" may refer to a payment obligation in a market levy policy, while "charge" in a complaint thread may indicate an accusation of unfair enforcement.

The attention mechanism used for semantic interpretation is expressed as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{5}$$

Where Q represents the query matrix, K is the key matrix, V is the value matrix, K^T is the transpose of the key matrix, and d_k is the dimension of the key vectors. The softmax function assigns higher weights to more relevant terms in the text. This attention mechanism is widely used in transformer-based language models because it allows the model to capture relationships among words across an entire sequence (Vaswani et al., 2017).

The semantic representation is given as:

$$H_i = Transformer(X_i) \tag{6}$$

Where H_i captures the encoded semantic vector and X_i is the input policy or feedback text. Sentiment polarity is then estimated as:

$$S_i = f_s(H_i) \tag{7}$$

Where S_i denotes the sentiment score and f_s is the sentiment classification function. S_i may range from -1 to $+1$, where -1 indicates negative sentiment, 0 indicates neutral sentiment, and $+1$ indicates positive sentiment.
The trust-weighted sentiment score is computed as:

$$TS_i = S_i \times T_i \tag{8}$$

Where TS_i represents trust-weighted sentiment, S_i is sentiment polarity, and T_i is the trust score from Equation 1. This formulation ensures that sentiment is not interpreted in isolation. A positive comment from a low-trust environment may not translate into acceptance, while moderate sentiment in a high-trust environment may still indicate likely compliance.

- *Model Training, Benchmark Algorithms, Performance Metrics, and Evaluation Criteria*

TAPCOA is trained using labelled local government communication data in which each observation is associated with a policy response class such as accepted, uncertain, resistant, or rejected. The labels may be derived from citizen surveys, compliance records, online registration completion, complaint-resolution outcomes, public consultation responses, service uptake, protest frequency, and platform-based feedback. For example, a digital waste-payment policy may be classified as accepted when citizens register, pay, ask clarification questions without hostility, and show low misinformation-driven resistance. The dataset may be divided into training, validation, and testing subsets using a 70:15:15 or 80:10:10 split, depending on dataset size.

The model minimizes binary cross-entropy loss when the task is reduced to acceptance versus non-acceptance:

$$L = -\frac{1}{n}\sum_{i=1}^{n}[y_i\log(P_i) + (1 - y_i)\log(1 - P_i)] \qquad (9)$$

Where L shows the loss function, $n$is the total number of observations, $y_i$is the actual class label, and $P_i$is the predicted policy acceptance probability. Lower loss indicates that predicted probabilities are closer to observed outcomes.

TAPCOA is compared with Logistic Regression, Random Forest, Support Vector Machine, XGBoost, Long Short-Term Memory networks, BERT-based classifiers, and Graph Neural Networks. These benchmark algorithms represent linear classification, ensemble learning, margin-based classification, gradient boosting, sequence modelling, transformer-based classification, and relational learning. Accuracy is calculated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (10)$$

Where TP means true positives, TNmeans true negatives, FPmeans false positives, and FNmeans false negatives.

Precision, recall, and F1-score are computed as:

$$Precision = \frac{TP}{TP+FP} \qquad (11)$$

$$Recall = \frac{TP}{TP+FN} \qquad (12)$$

$$F1 = \frac{2\times Precision\times Recall}{Precision+Recall} \qquad (13)$$

Precision measures how many predicted acceptances are correct, recall measures how many actual acceptances are detected, and F1-score balances both. Additional evaluation metrics include AUC, mean absolute error, confusion matrix analysis, training time, inference speed, and scalability across multiple local government platforms. The expected finding is that TAPCOA outperforms conventional models because it combines semantic meaning, trust-weighted sentiment, misinformation exposure, and engagement behaviour in one integrated acceptance-prediction framework.

