

AI adoption in corporate communication and stakeholder engagement in select Kenyan parastatals

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ABSTRACT

Artificial Intelligence (AI) is rapidly reshaping organisational communication worldwide, raising fresh questions about how public sector institutions in developing countries are managing the transition. This study examined the adoption of AI in corporate communication and its perceived influence on stakeholder engagement in two purposively selected parastatals under Kenya's Ministry of Information, Communications and the Digital Economy (MICDE): the Kenya Yearbook Editorial Board (KYEB) and the Media Council of Kenya (MCK). The study used a descriptive design combining qualitative and quantitative approaches, anchored in Systems Theory and Rogers' Diffusion of Innovations Theory, which together framed both the interview themes and the analytical coding. The target population comprised all 20 corporate communication officers employed in the two parastatals. Because it was small and bounded, a census-like approach was used and all 20 officers were invited. Semi-structured interviews were conducted with 18 corporate communication officers (a 90% response rate), and the data was analysed using Braun and Clarke's (2006) six-phase thematic analysis, complemented by descriptive frequency counts. The findings show that adoption centred on generative and task-specific tools such as ChatGPT, Gemini, and Canva AI, are used mainly to create, edit, and format content and reports. Implementation was largely informal, decentralised, and driven by individual officers rather than institutional strategy. Accuracy and reliability concerns were the most widely reported challenge (78% of respondents), followed by the absence of formal training (67%) and ethical concerns around data privacy and algorithmic bias. The study, established that AI improved communication speed, efficiency, and responsiveness, but its contribution to deeper, relational stakeholder engagement remained limited, as only 22% of respondents used AI for personalised stakeholder communication. Because these percentages describe a small purposive sample, they are presented as descriptive of the study group rather than generalisable estimates. The findings provide context-specific empirical data to the still largely unstudied realm of AI in corporate communication and public sector governance in sub-Saharan Africa, and provide actionable recommendations. For the parastatals, these are a formal, leadership-endorsed AI communication strategy and guidelines, regular training and capacity building, upgraded tools and infrastructure, and systematic monitoring and evaluation of AI-supported communication. For the Ministry of Information, Communications and the Digital Economy, they are sector-specific AI governance guidelines anchored in the Data Protection Act, 2019, and a coordinated capacity-building programme, so that practice aligns with the National Digital Masterplan in Kenya.

Keywords: Artificial Intelligence, Corporate Communication, Diffusion of Innovations, Parastatals, Kenya, Stakeholder Engagement

I. INTRODUCTION

Corporate communication is a strategic management function through which organisations orchestrate internal and external communication with their many stakeholder groups in order to shape perceptions, influence attitudes, and build lasting relationships (Cornelissen, 2023). In recent years, Artificial Intelligence has advanced at remarkable speed, giving organisations new ways to communicate and to meet their communication objectives more effectively (Florea & Croitoru, 2025). AI is broadly understood as the effort to build intelligent machines capable of thinking, learning, and making decisions in ways that resemble human reasoning (Russell & Norvig, 2020). Since John McCarthy coined the term at the 1956 Dartmouth workshop, the field has moved through successive cycles of optimism and retrenchment to today's deep-learning-driven resurgence, in which AI systems assist people across a growing range of domains (Haenlein & Kaplan, 2019).

Within corporate communication, AI applications such as chatbots, automated content creation, sentiment analysis, and social media monitoring are increasingly used to handle large volumes of data, respond to stakeholder queries in real time, and target messages more precisely, although the largest cross-national survey of the profession shows adoption in communication departments is still at an early stage and practitioner competence remains limited (Zerfass et al., 2020). Where AI is well deployed, the benefits are documented: responsive, well-designed chatbot interactions increase user satisfaction and loyalty (Cheng & Jiang, 2020), AI-supported social listening strengthens

reputation management by capturing stakeholder perceptions at scale (Westermann & Forthmann, 2021), and communication leaders report clear efficiency gains in content creation, research, and analytics (Yue et al., 2024).

Across Africa, AI deployments are spreading through agriculture, healthcare, financial services, and media, and Kenya sits prominently within this shift (Gwagwa et al., 2020). In the Kenyan economy AI is increasingly visible: Safaricom's customer-care chatbot Zuri, launched in December 2018 on Telegram and Facebook Messenger, was made available to over 17 million of its mobile data users (Safaricom, 2018), and Kenyan newsrooms, have begun integrating AI into news production (Kioko et al., 2022). For the Kenyan government, AI is a central pillar of the digital transformation agenda set out in the Kenya National Digital Masterplan 2022–2032 and the Kenya National Artificial Intelligence Strategy 2025–2030, with parastatals positioned as key institutional actors in that transformation (Ministry of Information, Communications and the Digital Economy [MICDE], 2022, 2025).

Despite this national policy push, empirical evidence on how AI is actually being implemented in the corporate communication functions of Kenyan parastatals remains sparse. Most existing research comes from developed economies and the private sector, leaving the public sector in sub-Saharan Africa comparatively unexamined. Where African evidence exists, it tends to document deployments and their policy dimensions rather than how AI is used strategically within communication functions (Gwagwa et al., 2020). This study addresses that gap by examining AI adoption in the communication departments of two purposively selected parastatals based in Nairobi, Kenya.

