Management Communication in the Era of Artificial Intelligence: Reframing Human Connection, Trust and Leadership Voice in the Algorithmic Workplace

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ABSTRACT

Artificial intelligence (AI) now drafts memos, summarises meetings, translates messages, analyses employee sentiment and answers customers, placing it at the centre of how managers communicate. This paper examines how these developments are reshaping management communication and what they demand of managers. Using a documented integrative review of 49 sources from management, organisational communication and human–computer interaction, it integrates media richness, sensemaking, sociotechnical systems and organisational trust theories into a multi-level account. A consolidated evidence table and a comparative analysis of seven AI applications show that AI improves the speed, clarity and reach of routine, informational communication, but that messages perceived as heavily AI-written lower judgements of the sender's sincerity, authenticity and trustworthiness, especially for relational and high-stakes messages, and that disclosure alone does not remove this penalty. The paper argues that AI changes the *mechanics* of management communication more readily than its *meaning*. It examines the Nigerian context in depth, including infrastructure, linguistic diversity, high power distance and the 2025 data protection directive, together with implementation barriers at technological, organisational, individual, cultural and regulatory levels. It then proposes the Human-Centred AI Communication (HCAIC) framework and positions it against existing frameworks. HCAIC comprises six practices (strategic intent, human oversight, authenticity and transparency, ethical data governance, capability building and employee participation), which act through perceived authenticity, message accuracy and psychological safety to produce trust, clarity and employee voice. Key concepts are operationalised and seven propositions are offered for empirical testing. The paper concludes that the defining managerial competence of the AI era is not generating messages, but making messages mean something to people.

Keywords: management communication; artificial intelligence; AI-mediated communication; organisational trust; Nigeria

INTRODUCTION

1.1 Background to the study

Communication has always been the medium through which management happens. Mintzberg's (1973) classic study of managerial work found that managers spend the greater part of their time communicating, acting as monitors, disseminators and spokespersons of information. Barnard (1938) went further, describing communication as the first function of the executive. Whatever the era, planning, organising, leading and controlling are only as effective as the messages that carry them.

That medium is now being transformed. Since the public release of large language models (LLMs) such as ChatGPT in late 2022, generative AI has diffused into everyday workplace tools at remarkable speed (Dwivedi et al., 2023). Managers can now draft a policy circular in seconds, receive an automatic summary of a meeting they did not attend, translate a message into several languages, and analyse thousands of employee comments

for sentiment. Customer-facing communication is increasingly handled by conversational agents. Hancock et al. (2020) describe this new condition as *AI-mediated communication* (AI-MC): communication in which an intelligent agent modifies, augments or generates messages on behalf of a human communicator.

These shifts raise questions that go to the heart of management. When a manager's message is drafted by a machine, whose voice is the employee hearing? When performance feedback is generated from dashboards, is it still feedback, or merely data? When employees suspect AI authorship, does trust in the manager rise, fall or remain unchanged? Early evidence suggests the answers are not straightforward (Jakesch et al., 2019; Hohenstein et al., 2023).

1.2 Statement of the problem

Much of the existing discussion of AI in organisations focuses on automation of tasks, productivity and labour displacement (Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018). Considerably less attention has been paid to how AI changes the *relational* and *symbolic* functions of management communication: building trust, giving meaning, sustaining culture and exercising leadership voice. In developing economies such as Nigeria, the problem is compounded by uneven digital infrastructure, limited AI literacy, and an emerging regulatory environment. Managers are adopting AI tools faster than organisations are developing the norms, skills and safeguards to use them well.

1.3 Objectives of the study

The study aims to:

1. Clarify and operationalise the key concepts of management communication in the context of artificial intelligence.
2. Integrate relevant theories into a coherent, multi-level account of how AI affects management communication.
3. Examine, using management-specific evidence, how AI is reshaping internal, people-management, decision, external and crisis communication, and compare the main AI applications.
4. Critically synthesise the opportunities, risks and unresolved tensions in the evidence.
5. Examine the Nigerian context and the barriers to implementation, including the role of employee participation.
6. Propose an original, operationalised framework, with testable propositions, to guide responsible, human-centred use of AI in management communication.

1.4 Research questions

1. How is artificial intelligence changing the practice of management communication?
2. What benefits and risks does AI introduce into managerial communication, and where does the evidence agree or conflict?
3. How should managers balance AI efficiency with authenticity, trust and ethical responsibility?
4. What capabilities do managers need to communicate effectively in AI-enabled organisations?
5. What barriers affect implementation in Nigerian organisations, and how can employees take part in shaping AI use?

1.5 Significance and contribution

The study makes three contributions. First, it moves the debate from what AI can *do* to what AI *means* for the communicative work of leadership, integrating media richness, sensemaking, sociotechnical systems and trust theories into a single multi-level account (Section 3.5). Second, it consolidates and critically synthesises the emerging management-specific evidence, including studies of supervisors' AI-assisted emails, AI-generated performance feedback and AI-written apologies, and identifies where that evidence converges, conflicts and falls silent (Sections 5 and 8). Third, it proposes the Human-Centred AI Communication (HCAIC) framework, positions it against existing frameworks, operationalises its constructs and derives seven testable propositions (Section 10).

For practitioners, the study offers a framework and an implementation roadmap that attends to barriers and employee participation (Section 11). For policy makers and educators, particularly in Nigerian universities and business schools, it shows why AI communication literacy belongs in management education and why national AI policy should reach into workplace communication.

Conceptual Clarifications

2.1 Management communication

Management communication refers to the purposeful exchange of information, meaning and influence by managers with employees, peers, superiors and external stakeholders in pursuit of organisational goals. It operates in several directions: downward (instructions, policies, feedback), upward (reports, proposals), lateral (coordination across units) and external (customers, regulators, communities, media). Beyond transmitting information, it performs at least four functions: *informational* (sharing what people need to know), *directive* (coordinating action), *relational* (building trust and commitment) and *sense-giving* (helping people interpret change and uncertainty) (Gioia & Chittipeddi, 1991; Weick, 1995).

2.2 Artificial intelligence

Artificial intelligence describes computer systems able to perform tasks that ordinarily require human intelligence, such as perceiving, reasoning, learning, predicting and generating language (Russell & Norvig, 2021). For management communication, three families of AI are most relevant:

- **Analytical AI**: machine learning that detects patterns in data, for example sentiment analysis of employee surveys or prediction of customer churn.
- **Conversational AI**: chatbots and virtual assistants that interact with employees or customers in natural language.
- **Generative AI**: large language and multimodal models that produce new text, images, audio and video, including drafts of emails, speeches, reports and presentations.

2.3 AI-mediated communication

AI-mediated communication (AI-MC) is interpersonal communication in which an intelligent agent operates on behalf of a communicator, modifying, augmenting or generating messages to accomplish communication goals (Hancock et al., 2020). Examples range from predictive text and smart replies to fully drafted messages and AI avatars. AI-MC differs from earlier computer-mediated communication because the machine is no longer merely a channel; it becomes a co-author of the message itself. This distinction is central to the argument of this paper.

2.4 Management communication in the AI era

Drawing these concepts together, this paper defines management communication in the AI era as *the managerial use of human and machine capabilities to create, deliver, interpret and respond to organisational messages, in*

which the manager remains accountable for the intent, accuracy and human consequences of every message, whoever or whatever drafts it.