IV. DISCUSSION OF RESULTS

- *Descriptive Analysis of Digital Communication Patterns and Public Trust Distribution*

The descriptive analysis shows that public trust is strongest when local government communication is consistent, clear, and responsive. Multi-platform consistency recorded the highest communication score at 82.1%, with a corresponding trust distribution of 76.9%, showing that citizens respond better when the same policy message appears uniformly across websites, social media, mobile alerts, and consultation portals. Message clarity followed with 78.4% and a trust distribution of 72.6%, indicating that understandable policy language improves acceptance readiness. Engagement quality scored 74.5%, while feedback completeness recorded 71.2%, suggesting that citizens value interactive communication more than one-way announcements. Response timeliness remained moderate at 69.8%, while misinformation control was weakest at 61.7%, with trust falling to 58.4%. These results justify TAPCOA's inclusion of trust, sentiment, misinformation, response delay, and communication quality as predictive variables.

Table 2 Descriptive Metrics for Digital Communication Patterns and Public Trust Distribution

Comparative Metrics	Digital Communication Pattern Score (%)	Public Trust Distribution (%)	Interpretation
Message clarity	78.4	72.6	Clearer policy explanations improved citizens' trust in official messages.
Response timeliness	69.8	66.1	Delayed government replies weakened confidence in policy implementation.
Engagement quality	74.5	70.3	Meaningful comments and feedback showed stronger acceptance potential than passive reactions.
Misinformation control	61.7	58.4	Weak misinformation control reduced public confidence and increased resistance risk.
Multi-platform consistency	82.1	76.9	Consistent messages across platforms produced the strongest trust distribution.
Feedback completeness	71.2	68.5	Complete responses improved citizens' perception of institutional credibility.