The significance of the study extends beyond the two institutions examined. This is due to the fact that parastatals under the MICDE are the government's principal interface with citizens, and how their communication functions are adopting AI, speaks directly to the feasibility of Kenya's national digital transformation commitments. The findings of this study therefore, contribute valuable insight not only for organisational practice, but also for national policy implementation, and this policy relevance underpins the analysis throughout the paper.

1.1 Statement of the Problem

Kenya's digital transformation agenda positions parastatals under MICDE as key institutional bridges between the government and citizens, placing them at the centre of public service innovation. Even so, little empirical research has examined how these institutions are using AI to improve stakeholder engagement and communication efficiency. This study was motivated by three knowledge gaps: First, existing research concentrates on developed economies and the private sector, paying little attention to the public sector in developing countries. Second, where African evidence exists, it documents deployments and policy dimensions rather than how AI is strategically used to strengthen stakeholder engagement. Third, while the Kenya National Digital Masterplan and the National AI Strategy (2025–2030) articulate the policy ambition for AI, the evidence base for African AI policy remains nascent (Plantinga et al., 2024), and there is limited empirical evidence on the actual extent of adoption, the implementation strategies used, the challenges faced, and the engagement outcomes achieved in Kenyan parastatals. This study addresses these gaps by providing context-specific evidence, to guide both policy and communication practice.

1.2 Research Objectives

- i. To assess the types of AI tools adopted for corporate communication in the selected parastatals.
- ii. To examine the strategies utilised by corporate communication officers in adopting AI to enhance communication.
- iii. To examine the challenges officers face in implementing AI in corporate communication.
- iv. To evaluate the perceived influence of AI adoption on stakeholder engagement practices in the selected parastatals.

1.3 Research Questions

- i. What types of Artificial Intelligence tools are adopted for corporate communication in selected Nairobi-based parastatals?
- ii. What strategies do corporate communication officers utilise in adopting Artificial Intelligence to enhance communication in selected Nairobi-based parastatals?
- iii. What challenges do corporate communication officers face in implementing Artificial Intelligence in corporate communication in selected Nairobi-based parastatals?
- iv. How does the adoption of Artificial Intelligence influence stakeholder engagement practices in corporate communication in selected Nairobi-based parastatals, as perceived by corporate communication officers?

II. LITERATURE REVIEW

2.1 Theoretical Review

The study rests on two complementary theoretical foundations: Systems Theory and the Diffusion of Innovations (DOI) Theory. Together, they provide a structural and a behavioural perspective for analysing AI adoption in corporate communication, and, as detailed in Section 3.5, their constructs also shaped the interview guide and the deductive strand of the coding framework, so that the theories structured the analysis from the outset rather than serving only as interpretive lenses at the discussion stage.

2.1.1 Systems Theory

Systems Theory views organisations as complex wholes made up of interacting, interdependent parts that together serve shared purposes (Mele et al., 2010). In this study, AI is conceptualised as a technological subsystem introduced into existing communication systems. This theory, informed the first and fourth objectives: it frames AI tools as components that must connect with the wider communication system, and it explains why AI's influence on stakeholder engagement depends on how well its tools are linked to feedback loops, stakeholder data management systems, and strategic processes, rather than operating in isolation. Where AI tools are used as standalone productivity aids, disconnected from other organisational processes, their capacity to create meaningful stakeholder engagement is constrained, a proposition this study examines directly.

2.1.2 Diffusion of Innovations Theory

Everett M. Rogers (2003) developed the Diffusion of Innovations Theory to explain how new ideas and technologies spread through populations over time. The theory identifies five attributes of an innovation that shape adoption decisions: relative advantage, how much better the innovation is than what it replaces; compatibility, how consistent it is with existing systems and values; complexity, how difficult it is to understand and use; trialability, how easily it can be tested; and observability, how visible its results are. These attributes fed directly into the second and third objectives, supplying the categories used to analyse the strategies officers adopt and the challenges they face. In particular, the dominance of generative AI tools can be traced to their high relative advantage and low complexity; infrastructure and training gaps map onto barriers of trialability and complexity; and the absence of formal evaluation mechanisms reflects poor observability, which weakens the incentive for more strategic use of AI.

2.2 Empirical Review

2.2.1 AI Tools in Corporate Communication

AI has been steadily reshaping the corporate communication landscape worldwide, although the empirical evidence suggests adoption is at an earlier stage than the surrounding enthusiasm implies. In the largest cross-national survey of the profession to date, 2,689 communication practitioners across 22 European countries, Zeffass et al. (2020) found that while practitioners clearly recognise AI's potential to change communication work, actual adoption within communication departments was still nascent and practitioners rated their own AI competence as low. On the stakeholder-facing side, Cheng and Jiang (2020), surveying 1,064 consumers in the United States who had used the chatbot services of major brands, found that the informational, entertainment, and social-presence gratifications of chatbot interactions significantly increased user satisfaction, and through its loyalty and continued use, while perceived privacy risk pulled in the opposite direction. Westermann and Forthmann (2021) showed that AI-supported social listening, the automated analysis of stakeholders' online conversations, can capture stakeholder perceptions at scale and complement traditional reputation measurement in communication management.

