

AI-Mediated Miscommunication in a Multilingual, High-Context Society: Encoding, Decoding, and Meaning Distortion Among Bangladeshi Youth

Md. Sipon Mia¹  Abhiaz Khan Rafi¹  Hajrat Hania³ 

Bangladesh University of Professionals¹, University of Dhaka³

Corresponding author: miamdshipon870@gmail.com

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Abstract

This qualitative study examines how AI-generated messages produce miscommunication and meaning distortion among Bangladeshi youth in a multilingual, high-context communication environment. Most existing scholarship on AI-mediated communication is grounded in Western, English-dominant settings; how generative AI functions where multilingual code-switching and high-context cultural norms shape meaning remains largely unexamined. Drawing on Stuart Hall's Encoding-Decoding Model and Human-Machine Communication (HMC) theory, the study uses semi-structured in-depth interviews with 12 Bangladeshi youth and four expert informants, analysed through a theory-driven thematic analysis that also allowed data-driven subthemes to emerge inductively within the theoretical categories. Six interconnected themes emerged: instrumental, purpose-bounded AI use; identity, authenticity, and impression management; tone and emotional misalignment; linguistic hybridity and translation breakdown; cultural incongruence and Western-centric framing; and calibrated trust and critical reliance. Findings indicate that participants primarily use AI as an editing and refinement aid for their own personal, academic, and professional messages rather than as a communicative substitute, and routinely revise AI-generated text before sending it, positioning the human user as an active co-encoder rather than a passive recipient of AI output. Miscommunication occurred most often in tone, register, hierarchy, cultural framing, and perceived message provenance rather than lexical accuracy alone, indicating a recurring risk that users actively manage rather than an inevitable or system-wide failure. The findings position AI as an active but culturally constrained co-encoder whose outputs require human contextualization and verification. The study illustrates and refines Hall's encoding-decoding framework and HMC theory within a non-Western, multilingual context, showing how linguistic hybridity and culturally situated interpretation shape AI-mediated meaning construction.

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Introduction

The proliferation of artificial intelligence (AI)-driven communication technologies has fundamentally restructured the nature of human digital interaction (Guzman & Lewis, 2020; Hancock et al., 2020). Natural Language Processing (NLP)-powered tools including ChatGPT, Google Gemini, and Meta AI are now routinely deployed to compose, translate, summarize, and respond to messages across personal, academic, and professional communication domains (Bender et al., 2021; Jurafsky & Martin, 2023).

Adoption has accelerated sharply since these tools first reached mainstream use: ChatGPT grew from roughly 100 million monthly users within two months of its late-2022 launch to more than 800 million weekly active users by late 2025 (OpenAI, 2023; Bellan, 2025), underscoring how deeply machine-generated text is now embedded in everyday communicative life. As AI systems increasingly co-produce communicative meaning alongside human users, meaning is no longer exclusively the product of human intentionality but emerges through algorithmic mediation between human interlocutors and machine encoders (Guzman, 2018).

In Bangladesh, this transformation is unfolding within a sociolinguistically complex environment that poses distinct challenges for AI-mediated communication. Bangla is the primary language of daily life, while English plays a significant role in education, professional communication, and digital media; movement between the two carries social meaning well beyond word choice.

Bangladeshi youths, numbering more than 36 million between the ages of 18 and 35, constitute the primary adopters of digital communication tools and are increasingly dependent on AI-assisted messaging and generative content production (Bangladesh Bureau of Statistics, 2022). Communication among this demographic is characterized by pervasive Bangla-English code-switching — sometimes referred to as “Banglish” — a hybrid linguistic practice in which the choice to switch languages, not simply the words chosen, signals identity, intimacy, hierarchy, politeness, formality, and social distance (Androutsopoulos, 2013; Myers-Scotton, 1993).

Bangladeshi communicative culture is also governed by high-context norms that foreground relational indirectness, face-saving politeness, and context-dependent meaning (Hall, 1976; Hofstede, 2001; Brown & Levinson, 1987). These norms can vary considerably by age, class, education, region, and relationship, and are treated here as a sensitizing concept rather than as evidence that Bangladeshi communicative practice is culturally uniform. They are, nonetheless, precisely the dimensions of human communication that AI systems trained predominantly on low-context, English-dominant corpora are least equipped to reproduce (Bender et al., 2021).

Miscommunication arising from AI-generated text in culturally specific contexts can take several forms: tone misalignment, in which outputs are semantically accurate but affectively inappropriate; cultural insensitivity, in which outputs unsettle local politeness conventions or social hierarchies; and meaning distortion, in which the encoded message is decoded in ways that diverge from communicative intent (Coiera, 2000; Spitzberg, 2006; Hancock et al., 2020).