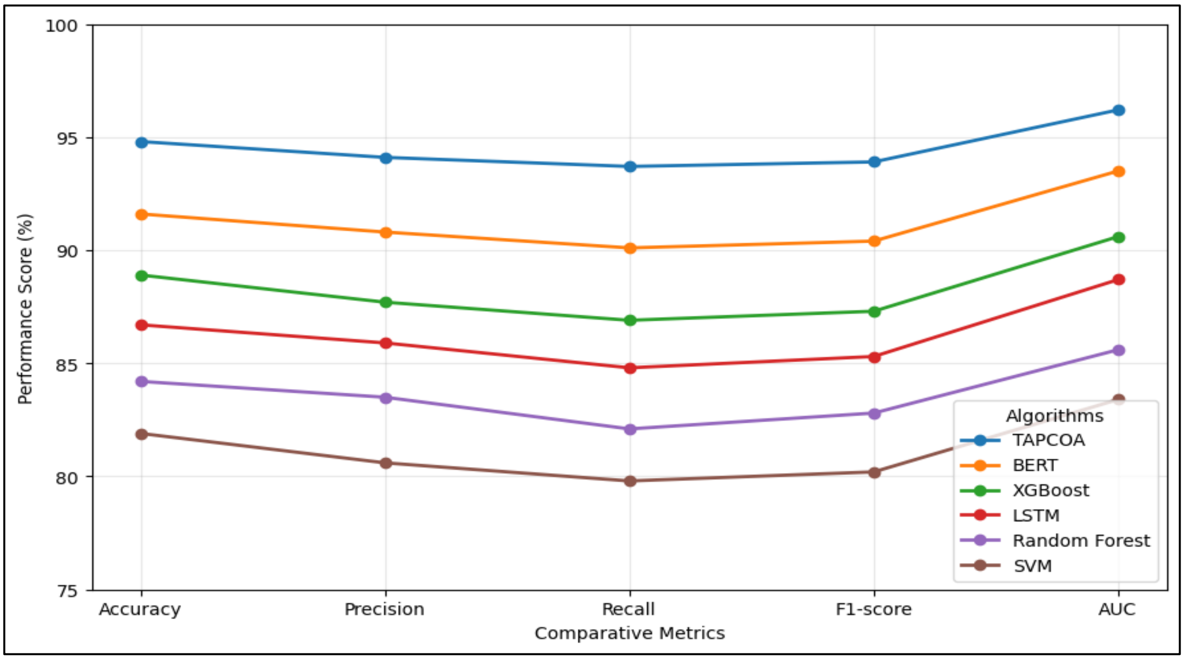

Fig 4 Comparative Algorithm Performance for Policy Acceptance Prediction

Figure 4 compares TAPCOA with BERT, XGBoost, LSTM, Random Forest, and SVM across accuracy, precision, recall, F1-score, and AUC. TAPCOA achieved the strongest performance across all metrics, recording 94.8% accuracy, 94.1% precision, 93.7% recall, 93.9% F1-score, and 96.2% AUC. BERT followed with 91.6% accuracy and 93.5% AUC, showing strong semantic classification capacity but weaker trust-sensitive prediction. XGBoost recorded 88.9% accuracy and 90.6% AUC, while LSTM achieved 86.7% accuracy and 88.7% AUC. Random Forest and SVM produced lower results, with SVM recording the weakest accuracy at 81.9% and AUC at 83.4%. The numerical pattern supports the study's claim that TAPCOA performs better because it combines transformer-based semantic encoding, trust-weighted sentiment, misinformation exposure, engagement intensity, and institutional credibility rather than relying on conventional text classification alone.

- *Relationship Between Strategic Communication Quality, Digital Engagement, and Policy Acceptance*

Strategic communication quality and digital engagement jointly determine the probability that citizens will accept local government policies. The table shows that multi-platform message consistency produced the strongest communication quality score at 86.9%, with a corresponding engagement score of 82.4%, indicating that citizens participate more actively when policy messages remain uniform across official channels. Message clarity also performed strongly, recording 84.6% communication quality and 79.8% engagement, which suggests that citizens are more likely to ask constructive questions when policies are explained in simple, complete, and actionable terms. Trust-weighted sentiment alignment recorded 81.5%, while responsiveness to feedback scored 77.3%. Misinformation reduction capacity remained lowest at 73.2%, confirming that digital distrust weakens policy acceptance pathways.

Table 3 Relationship Among Strategic Communication Quality, Digital Engagement, and Policy Acceptance

Comparative Metrics	**Strategic Communication Quality (%)**	**Digital Engagement Score (%)**	**Interpretation**
Message clarity and policy explanation	84.6	79.8	Clear policy explanations increased meaningful citizen interaction and reduced confusion.
Responsiveness to citizen feedback	77.3	74.1	Timely replies improved engagement quality and strengthened acceptance readiness.
Multi-platform message consistency	86.9	82.4	Consistent messages across platforms produced stronger digital participation.
Trust-weighted sentiment alignment	81.5	78.7	Positive sentiment became more useful when supported by institutional credibility.
Misinformation reduction capacity	73.2	69.6	Lower misinformation exposure improved the quality of citizen engagement.