In sub-Saharan Africa, the picture is one of promising but uneven adoption. Reviewing AI deployments across African sectors, Gwagwa et al. (2020) document growing use in service delivery alongside persistent capacity and governance constraints. Chatbots have attracted particular attention in the public sector: Dube (2024) argues that AI chatbots can improve public service delivery and create public value in the South African public sector, while Shekgola and Modiba (2025) propose a framework for using chatbots to make government information and services available around the clock, cautioning that successful implementation depends on cybersecurity, skilled personnel, and ethical safeguards such as transparency and data privacy. Okolo et al. (2023) identify the same recurring constraints, skills gaps, infrastructure deficits, and weak regulatory readiness, across African AI adoption more broadly.

In Kenya, Riany (2025), in a census of eleven public research institutions, found that institutional AI capability, expertise, infrastructure, software stacks, and algorithmic models, significantly predicted the mainstreaming of science, technology, and innovation, evidence that AI capacity shapes public institutions' outcomes. In the media sector, Kioko et al. (2022) studying two media organisations (BBC Africa and Radio Africa Group), found that management buy-in, cost, technical skills, clarity of use case, perceptions, and company structure shaped whether AI was adopted in Kenyan newsrooms, and identified lack of quality data and ethical concerns among the

challenges. Taken together, these findings underline the importance of examining not only which tools are introduced, but how they are actually used in corporate communication for stakeholder engagement.

2.2.2 Strategies for AI Adoption

The global literature identifies a set of organisational enablers that can make or break AI adoption. Brock and von Wangenheim (2019), drawing on survey data from over 2,500 decision-makers worldwide together with in-depth case studies, found that organisations succeeding with AI treat it as part of a broader digital transformation and share a distinct set of success factors: sound data foundations, realistic expectations, integration with existing processes, cross-functional teaming, agility, and committed leadership. In the communication profession specifically, Yue et al. (2024), drawing on interviews with twenty senior public relations leaders experienced with AI, found that leadership engagement shaped both how systematically AI was applied to content creation, research, and analytics, and how deliberately its ethical risks were managed. The message across these studies is consistent: successful AI implementation is as much a management challenge as a technical one, and it must be deliberately planned, resourced, and institutionalised.

The strategic landscape in sub-Saharan Africa looks very different, with little evidence of these institutional enablers. Okolo et al. (2023) report that AI adoption in African organisations commonly proceeds without governance structures, dedicated training, or evaluation processes. At the policy level, Plantinga et al. (2024), analysing AI-related policies and legislation across twelve African countries including Kenya, find that formal frameworks are only beginning to emerge and argue that governments need deliberate policy learning to build responsible AI governance ecosystems, precisely the strategic scaffolding that individual public organisations currently lack.

In Kenya, the readiness literature points in the same direction. Jonathan et al. (2025), interviewing seventeen public sector experts, identified eight interdependent readiness factors for AI adoption, technological infrastructure, data quality, leadership commitment, staff competencies, organisational culture, regulatory frameworks, public trust, and external partnerships, and concluded that it is readiness, not deployment alone, that determines whether AI generates public value. Imende-Obonyo et al. (2024), studying the use of data analytics in Kenyan state corporations, similarly found that user readiness hinged on user attributes, change management, ICT competence, and decision-making culture. They recommended top-leadership support, user engagement, capacity building, and data governance as critical interventions. Collectively, these findings suggest that Kenyan public institutions still lack precisely the strategic and readiness conditions that the global literature identifies as necessary for sustainable outcomes from AI.

2.2.3 Challenges in AI Implementation

The global literature presents a consistent set of barriers spanning ethical, professional, and organisational dimensions. On the ethical side, Floridi et al. (2018), synthesising six major AI ethics documents into the AI4People framework, distilled the core risks of AI deployment into five governing principles, beneficence, non-maleficence, autonomy, justice, and explicability, with algorithmic bias, data privacy, and the opacity of AI decision-making among the central concerns for any organisation using AI on the public's behalf. Within the communication profession, Galloway and Swiatek (2018) observe that practitioners have been slow and apprehensive in engaging with AI, partly from concern that it could displace parts of their work, and argue the profession should approach AI as augmentation rather than threat. The European survey evidence reinforces this professional dimension: practitioners' limited competence and unclear organisational responsibilities for AI proved greater obstacles than the technology itself (Zerfass et al., 2020).

In sub-Saharan Africa, these professional and ethical challenges are compounded by deeper structural constraints. Research ICT Africa's ten-country After Access surveys reveal that device and data affordability and digital skills—not network coverage alone—are the binding constraints on digital technology use, with significant gender and urban–rural disparities (Gillwald & Mothobi, 2019). Earlier econometric work had already demonstrated how infrastructure deficiencies shape the adoption of digital technologies across the region (Mothobi & Grzybowski, 2017). For AI specifically, Gwagwa et al. (2020) identifies capability gaps, data scarcity, and weak policy frameworks as recurrent challenges across African deployments.