2.5 Operationalising the key concepts

To make the argument testable, Table 1 sets out working definitions, observable indicators and candidate measures for the paper's key constructs. These operationalisations underpin the propositions in Section 10.4.

Table 1. Operational definitions of key constructs

Construct	Working definition	Indicators	Candidate measure
Degree of AI involvement	Extent to which AI modifies, augments or generates a message (Hancock et al., 2020)	None, assisted or generated; share of text produced by AI	Coding of drafts; low versus high assistance conditions (Cardon & Coman, 2025)
AI disclosure	Whether, when and how recipients are told that AI was used	Presence, placement and specificity of a disclosure	Experimental manipulation; audit of messages
Message equivocality	Degree to which a message is ambiguous, emotional or open to several interpretations (Daft & Lengel, 1986)	Routine versus non-routine content; emotional weight	Expert coding of message type, such as update, feedback or bad news
Perceived authenticity	Recipient's belief that a message reflects the sender's own intent and care	Perceived sincerity, authorship and ownership	Sincerity and authorship ratings (Cardon & Coman, 2025; Glikson & Asscher, 2023)
Trust in the manager	Willingness to be vulnerable to the manager based on perceived ability, benevolence and integrity (Mayer et al., 1995)	The three trust dimensions	Trust scales derived from Mayer et al. (1995)
Human oversight	Extent to which a named person reviews AI output before it is released	Review step, named owner, correction records	Process audit; errors per message released
Psychological safety	Shared belief that the team is safe for interpersonal risk-taking (Edmondson, 1999)	Willingness to ask, admit errors and raise concerns	Team psychological safety scale (Edmondson, 1999)
Employee voice	Constructive, change-oriented communication intended to improve the situation (Van Dyne & LePine, 1998)	Suggestions and concerns raised	Voice scale (Van Dyne & LePine, 1998)
Employee participation	Involvement of employees in deciding how AI is used in communication that affects them	Information, consultation, co-design, joint review	Participation index; records of consultation (Kochan et al., 2023)
Communication effectiveness	Extent to which a message is understood and acted on as intended	Clarity, comprehension, intended action	Recipient clarity ratings; comprehension checks

THEORETICAL FRAMEWORK

No single theory captures the full effect of AI on management communication. This paper therefore integrates four complementary lenses.

3.1 Media richness theory

Daft and Lengel (1986) argue that communication media differ in their capacity to carry rich information: immediate feedback, multiple cues, natural language and personal focus. Effective managers match the richness of the medium to the equivocality of the message. Routine information suits lean media; ambiguous, emotional or high-stakes messages require rich media such as face-to-face conversation. AI complicates this logic. It makes lean media more efficient and can simulate some features of richness (personalisation, instant response), yet it cannot fully replicate genuine human presence. The theory predicts that AI will be most valuable for routine, low-equivocality communication and least appropriate where messages carry emotional or moral weight, such as layoffs, discipline, grief or organisational crisis.

3.2 Sensemaking theory

Weick (1995) describes organisations as systems in which people continually construct meaning from ambiguous cues. Managers engage in *sense-giving*, shaping how others interpret events (Gioia & Chittipeddi, 1991). AI can supply information at scale, but meaning is co-constructed through social interaction, shared history and trust. The theory cautions that as AI increases the volume of information, the managerial task shifts from supplying information to helping people make sense of it.

3.3 Sociotechnical systems theory

Sociotechnical systems theory holds that organisational outcomes depend on the joint optimisation of technical and social subsystems (Trist & Bamforth, 1951). Introducing AI into communication without redesigning roles, norms, skills and accountability produces suboptimal results. Recent work on human–AI collaboration echoes this view, arguing that augmentation, in which humans and machines complement each other, outperforms pure automation in most managerial domains (Jarrahi, 2018; Raisch & Krakowski, 2021).

3.4 Organisational trust theory

Mayer et al. (1995) define trust as willingness to be vulnerable to another party based on perceived ability, benevolence and integrity. Management communication is a primary means by which these perceptions are formed. AI affects all three: it can enhance perceived ability (accurate, timely messages) while potentially undermining perceived benevolence and integrity if employees believe managers are outsourcing care to machines or concealing AI use. Research on trust in AI further shows that human trust in algorithms is shaped by tangibility, transparency, reliability and the nature of the task (Glikson & Woolley, 2020), and that people can swing between algorithm aversion (Dietvorst et al., 2015) and algorithm appreciation (Logg et al., 2019).

3.5 Integrating the four lenses

The four theories are not alternatives; they operate at different levels and answer different questions (Table 2). Media richness theory concerns the *message*: it indicates which messages can safely be delegated to AI. Sensemaking theory concerns *meaning*: it indicates what managers must still do once AI supplies information. Sociotechnical systems theory concerns the *organisation*: it indicates how roles, review processes and participation must be redesigned around AI. Organisational trust theory concerns the *relationship*: it indicates what is at stake, because every AI-assisted message is also evidence about the manager's ability, benevolence and integrity.

Read together, the lenses form a chain. The equivocality of a message (media richness) determines how much human sense-giving it needs (sensemaking); the organisation's design (sociotechnical systems) determines whether that human contribution is actually made; and recipients judge the result as evidence of the manager's trustworthiness (trust theory). Each link in the chain is reflected in the framework in Section 10.

Table 2. Integration of the theoretical lenses

Theory	Level and focus	Core claim	Implication for AI-era communication	Use in HCAIC
Media richness (Daft & Lengel, 1986)	Message and medium	Match the richness of the medium to the equivocality of the message	AI suits routine, low-equivocality messages; equivocal messages need human presence	Pillar 1; P2
Sensemaking (Weick, 1995; Gioia & Chittipeddi, 1991)	Meaning	Meaning is co-constructed, and leaders give sense	More AI-produced information raises demand for human interpretation	Pillars 1 and 5
Sociotechnical systems (Trist & Bamforth, 1951)	Organisation	Outcomes require joint optimisation of social and technical systems	AI adoption requires redesigned roles, review and participation	Pillars 2, 4 and 6; P3, P7
Organisational trust (Mayer et al., 1995)	Relationship	Trust rests on perceived ability, benevolence and integrity	AI may raise perceived ability but lower perceived benevolence and integrity	Pillar 3; P1, P5

Taken together, these theories support the paper's working proposition: **AI strengthens the informational and directive functions of management communication, but the relational and sense-giving functions remain dependent on human presence, judgement and accountability.** The rest of the paper examines this proposition against the evidence.

METHODOLOGY

4.1 Review design

The study adopts an integrative literature review design (Torraco, 2005; Snyder, 2019). Integrative reviews synthesise evidence from different disciplines and research designs into new conceptual frameworks; unlike systematic reviews, they do not aim at exhaustive retrieval or statistical pooling of effects. The design suits this topic for two reasons: research on AI and workplace communication is recent and spread across management, organisational communication, information systems, human–computer interaction and AI ethics; and the study's aim is theory building rather than estimating an average effect.

4.2 Search strategy

Table 3 summarises the search protocol. Searches combined keyword searching with backward and forward citation tracking from key studies, and targeted policy and statistical sources for the Nigerian context.