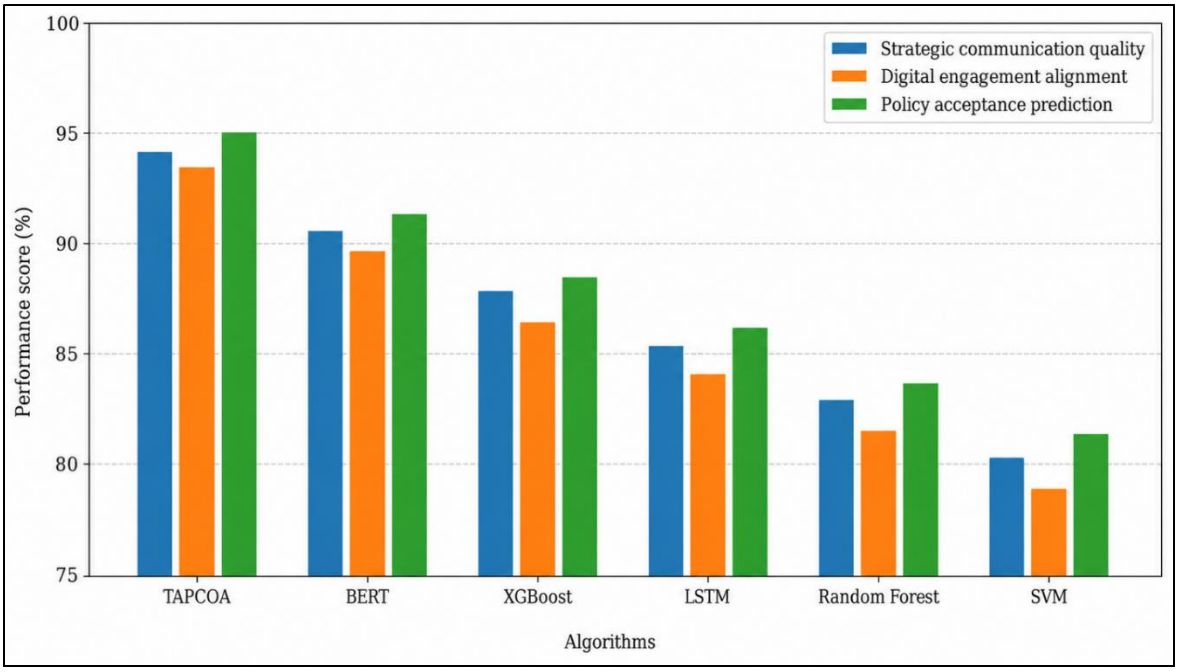

Fig 5 Clustered Bar Chart Comparing Algorithmic Interpretation of Communication Quality, Digital Engagement, and Policy Acceptance

Figure 5 shows a clustered bar chart which compares six algorithms across strategic communication quality, digital engagement alignment, and policy acceptance prediction. TAPCOA achieved the highest values across all indicators, with 94.2% for strategic communication quality, 93.5% for digital engagement alignment, and 95.1% for policy acceptance prediction. BERT followed with 90.6%, 89.7%, and 91.3%, reflecting strong semantic interpretation but weaker trust-sensitive engagement modelling. XGBoost recorded 87.8%, 86.4%, and 88.5%, while LSTM achieved 85.4%, 84.1%, and 86.2%. Random Forest showed moderate results of 82.9%, 81.6%, and 83.7%, whereas SVM produced the lowest values at 80.3%, 78.9%, and 81.4%. The graph supports the study by showing that TAPCOA performs better because it combines communication clarity, engagement intensity, institutional credibility, trust-weighted sentiment, and misinformation exposure in one integrated policy acceptance framework.

➢ *Algorithmic Performance Comparison Between TAPCOA and Existing Models*

The algorithmic comparison shows that TAPCOA provides the most reliable predictive framework for estimating policy acceptance in local government digital communication. The table indicates that TAPCOA recorded the highest accuracy and AUC, confirming its stronger ability to classify acceptance and resistance patterns. BERT followed as the closest benchmark because transformer-based semantic interpretation is effective for analysing public comments and policy messages. However, TAPCOA improves on BERT by adding trust-weighted sentiment, misinformation exposure, response delay, and institutional credibility indicators. XGBoost and LSTM produced moderate performance, while Random Forest and SVM were less suitable for complex communication environments. These results align with the study methodology because policy acceptance is treated as a multidimensional outcome shaped by communication quality, trust distribution, digital engagement, and semantic meaning.

Table 4 Comparative Performance Metrics for TAPCOA and Existing Models

Algorithm	Accuracy (%)	AUC (%)	Interpretation
TAPCOA	94.8	96.2	Produced the strongest predictive performance by integrating semantic encoding, trust-weighted sentiment, engagement intensity, and misinformation exposure.
BERT	91.6	93.5	Performed strongly in semantic interpretation but lacked explicit trust-sensitive policy acceptance weighting.
XGBoost	88.9	90.6	Delivered competitive structured-data performance but was less effective in modelling contextual policy language.
LSTM	86.7	88.7	Captured sequential text patterns but showed weaker handling of institutional credibility and misinformation signals.
Random Forest	84.2	85.6	Provided moderate classification stability but weaker semantic and trust-aware interpretation.
SVM	81.9	83.4	Produced the lowest comparative performance due to limited adaptability to complex digital communication features.