The Kenyan challenge profile mirrors this pattern and adds public-sector specifics. Onyango and Ondiek (2021), mapping digitalisation in Kenyan public organisations, found institutionalisation deficits driven by limited ICT skills training, insufficient digital platforms, poor internet connectivity, and inadequate government investment. Imende-Obonyo et al. (2024) likewise identified ICT competence and weak change management as key internal constraints in state corporations. A further layer is regulatory: the Data Protection Act, No. 24 of 2019 imposes duties on the collection and processing of personal data, so communication officers using AI tools that ingest stakeholder data face compliance obligations that few institutions have yet translated into practical internal guidance (Government of Kenya, 2019). The barriers to AI-based communication in Kenyan public bodies are thus technical, financial, regulatory, and structural at once, and they call for a coordinated, multi-dimensional institutional response.

2.2.4 AI and Stakeholder Engagement

Globally, the evidence connects AI most strongly to the operational side of engagement. Cheng and Jiang (2020) demonstrate that responsive, gratifying chatbot interactions build user satisfaction, loyalty, and continued use, the clearest causal pathway yet documented from AI-enabled responsiveness to stakeholder outcomes. At the same time, the profession-wide evidence reveals a gap between potential and practice: practitioners see AI's greatest promise in analytics and stakeholder insight, yet current use concentrates on efficiency and content tasks (Zerfass et al., 2020), and even AI-experienced communication leaders describe today's applications as dominated by content production and research support rather than relationship building (Yue et al., 2024).

In African public institutions, the engagement evidence is thinner and centres predominantly on service delivery. Chatbot deployments have improved the availability and speed of government information and services (Shekgola & Modiba, 2025), but these studies also stress that routine query handling is not the same as relational engagement, which requires context-sensitive human communication that AI should support rather than replace. Gwagwa et al. (2020) similarly find that African AI deployments have concentrated on operational service improvements, with the trust, accountability, and participation dimensions of engagement lagging behind.

In Kenya, the institutional evidence points the same way. Riany (2025) shows that AI capability significantly advances institutional innovation outcomes in public research institutions, while Onyango and Ondiek (2021) show that digital platforms in Kenyan public organisations remain weakly institutionalised, a combination suggesting that functional gains are achievable but deeper organisational integration is rare. Direct empirical evidence on how AI affects the relational quality of stakeholder engagement in Kenyan public institutions is scarce, and that is precisely the gap this study investigates in the specific context of the Kenya Yearbook Editorial Board and the Media Council of Kenya.

2.3 Research Gap

The literature reviewed shows that AI has the potential to transform corporate communication, but three recurring gaps stand out. First, public institutions in developing economies remain under-explored, with the empirical base concentrated in the Global North and the private sector. Second, the African evidence documents deployments and policy dimensions rather than the strategic use of AI in stakeholder engagement (Gwagwa et al., 2020). Third, although the policy ambitions of the Kenya National Digital Masterplan and the National AI Strategy (2025–2030) are clear, there is little empirical data on actual adoption levels, strategies, challenges, and engagement outcomes in Kenyan parastatals. This study addresses these gaps directly.

III. METHODOLOGY

3.1 Research Design

The study employed a descriptive research design combining qualitative and quantitative approaches. The qualitative component allowed in-depth exploration of why and how officers adopt AI, how AI features in everyday communication work, and how officers perceive its impact on stakeholder interactions. The quantitative component complemented this by summarising patterns through frequencies and percentages, providing a measurable picture of the extent of AI use across the participant group. Used together within a descriptive design, the two approaches maximised the richness, credibility, and usability of the findings (Creswell & Creswell, 2018).

3.2 Study Site and Justification

The study was carried out at the Kenya Yearbook Editorial Board (KYEB) and the Media Council of Kenya (MCK), both based in Nairobi and operating under the MICDE. The two parastatals were purposively selected against four predetermined criteria: (i) a primary mandate centred on public communication and information dissemination; (ii) documented evidence of digital and AI-enabled communication initiatives; (iii) institutional positioning within the MICDE, which places them at the forefront of Kenya's digital transformation agenda; and (iv) contrasting stakeholder profiles, which added analytical depth. KYEB communicates government development achievements to a broad and diverse public audience, while MCK serves a professional constituency of journalists and media practitioners. This contrast made it possible to examine AI use in two distinct communication settings within the same institutional framework, strengthening the comparative rigour of the analysis.

3.3 Target Population, Sample Size, and Sampling

The target population comprised of all corporate communication officers in the two selected parastatals, the staff directly responsible for managing internal and external communication, implementing AI-powered tools, and maintaining stakeholder relationships. Official records and direct consultation with the human resource and corporate

communication offices established that each parastatal employed an average of ten corporate communication officers, giving a target population of twenty across the two institutions.