Table 3. Search protocol

Element	Description
Sources searched	Google Scholar; publisher platforms (SAGE, Elsevier ScienceDirect, Wiley, INFORMS, Oxford Academic, ACM Digital Library); repositories and preprint services (SSRN, arXiv, PubMed Central); official websites for policy and statistics (Federal Ministry of Communications, Innovation and Digital Economy, NITDA, Nigeria Data Protection Commission, African Union, NIST, World Bank)

Element	Description
Period covered	January 2015 to October 2026; foundational theoretical works included regardless of date
Core search string	("management communication" OR "organisational communication" OR "leadership communication" OR "internal communication") AND ("artificial intelligence" OR "generative AI" OR "AI-mediated communication" OR chatbot* OR "algorithmic management")
Supplementary strings	(trust OR authenticity OR sincerity OR disclosure) AND ("AI-written" OR "AI-generated" OR "AI-assisted") AND (manager* OR supervisor* OR leader* OR employee*); (Nigeria OR Africa) AND "artificial intelligence" AND (workplace OR employee* OR organisation*)
Citation tracking	Backward and forward tracking from Hancock et al. (2020), Glikson and Woolley (2020) and Kellogg et al. (2020)
Language	English
Final searches	November 2026

4.3 Selection procedure

Selection followed four stages. In *identification*, records were retrieved through the searches in Table 3. In *screening*, titles and abstracts were checked against the inclusion criteria. In *eligibility*, full texts were read to confirm relevance and to extract each study's design, sample, setting and findings. In *inclusion*, retained sources were appraised (Section 4.4) and entered into an extraction matrix, summarised in Table 5. Because Google Scholar returns relevance-ranked rather than exhaustive results, counts of records identified would not indicate coverage and are not reported; instead, the composition of the final evidence base is reported in full (Table 4).

Sources were included where they addressed (a) the use of AI in organisational or managerial communication; (b) human responses to AI-generated or AI-mediated messages; (c) the governance, adoption or ethics of AI in workplaces; or (d) AI use, infrastructure or policy in Nigeria and Africa. Opinion pieces without evidence, vendor marketing material, studies of AI unrelated to communication and duplicate reports of the same study were excluded.

4.4 Appraisal

Each source was appraised for relevance, methodological rigour, credibility of the publication outlet and fit with the Nigerian context. Empirical studies were graded by strength of evidence: *strong* for field experiments and randomised experiments with large samples; *moderate* for controlled or scenario-based experiments; and *indicative* for surveys, qualitative studies, working papers and grey literature. Grades are reported in Table 5. News reports were used only to document cases or contextual facts.

4.5 Analysis and synthesis

Analysis proceeded in three steps. First, findings were coded descriptively by communication domain, AI application and outcome. Second, studies were compared to identify where findings converge, where they conflict and what remains unknown (Section 8). Third, the themes were mapped onto the four theoretical lenses (Table 2) to derive the framework and propositions in Section 10, in an abductive process that moved iteratively between theory and evidence. As a conceptual paper, the study does not test hypotheses; the propositions are offered for empirical testing.

4.6 Composition of the evidence base

The review draws on 49 sources, summarised in Table 4.

Table 4. Composition of the evidence base

Type of source	Number	Examples
Experimental and field studies	11	Tong et al. (2021); Cardon and Coman (2025); Brynjolfsson et al. (2025)
Surveys, qualitative and mixed-methods studies	3	Abdulhamid et al. (2024); PwC (2025); Idowu et al. (2026)
Reviews and research agendas	4	Hancock et al. (2020); Glikson and Woolley (2020); Kellogg et al. (2020)
Foundational theory, books and measurement	17	Daft and Lengel (1986); Mayer et al. (1995); Venkatesh et al. (2003)
Review methodology	2	Torraco (2005); Snyder (2019)
Policy, legal and governance frameworks	6	African Union (2024); Federal Republic of Nigeria (2023)
Statistical reports, industry reports and working papers	4	Kemp (2025); Lagos Business School et al. (2025); Kochan et al. (2023)
News reports	2	McDuffie (2023); Ebereonwu (2021)
Total	**49**	—

4.7 Rigour and positionality

Two further steps were taken to strengthen rigour. All sources were checked against publisher, repository or official records, and preprints and unpublished studies are labelled as such. In addition, the author works in university administration in Nigeria; this practitioner position informed the attention given to higher education and hierarchical organisational settings. To limit its influence, claims about Nigeria are grounded in documented sources, and statements based on practitioner observation are identified as such.

How Ai Is Reshaping Management Communication

The review identifies change across five domains of managerial communication. Before examining each, Section 5.1 consolidates the empirical evidence on which the analysis draws.

5.1 Overview of the evidence

Table 5 consolidates the key empirical studies. Two features stand out. Most rigorous evidence comes from experiments with participants in the United States, often using scenarios rather than real working relationships. And studies of managers specifically, rather than of communicators in general, are recent and few. Evidence from Nigeria and Africa is so far descriptive.

Table 5. Key empirical studies on AI in workplace and managerial communication

Study	Design and sample	Setting	Key finding	Strength
Dietvorst et al. (2015)	Series of experiments	Forecasting tasks	People avoided algorithms after seeing them err, even when the algorithms outperformed humans	Moderate
Jakesch et al. (2019)	Three online experiments	Airbnb host profiles	Profiles believed to be AI-written were trusted less, but only when readers saw a mix of AI and human texts	Moderate
Logg et al. (2019)	Series of experiments	Estimation tasks	Lay people often preferred algorithmic to human advice	Moderate

Study	Design and sample	Setting	Key finding	Strength
Hohenstein and Jung (2020)	Experiment	AI-mediated conversations	When conversations went wrong, participants shifted blame onto the AI	Moderate
Tong et al. (2021)	Field experiment	AI-generated performance feedback in a firm	AI feedback improved performance, but disclosing its AI source reduced it; the penalty was weaker for longer-tenured staff	Strong
Glikson and Asscher (2023)	Three scenario experiments	Workplace conflict; apologies	AI-written apologies seemed less authentic and earned less forgiveness; disclosure did not help; limited AI use caused no loss	Moderate
Hohenstein et al. (2023)	Two randomised experiments (n = 1,036)	Smart replies in chat	AI replies made talk faster and more positive, but suspected AI users were judged more negatively	Strong
Noy and Zhang (2023)	Online experiment	Professional writing tasks	ChatGPT raised writing speed and quality, most for weaker writers	Strong
Brynjolfsson et al. (2025)	Staggered deployment (n = 5,172 agents)	Customer support	An AI assistant raised productivity, most for novices, and improved customer sentiment	Strong
Cardon and Coman (2025)	Online experiment (n = 1,158)	Supervisors' emails	Supervisors were seen as sincere by 83% with low AI assistance and by 40–52% with high assistance	Moderate
Dell'Acqua et al. (2026)	Field experiment	Management consultants	AI raised quality on tasks within its capabilities but led to more errors outside them	Strong
Abdulhamid et al. (2024)	Interviews (27 participants, 21 firms)	Small businesses in Kenya and Nigeria	Users verified AI output; tools defaulted to Western examples and handled local languages poorly	Indicative
PwC (2025)	Survey (n = 1,753)	Five African countries, including Nigeria	64% had used AI at work in the past year, against 54% globally	Indicative
Idowu et al. (2026)	Mixed methods (370 lecturers; 24 interviews)	Universities in Southeast Nigeria	High awareness and moderate reliance on ChatGPT; concern about students' critical thinking	Indicative

5.2 Internal communication

Generative AI is now embedded in email clients, word processors, collaboration platforms and meeting tools. Managers use it to draft announcements, condense long reports, produce meeting minutes and action items, and tailor one message for different audiences. AI-powered internal assistants answer routine employee queries on

leave, benefits and policy, freeing managers and HR staff for higher-value conversations. Translation and transcription tools also make communication more inclusive across languages and for employees with hearing or visual impairments.