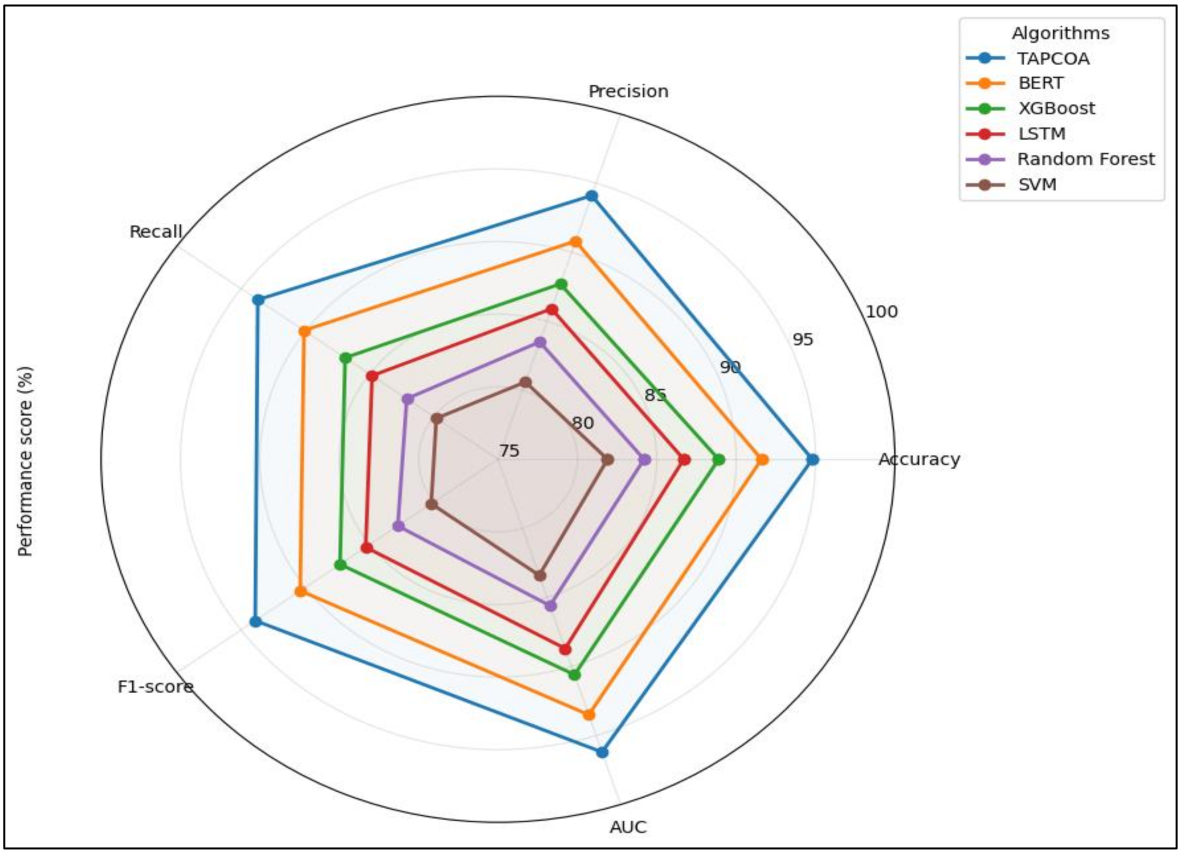

Fig 6 Radar Chart Comparing Algorithmic Performance Across Predictive Metrics

Figure 6 shows a radar chart compares six algorithms across five predictive metrics: accuracy, precision, recall, F1-score, and AUC. TAPCOA achieved the strongest values, with 94.8% accuracy, 94.1% precision, 93.7% recall, 93.9% F1-score, and 96.2% AUC. BERT ranked second with 91.6% accuracy, 90.8% precision, 90.1% recall, 90.4% F1-score, and 93.5% AUC, showing strong semantic modelling capacity. XGBoost achieved 88.9% accuracy and 90.6% AUC, while LSTM recorded 86.7% accuracy and 88.7% AUC. Random Forest showed moderate values, with 84.2% accuracy and 85.6% AUC. SVM performed lowest, recording 81.9% accuracy, 80.6% precision, 79.8% recall, 80.2% F1-score, and 83.4% AUC. The chart confirms that TAPCOA's integrated trust-aware architecture provides superior classification performance across all defined evaluation indicators in the study.