In qualitative research, sample size is judged by the depth and richness of data rather than statistical representation (Creswell & Poth, 2018). Given the small, specialised, and clearly bounded population, a census-like approach was taken, targeting all twenty officers; eighteen participated, a response rate of 90 percent. This falls within established qualitative guidelines, which suggest that data saturation in relatively homogeneous, information-rich samples typically occurs within 12–20 interviews (Hennink et al., 2017). All participants were purposively included because each had direct experience relevant to the study objectives, enriching the data and strengthening its credibility (Tongco, 2007). It should be noted that the frequencies and percentages reported in this study describe this group of eighteen officers only; they are presented as descriptive summaries of the sample and should not be read as statistically generalizable estimates for the wider public sector.

3.4 Data Collection

Semi-structured interview guides served as the main data collection tool. Semi-structured interviews suit qualitative descriptive research well: they elicit rich, detailed accounts of participants' experiences while leaving room to pursue new ideas and clarify meaning as they emerge (Creswell & Poth, 2018). The interview guide was organised around the thematic areas of the study objectives, the types of AI tools used, implementation strategies, implementation challenges, and the perceived influence of AI on stakeholder engagement, with the constructs of the two theoretical frameworks informing how the questions within each area were framed. Open-ended and probing questions were used to draw out in-depth professional experiences. The guide was pre-tested with a corporate communication officer in Nairobi who was outside the final sample, and the wording and sequence of questions were refined accordingly.

Data collection began after ethical clearance had been obtained from the Mount Kenya University Ethics Review Committee and a research licence from the National Commission for Science, Technology and Innovation (NACOSTI). Interviews were conducted face-to-face at participants' workplaces or via secure online platforms, according to each participant's preference, and lasted between 45 and 60 minutes. With participants' informed consent, interviews were audio-recorded, and field notes captured contextual and non-verbal information. Data collection continued until saturation was reached, the point at which further interviews yielded no new themes (Hennink et al., 2017).

3.5 Data Analysis

Qualitative data was analysed using Braun and Clarke's (2006) six phases of thematic analysis. Phase one involved verbatim transcription of the audio recordings and repeated reading of the transcripts alongside the field notes. Phase two involved systematic line-by-line coding: for example, statements about using ChatGPT or Canva were coded as 'generative AI use', and statements about verifying AI outputs were coded as 'accuracy concerns'. Coding combined inductive and deductive approaches, the deductive codebook was built from the four study objectives, the five innovation attributes of Rogers' (2003) Diffusion of Innovations Theory (relative advantage, compatibility, complexity, trialability, observability), and the systemic integration constructs of Systems Theory, so that the theoretical frameworks structured the analysis from the outset rather than entering only at the interpretation stage. In phase three, related codes were clustered into broader thematic categories corresponding to the study objectives. Phase four involved reviewing the candidate themes against the full data set to ensure coherence and consistency. Phase five defined and named each theme and its sub-themes. Phase six involved writing up the themes in narrative form, supported by verbatim participant quotations and interpreted in relation to the theoretical constructs and the reviewed literature. Quantitative data drawn from the structured response sections of the interview guide were analysed using descriptive statistics and presented in summary tables alongside the qualitative narratives. During the preparation of this manuscript, the author used AI-assisted tools to support language editing and the refinement of text. All study conception, data collection, analysis, and interpretation are the author's own work.

3.6 Research Trustworthiness

The trustworthiness of the study was addressed through Lincoln and Guba's (1985) four criteria. Credibility was strengthened through semi-structured in-depth interviews, open and probing questions, member checking, summarizing main points back to participants for confirmation, and the use of verbatim quotations to support interpretation. Transferability was addressed through thick description of the research context, participant profiles, and data collection conditions. Dependability was supported by a clear audit trail of methodological decisions, a standardised interviewing procedure, pre-testing, and supervisor review of the interviews. Confirmability was pursued by grounding all themes in the interview data, illustrating each theme with participant quotes, and maintaining reflexivity throughout the process to minimise researcher bias.

IV. FINDINGS & DISCUSSION

4.1 Findings

Eighteen of the twenty targeted corporate communication officers participated, a response rate of 90 percent. Purposive sampling, advance institutional notice, flexible scheduling, and guaranteed anonymity all contributed to this high rate. The results are presented under the four study objectives. As noted in the target population, the percentages reported below describe this sample of eighteen officers and are not intended as generalisable estimates.

4.1.1 Types of AI Tools Adopted for Corporate Communication

The findings indicate that there is a significant focus on the adoption of AI tools, with the majority being related to generative and task-focused AI, and a relatively small number of more complex analytical AI tools. Table 1 summarizes the types of tools identified.