The shift is not merely in speed. Controlled studies show that generative AI raises the quality and speed of professional writing tasks, with the largest gains among less experienced writers (Noy & Zhang, 2023). In a large field study of customer support agents, access to an AI assistant raised productivity on average and helped novice workers most, while also improving customer sentiment (Brynjolfsson et al., 2025). The implication for management is a compression of the skill gap in routine writing and a corresponding rise in the relative value of judgement, framing and relationship.

Evidence on managers specifically points to a cost. In an experiment with 1,158 professionals in the United States, a supervisor's congratulatory email written with low AI assistance was seen as sincere by 83% of respondents, compared with 40–52% when it was written with high AI assistance; ratings of professionalism fell from 95% to 69–73% (Cardon & Coman, 2025). Most respondents were comfortable with supervisors using AI, but they judged their own AI-assisted writing more favourably than their supervisors'. AI can make a message better while making its sender look less sincere.

5.3 Performance feedback and people management

AI-enabled HR platforms aggregate productivity data, peer input and goal progress to generate performance summaries and suggested feedback. This creates what Kellogg et al. (2020) describe as *algorithmic management*: the use of algorithms to direct, evaluate and discipline workers. While these tools can make feedback more frequent and evidence-based, they risk reducing feedback to metrics and displacing the developmental conversation in which a manager listens, coaches and builds commitment. Employees subject to opaque algorithmic evaluation often respond with distrust and resistance (Kellogg et al., 2020).

A field experiment by Tong et al. (2021) shows both sides of this trade-off. AI-generated feedback improved employees' performance because it was more accurate, consistent and relevant than managers' feedback; yet when employees learned that the feedback came from AI, performance fell, partly offsetting the gain. The negative disclosure effect was weaker for longer-tenured employees, and the authors recommend that firms explain the objectives, benefits and scope of AI feedback to employees in advance. AI can improve the content of feedback, but its acceptance depends on how managers communicate about it.

5.4 Decision communication and data storytelling

AI systems increasingly produce forecasts, dashboards and recommendations that managers must interpret and communicate. The manager's role shifts from originator of analysis to translator and explainer: turning model outputs into narratives that stakeholders understand, question and act upon. Where managers cannot explain how an AI-informed decision was reached, the legitimacy of the decision suffers. Explainability therefore becomes a communication competence, not just a technical property.

5.5 External and stakeholder communication

Conversational agents now handle a large share of first-line customer interaction. AI also supports social-media monitoring, reputation analytics, personalised marketing and investor communication. These tools allow organisations to listen at scale and respond around the clock. They also expose organisations to new reputational risks: chatbot errors, inappropriate automated responses, and public backlash when customers discover they were dealing with a machine without being told.

Nigerian banking illustrates the pace of change: by February 2025, 10 of the country's 26 commercial banks had adopted conversational AI (Lagos Business School et al., 2025).

5.6 Crisis and change communication

AI can detect early warning signals in social media and internal channels, model scenarios and draft holding statements quickly. Yet crisis and change communication are the domains in which the human dimension matters most. Stakeholders in crisis look for empathy, accountability and visible leadership. In February 2023, an office at Vanderbilt University's Peabody College emailed students after a fatal shooting at Michigan State University; a note at the foot of the message credited ChatGPT as the source of its text. Students reacted with anger, the college apologised, and a dean described the decision as poor judgement (McDuffie, 2023). The criticism arose precisely because the message signalled that care had been outsourced. The lesson for managers is that AI may assist the preparation of crisis messages, but the voice, presence and accountability must remain unmistakably human.

Experimental evidence supports this lesson. In three scenario studies of workplace conflict, apologies written with AI tools were seen as less authentic and earned less forgiveness; disclosing the AI use did not repair the damage, whereas limited AI use did not reduce perceived authenticity (Glikson & Asscher, 2023).

5.7 Comparative analysis of AI applications

AI is not one technology. Table 6 compares seven applications that managers commonly encounter, by their main benefit, their main risk and the human role that the evidence supports.

Table 6. Comparative analysis of AI applications in management communication

Application	Main benefit	Main risk	Key evidence	Recommended human role
Generative drafting of emails, memos and speeches	Speed, clarity, consistency	Lower perceived sincerity; errors; generic voice	Noy and Zhang (2023); Cardon and Coman (2025)	Manager edits, personalises and owns the message
Meeting transcription and summaries	Accurate records; access for absentees	Omissions; misattribution; recording without consent	Limited evidence	Check decisions and actions; obtain consent to record
Machine translation	Inclusion across languages	Errors in local languages and idiom	Abdulhamid et al. (2024)	Fluent-speaker review of important messages
Conversational agents for staff and customers	Round-the-clock answers at scale	Wrong answers; undisclosed bots; poor escalation	Adoption data only (Lagos Business School et al., 2025)	Disclose the bot; provide a route to a person
Sentiment and text analytics	Hearing many voices early	Surveillance; misread dialects; chilled voice	Kellogg et al. (2020)	Transparent purpose, aggregate reporting, consent
Algorithmic performance feedback	Frequent, data-rich feedback	Disclosure penalty; distrust; less coaching	Tong et al. (2021); Kellogg et al. (2020)	Manager interprets, delivers and discusses feedback
AI-written sensitive messages (apology, condolence, crisis)	Speed under pressure	Loss of authenticity; reputational damage	Glikson and Asscher (2023); McDuffie (2023)	Human-authored; AI used at most to check

Two patterns emerge from the comparison. First, the benefits of AI are concentrated in informational tasks, while its risks rise with the relational and emotional content of the message, as media richness theory predicts. Second, the recommended human role changes in kind, not only in degree: for routine applications the manager acts as editor and owner, for listening applications as guardian of consent and purpose, and for sensitive messages as author. The evidence base is also uneven: some widely used applications, such as meeting summaries, have barely been studied.

5.8 Summary of shifts

Table 7 summarises how AI-era management communication differs from traditional practice across seven dimensions.

Table 7. Traditional versus AI-era management communication

Dimension	Traditional management communication	AI-era management communication
Message creation	Authored by the manager or communications staff	Co-authored by manager and AI
Speed and scale	Limited by human time	Near-instant, at scale
Personalisation	Broad messages to groups	Tailored messages to individuals
Listening	Surveys, meetings, open doors	Continuous sentiment and text analytics
Feedback	Periodic, manager-led	Continuous, data-driven, partly automated
Manager's core role	Information source and transmitter	Curator, interpreter, sense-giver and guarantor of authenticity
Key risk	Information scarcity and distortion	Information overload, inauthenticity and loss of trust

Opportunities And Benefits

The literature points to six principal benefits of AI for management communication.

1. **Efficiency and time recovery.** By automating drafting, summarising and scheduling, AI returns time to managers. Used well, that recovered time can be reinvested in the high-value human interactions that AI cannot perform: coaching, listening and relationship building.

2. **Clarity and quality.** AI tools can improve structure, grammar, tone and readability, and can flag jargon or ambiguity before a message is sent (Noy & Zhang, 2023).

3. **Personalisation at scale.** Messages can be adapted to the role, language, location or learning preference of each recipient, increasing relevance and comprehension.

4. **Listening at scale.** Sentiment analysis and text analytics allow managers to hear patterns across thousands of employee or customer voices that would otherwise be lost, enabling earlier response to disengagement or dissatisfaction.