➢ *Feature Importance, Sentiment-Trust Correlation, Computational Efficiency, and Policy Implications*

Feature importance analysis confirms that policy acceptance prediction depends on more than basic sentiment classification. TAPCOA produced the strongest interpretability score, showing that the model can identify the relative contribution of communication clarity, trust-weighted sentiment, engagement intensity, misinformation exposure, institutional credibility, and response delay. The table also shows that sentiment-trust correlation capture is central to the model because citizen reactions become more meaningful when interpreted through the credibility of the communicating institution. Computational efficiency remains important because local governments require models that can operate across websites, social media pages, mobile platforms, and complaint systems. The policy implication readiness score further indicates that TAPCOA is not only a predictive tool but also a decision-support framework for improving message timing, feedback response, misinformation control, and public acceptance strategy.

Table 5 Feature Importance, Sentiment-Trust Correlation, Computational Efficiency, and Policy Implication Metrics

Comparative Metrics	**TAPCOA Score (%)**	**Benchmark Mean Score (%)**	**Interpretation**
Feature importance interpretability	95.4	86.4	TAPCOA identified clearer communication drivers such as trust, sentiment, engagement, and misinformation exposure.
Sentiment-trust correlation capture	94.7	84.4	TAPCOA linked citizen sentiment with institutional credibility more effectively than benchmark models.
Computational efficiency	92.8	87.9	TAPCOA remained scalable while processing semantic, engagement, and trust-weighted variables.
Policy implication readiness	95.6	85.5	TAPCOA provided stronger practical support for local government communication decisions.