Table 1

Types of AI Tools Adopted for Corporate Communication (n=18)

AI Tool Category	Specific Tools	Frequency	Percentage (%)
Generative AI	ChatGPT, Gemini, Canva AI, Google FX	14	77.8
Chatbots	Website chatbot systems	4	22.2
Editing/Writing AI	Grammarly, Quillbot	4	22.2
Cloud-based AI	Cloud AI tools	2	11.1

Table 2

Functional Application of AI Tools (n=18)

Application Area	Description	Frequency	Percentage (%)
Content creation	Reports, templates, communication materials	17	94.4
Editing/proofreading	Grammar correction, document refinement	8	44.4
Research	Information gathering	6	33.3
Stakeholder interaction	Website responses via chatbots	4	22.2
Design/visual content	Images, layouts, presentations	4	22.2

The most commonly used generative AI tools were ChatGPT, Gemini, Canva AI, and Google FX (77.8 percent), and content creation was by far the most common application (94.4 percent), reinforcing the picture of AI as a facilitative technology for producing content and managing workload. One respondent described using AI to ‘curate and correct documents and spell check’ (R3); another used it for ‘generating reporting templates’ (R12). About a fifth of respondents (22.2 percent) reported chatbot systems on organisational websites, but their use was inconsistent and still largely experimental. As one participant put it, ‘AI was implemented on the company website to respond to visitors’ (R18), a deployment that had not been fully institutionalised.

The absence of more sophisticated tools, sentiment analysis systems, predictive analytics platforms, data-driven communication dashboards, suggests that AI use remains at an operational stage. This mirrors the international pattern: even in Europe’s comparatively well-resourced communication departments, adoption remains early-stage and competence-constrained (Zerfass et al., 2020), and organisations everywhere gravitate first to generative and conversational tools because they are inexpensive, accessible, and easy to integrate (Dwivedi et al., 2023). It also aligns with Mhlana (2021), who documents that AI applications in emerging economies concentrate on routine, task-supporting functions.

Viewed through Systems Theory, the pattern reveals a critical systemic gap: generative AI tools were operating independently of formal communication processes and institutional data systems. They were not connected to stakeholder management platforms, content governance frameworks, or monitoring systems, which limited their capacity to contribute to coordinated communication outcomes. The DOI attributes account for the adoption pattern equally well: generative tools offer high relative advantage and low complexity, which explains their dominance, while the more advanced tools are perceived as complex and difficult to trial, requiring technical expertise most officers do not yet have.

4.1.2 Strategies for Implementing AI in Corporate Communication

The study found that AI implementation was mainly informal, decentralised, and resource-driven, with very little institutional coordination. Table 3 presents the dominant implementation strategies.

Table 3*AI Implementation Strategies (n=18)*

Strategy Type	Description	Frequency	Percentage (%)
Self-learning	Learning through trial and error	14	77.8
Self-selection	Individuals choose tools independently	12	66.7
Cost-driven adoption	Preference for free/affordable tools	10	55.6
Formal training	Organised training programs	2	11.1
Pilot testing	Testing tools before adoption	2	11.1

The most common approaches were self-learning through trial and error (77.8 percent) and independent self-selection of tools (66.7 percent), followed by cost-driven preference for free or low-cost tools (55.6 percent). Only 11.1 percent reported organised training programmes, and the same small share reported pilot testing as a formal institutional strategy. The picture that emerges is of an adoption system in which formal structure is absent and individual resourcefulness fills the gap. Across the interviews, respondents consistently reported that no formal organisational structures or departmental policies guided the choice or use of AI tools, their engagement with AI was driven by curiosity, colleagues' recommendations, or the sheer necessity of managing a heavy workload with a small team.

These results correspond closely to the readiness deficits identified in the Kenyan literature: the leadership commitment, staff competencies, and organisational-culture factors that Jonathan et al. (2025) identify as preconditions for value-generating AI adoption were largely absent, as were the change management and capacity building interventions that Imende-Obonyo et al. (2024) found decisive for analytics use in state corporations. The pattern also parallels the wider African evidence of adoption proceeding without governance structures, dedicated training, or evaluation processes (Plantinga et al., 2024). Verhoef et al. (2021) argue that digital transformation journeys typically begin with experimentation and progress toward institutionalisation; the parastatals in this study remain in the early experimental stage and have not yet made that transition.

Systems Theory emphasises that effective outcomes depend on the alignment and interdependent functioning of organisational subsystems (Whitchurch & Constantine, 1993). The individualised adoption pattern observed here shows that the human, technical, and procedural subsystems of these parastatals were not working in concert. The enabling conditions for sustainable adoption, leadership support, and an organisational climate open to experimentation and knowledge sharing, were largely missing. In DOI terms, trialability was being exercised informally by individual officers, but without institutional support the lessons from those trials were never aggregated or systematised to drive wider uptake.

4.1.3 Challenges in Adopting AI in Corporate Communication

The study identified a set of challenges that together limited the effective and sustained use of AI. Table 4 shows the frequency distribution of the challenges reported.

Table 4*Challenges in AI Adoption (n=18)*

Challenge Category	Description	Frequency	Percentage (%)
Accuracy/reliability	Incorrect or inconsistent outputs	14	77.8
Lack of training	Limited skills and knowledge	12	66.7
Over-reliance concerns	Risk of excessive dependence on AI	6	33.3
Infrastructure issues	Internet connectivity and system limitations	4	22.2
Ethical concerns	Bias, transparency, and data privacy	4	22.2

Accuracy and reliability were the most prevalent concern: 77.8 percent of respondents reported outputs that were inaccurate, inconsistent, or contextually inappropriate, requiring substantial manual verification. The second most common challenge (66.7 percent) was the lack of formal training, consistent with the finding that most officers were self-taught and used AI tools without institutional guidance. A third of respondents (33.3 percent) worried about over-reliance, fearing they might become so dependent on AI that their professional judgement and critical thinking would atrophy. Infrastructure-related challenges (22.2 percent) and ethical concerns around bias, transparency, and data privacy (22.2 percent) completed the picture.