5. **Inclusion and accessibility.** Real-time translation, captioning and text-to-speech widen participation across linguistic, geographic and ability differences, which is particularly valuable in multilingual societies such as Nigeria.

6. **Better-informed decisions.** AI-generated insights, communicated well, can ground managerial messages in evidence rather than intuition alone, strengthening the credibility of decisions.

A central insight from the field evidence is that AI tends to *democratise* baseline communication competence: those with weaker writing skills benefit most (Brynjolfsson et al., 2025; Dell'Acqua et al., 2026). This can raise

the floor of organisational communication quality, but it also means that differentiation among managers will increasingly come from human qualities such as credibility, empathy and judgement.

Challenges, Risks And Ethical Concerns

7.1 Authenticity and the trust penalty

The most distinctive risk of AI-mediated management communication is the erosion of perceived authenticity. Experimental research shows that when people believe a message was written by AI, they tend to rate the sender as less trustworthy, even if the content is identical (Jakesch et al., 2019). Hohenstein et al. (2023) found that AI-suggested replies could make conversations more positive and efficient, yet people who were suspected of using AI were judged more negatively. For managers, whose influence rests on credibility, this creates a paradox: AI can make messages better while making the messenger seem less genuine. Transparency about AI use, combined with clear human ownership of the message, is the most promising response.

7.2 Accuracy, hallucination and accountability

Generative AI can produce fluent but false content, including fabricated facts, figures and references (Dwivedi et al., 2023). A manager who circulates an AI-generated error bears the reputational and sometimes legal consequences. Hohenstein and Jung (2020) further show that when AI-mediated conversations go wrong, people may assign blame to the AI, a "moral crumple zone" that can obscure human accountability. Organisations need explicit norms that the human sender is fully responsible for every message, regardless of how it was produced.

7.3 Bias and fairness

AI systems trained on historical data may reproduce biases related to gender, ethnicity, age, accent or dialect. In management communication this can surface in biased performance summaries, skewed sentiment classification of non-standard English, or recruitment messages that systematically discourage some groups. Without auditing, AI can silently amplify inequity through everyday communication.

7.4 Privacy and surveillance

Listening at scale can become surveillance. Analysing employee messages, meetings and keystrokes for sentiment or productivity raises serious privacy and dignity concerns (Kellogg et al., 2020). Where employees feel watched, they communicate more guardedly, undermining the psychological safety that open communication requires (Edmondson, 1999). Data protection obligations, including Nigeria's Data Protection Act 2023, also place legal limits on how personal data in communications may be processed.

7.5 Over-reliance and skill erosion

If managers delegate most of their writing and thinking to AI, their own communicative and critical-thinking capacities may weaken. Field-experimental evidence suggests that professionals using AI on tasks outside its competence can perform worse than those working without it, because they accept plausible but wrong outputs (Dell'Acqua et al., 2026). The capacity to judge AI output depends on retaining the very skills AI is tempted to replace.

7.6 Homogenisation and loss of voice

When many managers use the same tools, communications risk becoming generic, polished and interchangeable. Distinctive leadership voice, local idiom and cultural nuance may be flattened. Hohenstein et al. (2023) note that AI-generated suggestions can shift the language people use. Over time this can weaken the symbolic power of leadership communication, which depends partly on being recognisably one's own.

7.7 Information overload

Because AI makes producing content almost costless, organisations may experience a surge in messages, reports and summaries. The scarce resource shifts from information to attention. Managers who use AI to produce more communication, rather than better communication, may worsen overload and reduce the signal value of their messages.

7.8 Digital divide

Access to AI tools, reliable connectivity, electricity and AI literacy is uneven across and within organisations. Where only some managers or employees can use AI effectively, existing inequalities in voice and influence may widen. This risk is especially relevant to developing economies, discussed in Section 9.

Critical Synthesis: Convergence, Tensions And Gaps

Sections 5 to 7 described what AI does to management communication. This section asks what the evidence, taken as a whole, does and does not establish.

8.1 Where the evidence converges

Three findings recur across designs and settings. First, AI reliably improves the efficiency and surface quality of routine writing, with the largest gains for less skilled writers (Noy & Zhang, 2023; Brynjolfsson et al., 2025). Second, recipients evaluate not only a message but its perceived authorship: when they believe AI wrote or heavily shaped a message, their judgements of the sender's sincerity, trustworthiness or authenticity fall (Jakesch et al., 2019; Hohenstein et al., 2023; Glikson & Asscher, 2023; Cardon & Coman, 2025). Third, the penalty depends on the degree of AI involvement: limited assistance carries little cost, while heavy assistance carries a substantial one (Glikson & Asscher, 2023; Cardon & Coman, 2025).

8.2 Where the evidence conflicts

The evidence also contains tensions that a simple prescription, such as "always disclose AI use", would miss.

- **The disclosure paradox.** Transparency is widely recommended, yet disclosure did not restore the authenticity of AI-written apologies (Glikson & Asscher, 2023), and disclosing that feedback came from AI reduced employees' performance (Tong et al., 2021). Distrust of AI-written profiles, meanwhile, appeared only when readers saw a mixture of AI and human texts (Jakesch et al., 2019). Disclosure is therefore necessary for integrity but not sufficient for trust; what recipients appear to value is evidence that the sender remains the real author.

- **Better conversations, worse impressions.** AI-suggested replies made conversations faster and more positive, yet people suspected of using AI were judged more negatively (Hohenstein et al., 2023). The same tool can improve an interaction while damaging the reputation of the person using it.

- **Aversion and appreciation.** People sometimes reject algorithms after seeing them err (Dietvorst et al., 2015) and sometimes prefer them to human judgement (Logg et al., 2019). The difference appears to lie partly in the task: algorithmic input is more readily accepted for objective estimates, while relational messages invite closer scrutiny of the sender's intent.

- **Performance and acceptance.** AI feedback improved performance while its disclosure undermined it (Tong et al., 2021), suggesting that the quality of a message and its acceptance are separate outcomes that managers must attend to separately.

8.3 What the evidence cannot yet show

Four gaps limit what can be concluded. Most studies are short, scenario-based experiments rather than observations of real working relationships over time. Most participants are in the United States; evidence from Nigeria and Africa is descriptive and does not measure trust or authenticity directly (Abdulhamid et al., 2024; PwC, 2025; Idowu et al., 2026). Studies concentrate on downward, written messages, so little is known about upward and lateral communication, meetings or multilingual exchanges. And almost no studies examine the organisational conditions, such as policies, review processes and employee participation, under which AI-assisted communication succeeds.

8.4 Implications for theory

The tensions largely resolve when the evidence is read through the integrated lenses in Section 3.5. The effect of AI on trust appears to depend on three variables acting together: the degree of AI involvement in a message, the message's equivocality, and the visible presence of the sender's own intent. This interaction, rather than AI use as such, is what the HCAIC framework in Section 10 is designed to manage, and it is the basis of propositions P1 and P2.

The African And Nigerian Context

Most research on AI and workplace communication comes from North America, Europe and East Asia (Section 8.3). Applying its conclusions to Nigerian organisations requires attention to six contextual conditions.