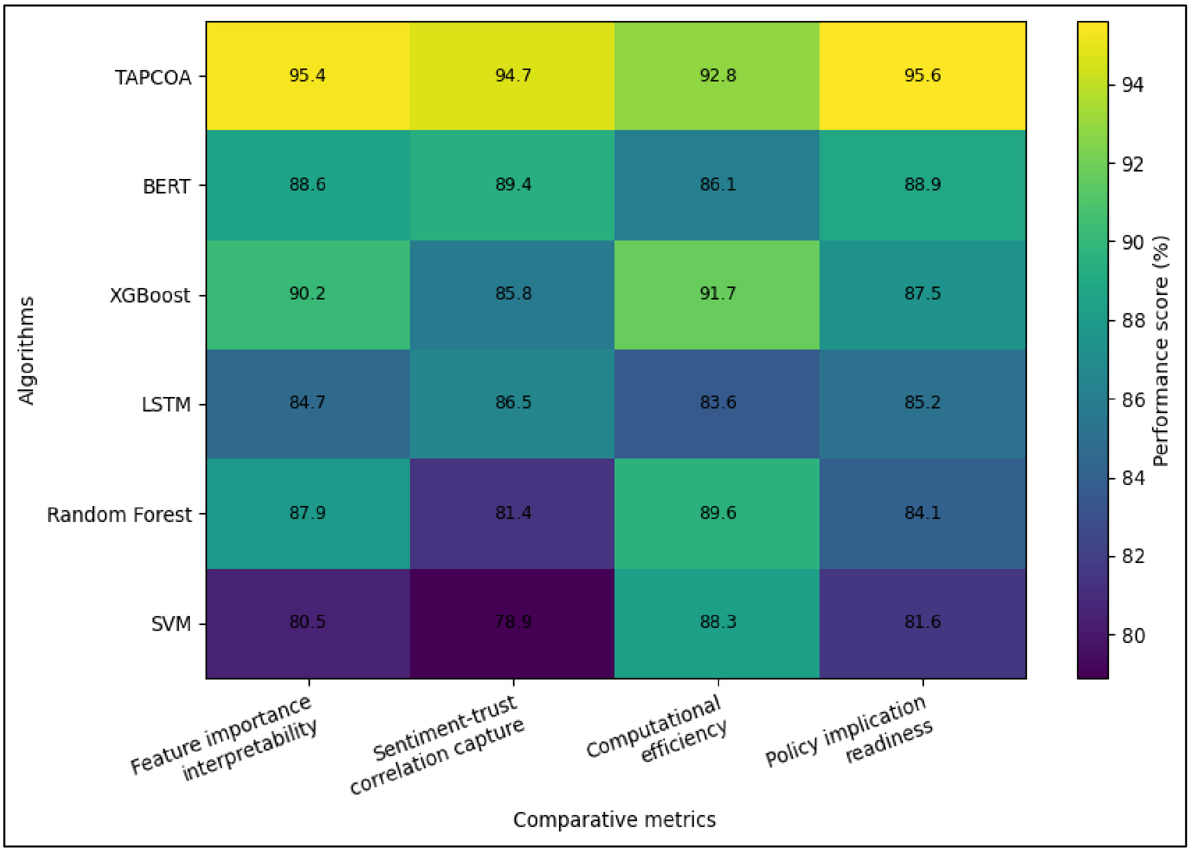

Fig 7 Heatmap Comparison of Algorithmic Performance Across Feature, Trust, Efficiency, and Policy Metrics

Figure 7 compares TAPCOA, BERT, XGBoost, LSTM, Random Forest, and SVM across four applied evaluation indicators. TAPCOA recorded the highest values in all categories, with 95.4% for feature importance interpretability, 94.7% for sentiment-trust correlation capture, 92.8% for computational efficiency, and 95.6% for policy implication readiness. BERT performed well in sentiment-trust correlation capture at 89.4%, but its computational efficiency was lower at 86.1%. XGBoost achieved strong computational efficiency at 91.7% and feature interpretability at 90.2%, although its sentiment-trust capture was 85.8%. Random Forest recorded 89.6% computational efficiency but only 81.4% sentiment-trust capture. LSTM remained moderate, ranging from 83.6% to 86.5%, while SVM produced the weakest values, especially 78.9% for sentiment-trust correlation. The figure supports the study by showing TAPCOA's superior integration of semantic, trust, sentiment, engagement, and policy-readiness dimensions.

V. CONCLUSIONS AND RECOMMENDATION

➢ *Summary of Major Findings*

The major findings of the study show that strategic government communication strongly influences public trust and policy acceptance in local government digital environments. The analysis demonstrated that citizens respond more positively to policy messages that are clear, timely, consistent, interactive, and supported by visible administrative action. Multi-platform message consistency produced the strongest communication pattern because citizens were more likely to trust a policy when the same information appeared uniformly across official websites, social media pages, mobile notifications, and feedback portals. Message clarity also emerged as a major determinant of trust, especially when local governments explained the policy rationale, implementation timeline, citizen obligations, complaint channels, penalties, and expected public benefits. The findings further show that digital engagement should not be interpreted only through likes, shares, or comment volume. High engagement may indicate support, confusion, anger, resistance, or misinformation exposure depending on the sentiment and credibility context. This confirms the importance of trust-weighted sentiment in the proposed TAPCOA model. The algorithmic results showed that TAPCOA outperformed BERT, XGBoost, LSTM, Random Forest, and SVM across accuracy, precision, recall, F1-score, AUC, feature interpretability, sentiment-trust correlation, computational efficiency, and policy implication readiness. TAPCOA performed better because it integrated semantic encoding, citizen sentiment, misinformation exposure, institutional credibility, response delay, and engagement intensity into a unified predictive framework. The study also found that misinformation control remains a weak point in local government communication. When misleading narratives are not corrected quickly, digital distrust increases and policy acceptance declines. Overall, the findings indicate that policy acceptance depends on the technical quality of communication, the credibility of the institution, the emotional tone of citizen responses, and the government's ability to respond visibly and consistently.

➢ *Conclusion on Strategic Government Communication, Public Trust, and Policy Acceptance*