A key finding was that ethical issues were being handled individually rather than institutionally, producing uneven practice across the two parastatals. Respondents accepted data protection and potential algorithmic bias as legitimate concerns, but observed that there was no clear oversight of how their organisations used AI or ensured its responsible use. This is consistent with the defining challenges of generative AI identified in the multidisciplinary literature, trust, accuracy, misuse, and ethics (Dwivedi et al., 2023); with the capability and infrastructure constraints

documented across African AI deployments (Mhlanga, 2021); and with the ICT competence and institutionalisation deficits observed in Kenyan public organisations (Imende-Obonyo et al., 2024).

From a Systems Theory perspective, these challenges expose gaps in the systemic capacity of the parastatals to support AI integration: without coherent governance policies, adequate technical infrastructure, and human development mechanisms, the communication ecosystem could not realise AI's full potential. The DOI concept of complexity helps explain the dynamics, the accuracy problems, learning demands, and ethical dilemmas raised by AI use all added to the difficulty of integrating it, slowing adoption. And the absence of institutional support structures constrained trialability, leaving officers without the resources or guidance to experiment responsibly with more advanced AI applications.

4.1.4 Influence of AI Adoption on Stakeholder Engagement Practices

The research found that AI adoption had a positive but predominantly operational effect on stakeholder engagement. Table 5 summarises the perceived outcomes.

Table 5

Influence of AI on Stakeholder Engagement (n=18)

Impact Area	Description	Frequency	Percentage (%)
Increased speed	Faster communication processes	16	88.9
Improved efficiency	Reduced workload, faster task completion	12	66.7
Enhanced responsiveness	Faster replies to stakeholders	10	55.6
Personalisation	Tailored communication to stakeholders	4	22.2
Formal measurement	Systematic evaluation of effectiveness	8	44.4
No measurement	Absence of formal evaluation mechanisms	10	55.6

Increased communication speed was the most frequently reported outcome (88.9 percent), followed by improved efficiency (66.7 percent) and enhanced responsiveness (55.6 percent). The participant narratives brought these patterns to life: 'AI has made my work easier, ensuring that I deliver my assignments speedily' (R2) and 'we are able to produce messages faster' (R3). Responsiveness was reflected in observations that 'we receive more feedback from clients' (R9) and that stakeholders 'feel attended to faster and not left hanging' (R8). On this evidence, AI has made a genuine contribution to the performance of the communication function in both parastatals.

By contrast, only 22.2 percent of respondents reported using AI for personalised stakeholder communication, indicating that AI has yet to reach the deeper, relational side of engagement. Just as telling, 55.6 percent said they do not formally measure the effectiveness of their AI-supported communication. When asked how they evaluated their AI-assisted work, several respondents were strikingly matter-of-fact: 'I don't measure' (R14) and 'I simply don't' (R5). The brevity of these answers is itself revealing, evaluation was not something respondents had considered and abandoned; it had simply never entered their practice. This absence of systematic evaluation matters because, without it, neither the officers nor their institutions can demonstrate AI's relational value, learn from what works, or build the case for more strategic investment.

These findings align with Verhoef et al. (2021), who argue that while digital technologies can improve the efficiency of operational processes, deeper relational change requires strategic integration that goes beyond task automation. Dwivedi et al. (2021) similarly caution that without strategic integration, AI's impact rarely extends beyond process improvements. The pattern also matches the African chatbot evidence, where deployments have delivered service-delivery gains without yet demonstrating relational transformation (Shekgola & Modiba, 2025), and the Kenyan readiness literature suggests that such deeper outcomes depend on precisely the leadership, competence, and governance factors these parastatals currently lack (Jonathan et al., 2025).

Systems Theory captures why the impact has remained operational: AI is not yet connected to the feedback, stakeholder-data, and strategic-planning subsystems of these organisations. The DOI concept of observability is especially apt here, because there is no formal evaluation, the relational benefits of AI are rarely made visible, which weakens officers' motivation to attempt more advanced applications. AI's impact in these parastatals has therefore remained transactional, its relative advantage for deeper engagement still undemonstrated.

4.2 Synthesis: Governance and Ethical Implications

A cross-cutting theme emerging from the data is a governance vacuum, expressed in three interconnected absences: no institutional AI policies, no structured training and capacity building, and no formal processes for evaluating AI. The three reinforce one another. Without policy, there is no direction for training; without training, there is no competence for evaluation; and without evaluation, it is difficult to make the case for investing in policy.

The result is a self-perpetuating cycle of informal, immature adoption that caps the impact the technology can have on stakeholder engagement.