9.1 Infrastructure and access

In 2023, 61% of Nigerians had access to electricity, leaving 86.8 million people without it, the largest such population of any country (World Bank et al., 2025). At the start of 2025, 45.4% of the population, about 107 million people, used the internet (Kemp, 2025). Cloud-based AI tools therefore cannot be assumed to reach every employee, student or customer. AI-enabled communication strategies need low-bandwidth and offline fallbacks, and important messages should not depend on a single digital channel.

9.2 Language

Nigeria is home to hundreds of languages, and workplace communication often blends English, Nigerian Pidgin and indigenous languages. Knowledge workers in Nigerian and Kenyan businesses report that generative AI tools default to Western examples and handle languages such as Hausa poorly (Abdulhamid et al., 2024). Machine translation and sentiment analysis therefore carry a higher risk of misinterpretation in Nigeria than the international evidence suggests, and important translated messages need review by fluent speakers.

9.3 Organisational culture

Nigeria scores high on power distance (80) and low on individualism (30) on Hofstede's cultural dimensions (Ebereonwu, 2021; Hofstede et al., 2010). Two implications follow. High power distance means that employees may be reluctant to question a directive from a superior, even when it was drafted by AI and contains errors, which raises the importance of human oversight (Pillar 2) and of protected channels for raising concerns (Pillar 6). A collectivist, relational culture places a high value on personal attention and warmth, so impersonal or obviously automated communication from leaders may be read as disrespect; the authenticity penalty may therefore be larger in Nigeria (Proposition P6). Communication norms that rely on formal titles, protocol and courtesy may also be poorly served by AI tools that default to informal Western styles.

9.4 Adoption and skills

Adoption is outpacing preparation. A 2025 survey of 1,753 workers in five African countries, including Nigeria, found that 64% had used AI at work in the past year, compared with 54% globally, but only 35% believed their current skills would remain relevant in three years (PwC, 2025). In Nigerian banking, 10 of 26 commercial banks

had adopted conversational AI by February 2025, while organisations face shortages of AI skills, the cost of computing infrastructure and incomplete data (Lagos Business School et al., 2025). In higher education, a study of 370 lecturers in Southeast Nigeria found high awareness and moderate reliance on ChatGPT, together with concern about students' critical thinking (Idowu et al., 2026). The national AI strategy targets equipping at least 70% of young workers aged 16–35 with AI-related skills (Federal Ministry of Communications, Innovation and Digital Economy [FMCIDE], 2025), which signals the scale of the gap.

9.5 Policy and regulation

The Nigeria Data Protection Act 2023 (Federal Republic of Nigeria, 2023) governs the processing of personal data, including AI-driven analysis of employee and customer communications. Its General Application and Implementation Directive, issued in March 2025 and effective from 19 September 2025, sets mandatory requirements to be met before deploying emerging technologies, including artificial intelligence, and introduces a standard template for data privacy impact assessments (Nigeria Data Protection Commission [NDPC], 2025). Organisations that use AI to analyse staff messages or meetings should therefore treat an impact assessment as a legal step, not an optional one. In September 2025, the Federal Ministry of Communications, Innovation and Digital Economy published the National Artificial Intelligence Strategy for 2025–2029 (FMCIDE, 2025); the Code of Practice for Artificial Intelligence issued by the National Information Technology Development Agency remains in draft (National Information Technology Development Agency [NITDA], 2025); and the African Union adopted a Continental Artificial Intelligence Strategy in July 2024 (African Union, 2024). None of these instruments yet offers guidance on AI in workplace communication.

9.6 Higher education and public administration

Universities and public bodies are among Nigeria's largest employers and communicators. In the author's practitioner observation, administrative communication with staff and students in Nigerian universities typically combines formal memos and circulars with informal messaging groups. AI could make such communication faster, more consistent and more accessible, for example by drafting routine notices or answering frequent student enquiries. But administrative messages often affect students' academic standing, welfare and finances, and must be defensible before senates, regulators and courts, which makes human oversight and clear accountability especially important. Staff unions and associations, such as the Academic Staff Union of Universities (ASUU) and the Senior Staff Association of Nigerian Universities (SSANU), also provide established channels through which employees can take part in decisions about AI use (Section 11.2).

9.7 Opportunity

Despite these constraints, Nigeria's young, mobile-first population and growing technology sector create real opportunities. AI-powered translation could improve communication with multilingual workforces and communities; conversational agents delivered through widely used messaging platforms could extend access to information; and analytics could help large institutions listen to students and staff more systematically. The decisive variable is not the technology, but whether managers adopt it with a clear human-centred intent.

Proposed Framework: Human-Centred Ai Communication (Hcaic)

10.1 Positioning and originality

Several existing frameworks address parts of the problem examined in this paper, and Table 8 compares them. Each is valuable, but none takes the managerial communication act as its unit of analysis, and none explains how AI use in that act affects employees' trust in their manager.

Table 8. Positioning HCAIC against existing frameworks

Framework	Primary focus	What it contributes	What it leaves open for management communication
AI-mediated communication (Hancock et al., 2020)	How AI alters messages between individuals	Dimensions of AI involvement in messages; a research agenda	Managerial roles, hierarchy and organisational governance
Human trust in AI (Glikson & Woolley, 2020)	Antecedents of trust in AI systems	Tangibility, transparency and reliability as drivers of trust	Trust in the manager who communicates through AI, rather than in the AI
Automation–augmentation paradox (Raisch & Krakowski, 2021)	Division of labour between managers and AI	Automation and augmentation are interdependent	The relational and symbolic functions of communication
Human-centred AI (Shneiderman, 2022)	Design of AI systems that combine high human control with high automation	Principles for reliable, safe and trustworthy systems	Everyday managerial practice in using such systems
AI Risk Management Framework (National Institute of Standards and Technology [NIST], 2023)	Organisational management of AI risk	Govern, Map, Measure and Manage functions	Meaning, voice and trust in leaders
Nigerian AI and data protection policy (FMCIDE, 2025; NDPC, 2025)	National strategy and lawful data processing	Skills targets; impact assessments before deployment	Guidance on workplace communication practice

HCAIC contributes in five ways. First, its unit of analysis is the managerial communication act: a specific message from a manager to employees or stakeholders. Second, it makes the appropriate level of AI involvement contingent on the message's function and equivocality, rather than prescribing a single rule. Third, it explains outcomes through mechanisms drawn from trust theory (perceived authenticity, message accuracy and psychological safety), which allows the conflicting evidence in Section 8.2 to be reconciled. Fourth, it treats employee participation and national context as integral to the framework rather than as afterthoughts. Fifth, its constructs are operationalised (Table 1) and its claims are stated as testable propositions (Section 10.4). HCAIC complements rather than replaces the frameworks in Table 8: its practices can, for example, sit within the Govern and Manage functions of the NIST framework at organisational level.

10.2 Components

The framework's goal is trusted, meaningful and effective management communication. It comprises six practices, or pillars, resting on a foundation of organisational culture and leadership example.

Pillar 1: Strategic intent. Every use of AI in communication should begin with a human purpose: what the message must achieve, for whom and why. AI is a means, not the author of intent. Managers should classify messages by equivocality and emotional weight, reserving AI-led drafting for routine content and keeping high-stakes messages (bad news, discipline, crisis, recognition, condolence) primarily human-authored.

Pillar 2: Human oversight ("human in the loop"). No AI-generated message should reach stakeholders without human review for accuracy, tone and context. The sender owns the message. Clear lines of accountability counter the "moral crumple zone" effect (Hohenstein & Jung, 2020), and they matter most in high power distance settings, where recipients may be reluctant to question a superior's message (Section 9.3).