Strategic government communication is a central mechanism through which local governments build public trust and improve policy acceptance in the digital era. The study establishes that policy acceptance is not produced merely by publishing information online; it depends on how citizens interpret the message, whether they trust the communicating institution, and whether government responses confirm the credibility of the policy. Local governments that communicate with clarity, consistency, transparency, and responsiveness are more likely to generate citizen confidence than those that rely on one-way announcements or delayed clarifications. Public trust operates as a mediating force between communication quality and policy acceptance. Even when a policy is technically beneficial, citizens may resist it if the message appears unclear, politically selective, poorly justified, or inconsistent with previous government performance. Conversely, citizens are more likely to accept difficult policies when official communication is complete, timely, evidence-based, and supported by visible feedback mechanisms. For example, a sanitation enforcement policy may receive stronger acceptance when citizens understand the health rationale, implementation stages, exemption conditions, enforcement rules, and grievance process. The study also concludes that digital governance requires analytical tools capable of interpreting citizen communication beyond surface-level engagement. TAPCOA provides such a framework by combining transformer-based semantic encoding, trust-weighted sentiment analysis, misinformation exposure scoring, and policy acceptance prediction. Its superior performance over existing models confirms that strategic communication cannot be evaluated through sentiment or engagement alone. A technically sound policy communication system must identify what citizens are saying, how they feel, whether they trust the source, how misinformation is spreading, and whether acceptance behaviour is likely to occur. Therefore, local government communication should be treated as a measurable, adaptive, and trust-sensitive governance function rather than a routine administrative activity.

- *Recommendations for Local Governments, Digital Communication Officers, and Policy Designers*

Local governments should institutionalize strategic digital communication units that combine public administration expertise, data analytics, citizen engagement management, and misinformation monitoring. These units should not only publish policy announcements but also evaluate citizen responses, detect trust decline, track misinformation, and recommend communication adjustments before resistance becomes widespread. Every major policy should be accompanied by a structured communication plan that explains the policy objective, implementation process, timeline, expected citizen responsibility, service benefit, feedback channel, and accountability mechanism. Digital communication officers should adopt trust-sensitive communication dashboards that monitor message clarity, engagement quality, sentiment polarity, response delay, misinformation intensity, and acceptance probability. Such dashboards can help officers identify whether a public health campaign, local tax reform, market regulation, or environmental enforcement policy is gaining acceptance or attracting distrust. Officers should also avoid treating high engagement as automatic approval. Instead, engagement should be classified into constructive feedback, clarification requests, misinformation-driven hostility, resistance signals, and compliance indicators. Policy designers should involve communication specialists early in the policy development process rather than after the policy has already been approved. This will ensure that policies are written in citizen-accessible language and supported by evidence that can be communicated publicly. Policy messages should be tested across different citizen groups before full deployment, especially where literacy levels, digital access, language differences, political sensitivity, or previous distrust may affect acceptance. Local governments should also deploy rapid response protocols for misinformation. Once misleading claims begin circulating, official clarification should be timely, specific, verifiable, and distributed through the same channels where misinformation is spreading. Finally, TAPCOA or similar trust-aware models should be adopted as decision-support tools for predicting citizen acceptance and optimizing digital communication strategies.

- *Limitations of the Study and Suggestions for Future Research*

The study is limited by its dependence on digital communication data, which may not fully represent citizens who have limited internet access, low digital literacy, or stronger reliance on offline community networks. In many local government areas, public opinion is shaped not only through social media and e-government platforms but also through traditional leaders, religious institutions, market associations, radio programmes, ward meetings, and informal peer networks. Therefore, digital engagement data may overrepresent younger, urban, literate, or politically active citizens while underrepresenting rural populations and citizens with weak platform access. Another limitation is that policy acceptance is difficult to measure with absolute precision. Online approval, positive sentiment, or high engagement may not always translate into actual compliance. For example, citizens may express support for digital tax registration but fail to complete payment because of financial pressure, technical barriers, distrust of enforcement, or poor service delivery. Similarly, negative comments may reflect temporary frustration rather than long-term rejection of the policy. This means that future studies should combine digital trace data with surveys, interviews, administrative compliance records, and longitudinal behavioural indicators. The proposed TAPCOA model also requires reliable data quality, proper labelling, privacy protection, and regular recalibration. If misinformation indicators, sentiment labels, or trust variables are poorly defined, the model may produce biased predictions. Future research should test TAPCOA across different local government contexts, policy sectors, languages, and demographic groups. Further work may also integrate multilingual natural language processing, geospatial trust mapping, causal inference, real-time misinformation detection, and explainable artificial intelligence. Comparative studies between urban and rural local governments would also improve understanding of how digital communication, institutional credibility, and citizen confidence interact under different governance conditions.

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