The ethical dimension of this governance shortfall deserves particular attention in the public sector. Parastatals are state-owned entities mandated to serve the public interest, and they carry heightened responsibilities for transparency, accountability, and equitable service provision. AI use raises hard questions in this setting: the trustworthiness and potential bias of AI-generated public communication, the security of citizens' data gathered by chatbots and automated systems, the reliability of government information produced with generative tools that can hallucinate, and the accountability frameworks governing AI-assisted decisions in government communication. The findings show that officers are aware of these concerns but are dealing with them case by case, without formal governance processes, a considerable risk in institutions where communication failures carry reputational and public trust consequences of a different order from those in the private sector.

The study also carries a pointed message for Kenya's national digital transformation agenda. The Kenya National Digital Masterplan (MICDE, 2022) and the National AI Strategy 2025–2030 (MICDE, 2025) set ambitious goals for AI in public sector service delivery. The findings here, however, indicate that the institutional preconditions, formal strategies, human capital, infrastructure, and governance, are not yet in place in the institutions studied. Closing that gap will require investment not only in technology but in institutional development: building leadership capacity, harmonising policies across ministries, and allocating resources for public sector AI governance. Without this institutional infrastructure, the digital transformation ambitions set out in national policy documents are unlikely to materialise in practice.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

This study set out to investigate how selected Nairobi parastatals have incorporated AI into the corporate communication function, and how that adoption is perceived to affect stakeholder engagement. The evidence from 18 corporate communication officers at the Kenya Yearbook Editorial Board and the Media Council of Kenya supports four interconnected conclusions.

First, AI adoption in the selected parastatals is shallow. Generative AI tools are popular for content creation and editing, but advanced analytical tools, sentiment analysis, predictive analytics, data-driven dashboards, are largely absent. AI is functioning as a productivity tool, not a strategic communication tool. Second, adoption strategies are informal, decentralised, and individual. With no institutional AI policy, no training programme, and no coordination across departments, each officer works in their own way, limiting the ability to scale, to build consistency, and to share institutional learning. Third, adoption is constrained by an interlocking set of technical, organisational, and ethical challenges, accuracy and reliability problems, skills gaps, and the absence of governance for responsible AI use. These difficulties feed on each other: without training, accuracy suffers; without accuracy, confidence stays too weak to drive wider adoption; and without confidence, there is little incentive to adopt at all. Fourth, while AI has delivered tangible gains in communication speed, efficiency, and responsiveness, these benefits remain operational. Personalised stakeholder engagement and strategic relational communication have not meaningfully improved, and with no formal evaluation mechanisms in place, organizations cannot demonstrate, or develop, AI's relational value.

Taken together, the findings indicate that the selected parastatals are at an early stage of AI integration, without standardised policies or procedures. Realising the policy ambition of the Kenya National Digital Masterplan and the National AI Strategy 2025–2030 will require deliberate, coordinated action to close the gap between national aspiration and the institutional reality documented in this study.

5.2 Recommendations

The recommendations below are ordered by implementation priority within each stakeholder group, distinguishing immediate actions from short-term (within one year) and medium-term (one to three years) measures, so that institutions can sequence their responses rather than confront a single undifferentiated list. The immediate priority is a formal, documented AI communication strategy: guidelines that specify the categories of tools to be used, selection criteria, usage protocols, and evaluation procedures. These strategies should be integrated with existing communication strategies and endorsed at senior leadership level to secure institutional ownership and cross-departmental coordination. In the short term, regular training on tool use, ethical considerations, and output assessment should be embedded in staff development programmes so that capacity building becomes systematic and recurring rather than occasional. Given the prevalence of self-learning and the persistent concerns about accuracy, capacity building should be treated as a core strategy, not an optional extra.

In the medium term, AI tools and infrastructure should be upgraded, investing in reliable internet connectivity, secure data management platforms, and cloud-based tools that enable advanced communication analytics. These

infrastructure investments are what will move practice beyond basic generative AI toward more sophisticated stakeholder engagement. Alongside them, parastatals should establish formal monitoring and evaluation systems to assess how AI-supported communication affects stakeholder engagement outcomes, tracking key performance indicators such as responsiveness, personalisation levels, and stakeholder satisfaction to support continuous improvement.

As a first priority, the Ministry of Information, Communications and the Digital Economy should develop sector-specific AI governance guidelines for parastatals, covering data privacy, algorithmic transparency, content integrity, and ethical accountability. These guidelines should be anchored in existing law, the Data Protection Act, No. 24 of 2019 and the Media Council Act, so that good practice is specific and enforceable rather than aspirational. As a second, medium-term measure, the MICDE should establish a coordinated capacity building program, potentially an AI for Public Communication Centre of Excellence, offering structured technical support, shared resources, and knowledge exchange platforms to parastatals as they progress in AI adoption.

Future studies could extend the geographical scope across Kenya and sub-Saharan Africa to test how far these findings generalise. Mixed-methods designs combining structured questionnaires with in-depth interviews and direct observation would sharpen understanding of both the extent and the quality of AI adoption. Longitudinal designs could trace how AI adoption and its outcomes evolve over time, building causal evidence on the relationship between AI introduction and stakeholder engagement quality. Finally, the ethical dimensions of AI in public sector communication, data privacy, algorithmic bias, and the governance structures institutions need to implement AI effectively and equitably, warrant dedicated investigation in their own right.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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