Pillar 3: Authenticity and transparency. Organisations should adopt proportionate disclosure norms about when AI is used. Because disclosure alone does not restore authenticity (Glikson & Asscher, 2023), managers should also keep AI involvement limited in relational messages, edit AI drafts, add personal context and communicate face-to-face where relationships are at stake. Authenticity is protected not by avoiding AI, but by ensuring the message genuinely reflects the manager's own view and care.

Pillar 4: Ethical data governance. Listening tools should be governed by explicit policies on consent, purpose limitation, anonymity, bias auditing and compliance with data protection law. In Nigeria, this includes a data privacy impact assessment before AI analytics are deployed (NDPC, 2025). Employees should know what is analysed and why. Analytics should inform dialogue, not replace it.

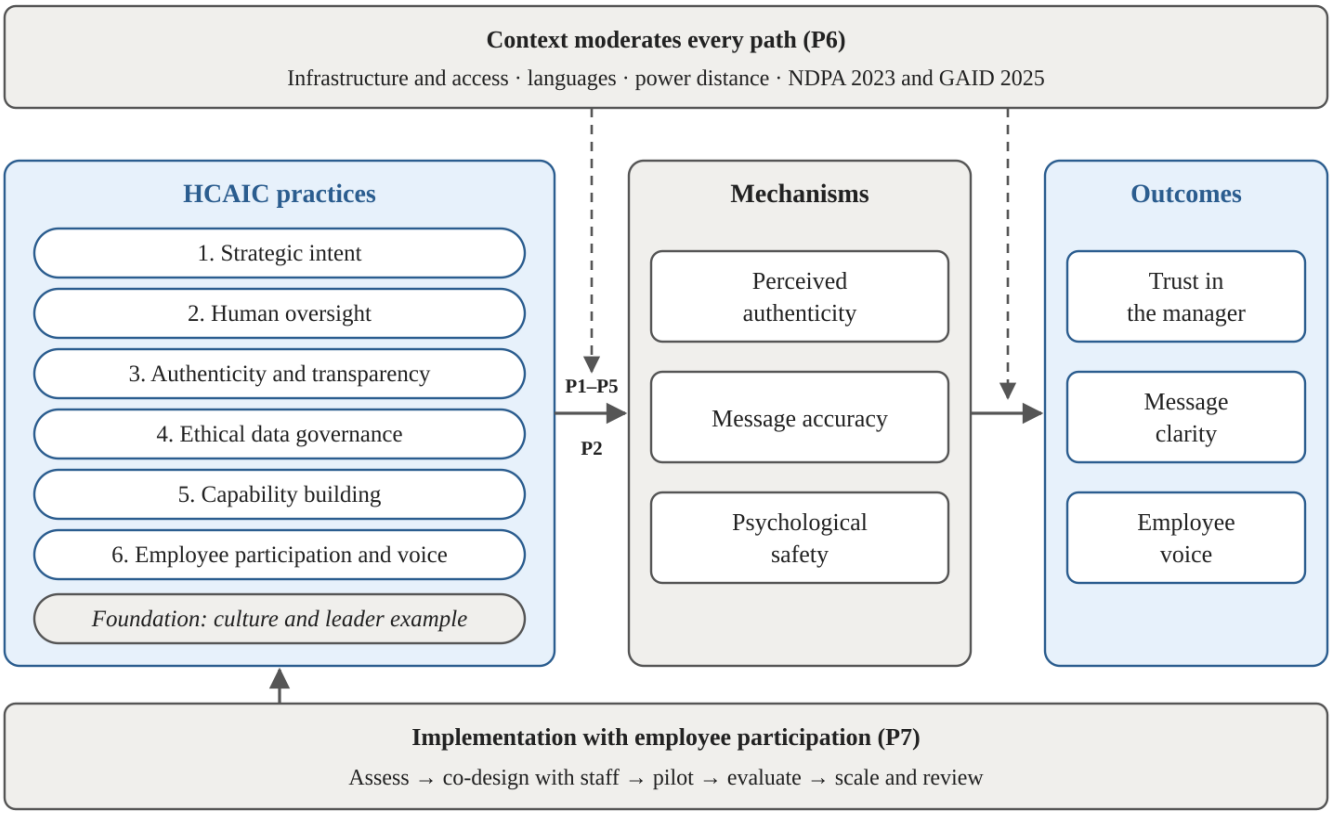
Pillar 5: Communication capability building. Organisations should invest in AI communication literacy: prompting, critical evaluation of output, verification, and the ethics of AI use. Equally, they should strengthen the human competencies that grow in value as AI spreads: active listening, empathy, storytelling, sense-giving, and the courage to hold difficult conversations in person.

Pillar 6: Employee participation and voice. Employees should help decide how AI is used in communication that affects them: which messages may be AI-assisted, what is disclosed and how listening tools are governed. Participation draws on employees' knowledge of their own communication needs, improves acceptance and signals respect (Kochan et al., 2023). It also addresses the disclosure penalty: Tong et al. (2021) recommend explaining the objectives, benefits and scope of AI tools to employees before they are used. In high power distance settings, participation should include anonymous channels so that staff can raise concerns without fear.

Foundation: culture and leadership example. The framework rests on a culture of psychological safety (Edmondson, 1999) and on senior leaders who model responsible AI use. Employees take their cue from how leaders actually communicate, not from what policies say.

10.3 Conceptual model

Figure 1 sets out the framework as a conceptual model. The six HCAIC practices act on three mechanisms: perceived authenticity, message accuracy and psychological safety. These mechanisms, in turn, shape three outcomes: trust in the manager, message clarity and employee voice. Message equivocality moderates the path from practices to mechanisms (P2); the national and organisational context moderates every path (P6); and implementation with employee participation sustains the practices over time (P7).



P2: message equivocality moderates the path from practices to mechanisms. Dashed arrows: moderation.

Figure 1. The HCAIC conceptual model

The model sets out hypothesised relationships rather than established findings; the propositions in Section 10.4 state them in testable form.

10.4 Propositions for empirical testing

The framework yields seven propositions, each linked to the evidence that motivates it. Table 1 sets out candidate measures for each construct.

- **P1 (AI involvement, ownership and disclosure).** Trust in a manager will fall as the perceived degree of AI involvement in a message rises. The fall will be smaller when AI involvement is limited and the manager visibly owns the message, and disclosure alone will not remove it (Jakesch et al., 2019; Glikson & Asscher, 2023; Cardon & Coman, 2025).

- **P2 (equivocality).** The penalty for AI involvement will be larger for equivocal, emotional and high-stakes messages, such as bad news, discipline, apology and condolence, than for routine messages (Daft & Lengel, 1986; Glikson & Asscher, 2023).

- **P3 (oversight).** Human review of AI-drafted messages will reduce factual errors and tone failures, and will reduce the tendency to shift blame onto AI when errors occur (Hohenstein & Jung, 2020).

- **P4 (listening governance).** Employees will show less psychological safety and voice where AI analysis of their communication is undisclosed, and more where its purpose and limits are transparent (Edmondson, 1999; Kellogg et al., 2020).

- **P5 (capability).** Managers trained in both AI literacy and human communication skills will achieve higher trust and clarity ratings from their teams than managers trained in AI tools alone.

- **P6 (context).** The authenticity penalty will be larger in high power distance, collectivist organisational cultures, such as many in Nigeria, than in more individualist ones (Section 9.3).

- **P7 (participation).** AI communication practices designed with employee participation will gain greater acceptance and produce higher psychological safety and voice than practices introduced without consultation (Tong et al., 2021; Kochan et al., 2023).

Implementing Hcaic: Barriers And Employee Participation

11.1 Implementation barriers

Technology acceptance research shows that people use a technology when they expect it to improve their performance, find it easy to use, feel social pressure to use it and have conditions that support its use (Venkatesh et al., 2003). Human-centred use adds a further requirement: the conditions that support *responsible* use, such as review processes, policies and skills. Table 9 summarises the barriers that Nigerian organisations are likely to face at five levels, with the HCAIC practice that addresses each.

Table 9. Barriers to implementing HCAIC in Nigerian organisations

Level	Barrier	Evidence	Response
Technological	Unreliable electricity and connectivity; cost of tools and computing	61% electricity access and 45.4% internet use (World Bank et al., 2025; Kemp, 2025); infrastructure costs (Lagos Business School et al., 2025)	Offline and low-bandwidth fallbacks; shared institutional licences
Data and language	Weak performance in local languages; incomplete organisational data	Abdulhamid et al. (2024); Lagos Business School et al. (2025)	Fluent-speaker review; data clean-up before analytics
Organisational	No AI communication policy; unclear accountability for AI-drafted messages	National code still in draft (NITDA, 2025); fragmented regulation (Lagos Business School et al., 2025)	Written policy; a named owner for every message (Pillar 2)
Individual	Low AI literacy; fear of job loss; over-reliance	Only 35% expect their skills to stay relevant (PwC, 2025); fear of replacement (Lagos Business School et al., 2025)	Capability building (Pillar 5); clear commitments on roles
Cultural and regulatory	Reluctance to challenge superiors; data protection duties	High power distance (Ebereonwu, 2021); NDPA 2023 and GAID 2025	Anonymous and protected channels (Pillar 6); impact assessments (Pillar 4)

11.2 Employee participation

Sociotechnical systems theory holds that technical change succeeds when those who do the work help to shape it (Trist & Bamforth, 1951). Applied to AI in communication, employees know which messages they rely on, which channels they trust and where AI is likely to misread them. Their participation also matters in its own right: being consulted about tools that analyse one's messages signals respect, and the absence of consultation can turn listening into perceived surveillance (Kellogg et al., 2020). Evidence from the United States suggests that involving workers in the design and deployment of generative AI improves both adoption and job quality (Kochan et al., 2023).

Participation can take four forms of increasing depth: *information*, telling staff which AI tools are used and why; *consultation*, inviting views before decisions; *co-design*, developing disclosure norms, message classifications and listening policies with staff representatives; and *joint review*, evaluating outcomes together. In Nigerian universities and public bodies, staff unions and associations provide established channels for such participation (Section 9.6). In high power distance settings, participation is genuine only if staff can speak without fear, so anonymous feedback channels and visible responses to concerns are essential.

11.3 An implementation roadmap

1. **Assess.** Audit current AI use in communication, classify message types by equivocality and complete a data privacy impact assessment for any AI analytics.
2. **Co-design.** With staff representatives, agree which messages may be AI-assisted, how AI use is disclosed and who reviews what.
3. **Pilot.** Start with low-risk, routine messages, with fallbacks for staff who lack reliable access.
4. **Evaluate.** Measure trust, clarity, psychological safety and voice using the measures in Table 1, and review errors.
5. **Scale and review.** Extend use to further message types only where evaluation supports it, and review the policy at least annually.

Implications For Practice And Policy

12.1 For managers

1. **Use AI for the routine; reserve yourself for the relational.** Delegate drafting of routine updates, summaries and FAQs. Personally deliver messages involving emotion, conflict, recognition or loss.
2. **Edit, never just forward.** Treat every AI output as a first draft. Verify facts, adjust tone, and add the context only you know.
3. **Reinvest saved time in presence.** Use time recovered through AI for one-to-one conversations, walking the floor, and listening.
4. **Be open about AI use.** Disclose proportionately and explain why you use it, but remember that disclosure alone does not restore trust: keep AI involvement limited in relational messages and make your own voice visible.
5. **Communicate the "why" behind AI-informed decisions.** Be able to explain, in plain language, how data and AI shaped a decision and where human judgement was applied.
6. **Guard your voice.** Keep a recognisable personal style. People follow leaders, not templates.

12.2 For organisations

- Develop an AI communication policy covering acceptable use, disclosure, review responsibilities and data protection.
- Classify communication types by equivocality and specify the required level of human involvement for each.
- Involve staff and their representatives in designing that policy, and provide anonymous channels for concerns.

- Complete a data privacy impact assessment before deploying AI analytics on staff communication.
- Audit AI tools for bias, particularly with respect to local languages and dialects.
- Build AI literacy and human communication skills together in leadership development programmes.
- Measure outcomes that matter, such as trust, clarity and employee voice, not merely the volume and speed of messages.

12.3 For educators and policy makers

- Management curricula, including MBA and executive programmes, should integrate AI-mediated communication, its ethics and its limits.
- Regulators should translate national AI and data protection frameworks into practical guidance for workplace communication and employee monitoring.
- In Nigeria and across Africa, investment in infrastructure, local-language AI and digital skills is needed to ensure that the benefits of AI-enabled communication are broadly shared.

CONCLUSION

Artificial intelligence is changing management communication more profoundly than any technology since the arrival of email. It makes communication faster, more personalised, more data-informed and more accessible. It also introduces new risks to authenticity, accuracy, fairness, privacy and the very skills managers rely upon. This review supports the proposition that AI strengthens the informational and directive functions of management communication, while the relational and sense-giving functions remain fundamentally human.

The central conclusion is that AI changes the *mechanics* of management communication far more readily than its *meaning*. Messages can be generated by machines; meaning, trust and commitment are still created between people. The managers who thrive in the AI era will not be those who produce the most content, but those who combine machine capability with human credibility: who use AI to free time for presence, who own every word they send, and who know when a message must come from a human voice alone. The HCAIC framework offers one structured path toward that balance, and the seven propositions in Section 10 provide a route for testing these claims empirically.

13.1 Limitations

This is a conceptual paper based on an integrative review. The review is integrative rather than systematic: sources were selected purposively rather than retrieved exhaustively, so relevant studies may have been missed, and the propositions in Section 10 remain untested. Much of the management-specific evidence comes from short scenario experiments with participants in the United States, and few studies observe managers in real organisations over time. It does not provide primary empirical data, and the pace of AI development means that some findings may date quickly. The evidence base is also concentrated in high-income countries, which limits its direct transferability to African settings.

13.2 Directions for future research

- Empirical testing of the HCAIC framework and propositions P1–P7 in organisations, including Nigerian universities, banks and public bodies.
- Field studies of how employees in high power distance, collectivist cultures perceive AI-assisted messages from managers.

- Experiments comparing disclosure, limited AI involvement and visible ownership as ways of protecting trust.
- Research on AI translation and sentiment tools across Nigerian languages and varieties of English.
- Studies of upward and lateral communication, meetings and multilingual exchanges, which current research largely neglects.
- Evaluation of participatory approaches to AI adoption, including the role of staff unions and associations.
- Longitudinal studies of whether sustained AI use erodes or enhances managers' own communication competence.

Declarations

Ethical approval. This is a conceptual paper based on a review of published literature. It involved no human participants, animals or personal data, so ethical approval was not required.

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