Grice's (1975) cooperative principle holds that successful communication depends on maxims of quality, quantity, relation, and manner — maxims that AI systems can struggle to satisfy in culturally specific encounters. Clark and Schaefer's (1989) grounding theory suggests that shared understanding depends on iterative interlocutor adjustment, a collaborative process that current AI systems can only partially approximate because they lack access to shared history, relational context, and nonverbal cues. Rather than positioning such failures as an inevitable or structurally embedded property

of the technology, this study treats them as a recurring risk that arises when AI-generated text circulates in high-context, multilingual settings, and as a risk that human users actively identify, correct, and manage (Hutchby, 2001; Walther, 1996).

Despite growing scholarly attention to AI communication tools, a gap remains in research examining how AI-generated messages produce miscommunication in culturally and linguistically complex contexts such as Bangladesh. Existing studies disproportionately emphasize efficiency gains and productivity benefits, giving less attention to unintended consequences such as misinterpretation of tone, distortion of pragmatic meaning, and cultural-communicative mismatch (Guzman & Lewis, 2020; Sundar & Limperos, 2013; Bender et al., 2021).

Foundational communication theories, including Shannon and Weaver's (1949) transmission model and Berlo's (1960) SMCR model, conceptualize communication as a human-to-human process and do not account for AI as a communicative agent, leaving a theoretical gap in explaining AI-mediated meaning distortion (Guzman, 2018; Morley, 1992). Recent scholarship on how automated systems misrecognize the users they serve reinforces the need for qualitative accounts that centre user experience rather than system performance metrics alone (Gao & Liu, 2026). Empirically grounded qualitative research on AI-mediated miscommunication in South Asian contexts remains scarce, motivating the present inquiry.

This study therefore examines how AI-generated messages produce meaning distortion and miscommunication among Bangladeshi youth, with particular attention to the intersecting roles of linguistic hybridity and cultural communication norms. Two complementary theoretical frameworks guide the inquiry: Stuart Hall's (1980) Encoding-Decoding Model, which provides conceptual tools for analysing how AI-generated meaning is produced and interpreted asymmetrically, and Human-Machine Communication (HMC) theory (Guzman, 2018), which repositions AI as an active participant in meaning-making rather than a neutral channel.

The study does not treat these as the only frameworks capable of explaining Bangla-English code-switching; rather, it applies and refines them within a multilingual, non-Western context, and identifies where a dedicated sociolinguistic framework would extend the analysis further (see Section 3.1). By generating original qualitative evidence on how algorithmic encoding interacts with Bangla-English hybridity and high-context cultural norms to produce meaning distortion, this study contributes to both communication theory and AI ethics scholarship in non-Western digital contexts.

The study pursues three objectives: (1) to investigate how Bangladeshi youth use AI tools in everyday communication across social, academic, and professional settings; (2) to identify and categorize the forms of miscommunication (e.g., tone misalignment, linguistic errors, cultural misunderstanding) arising from AI-generated messages; and (3) to analyse how linguistic hybridity (Bangla-English code-switching) and cultural norms influence the interpretation and misinterpretation of AI-generated communication.

Correspondingly, three research questions guide the inquiry. RQ1: How do Bangladeshi youth use AI-generated tools in their everyday digital communication across different contexts? RQ2: What types of miscommunications emerge from AI-generated messages among Bangladeshi youth? RQ3: How do linguistic hybridity and cultural context influence the interpretation and misinterpretation of AI-generated communication?

LITERATURE REVIEW

AI in digital communication and human-machine interaction

The rise of AI in digital communication has been theorized through the Human-Machine Communication (HMC) framework, which reconceptualizes machines as communicative agents rather than transmission channels (Guzman, 2018; Guzman & Lewis, 2020). Guzman (2018) argues that AI systems function as co-communicators that generate, interpret, and respond to meaning in ways structurally parallel to human communicative agency, yet operate through statistical pattern recognition rather than socially embedded understanding.

Natural Language Processing (NLP), the computational foundation of AI-generated text, enables systems to produce linguistically plausible outputs by learning probabilistic associations across large training corpora (Jurafsky & Martin, 2023). Bender et al. (2021) caution that large language models can acquire linguistic form without grounded meaning, generating syntactically coherent outputs whose fluency can outpace their sensitivity to the communicative context they simulate; this is a caution about the risk of overinterpreting fluency as understanding, not a claim that all AI output is meaningless, and it is cited here accordingly.

Two further strands of theory are relevant to how users relate to AI-generated output, and they should not be treated as interchangeable. Nass and Moon (2000) do not argue that users anthropomorphize computers in the sense of consciously believing machines are human; their central finding is a mindlessness account — people apply social scripts to computers automatically, via superficial cues, even while explicitly knowing the computer is not a person. Sundar and Limperos (2013), by contrast, extend uses-and-gratifications theory to new media affordances and are concerned with the gratifications users seek from technology rather than with automatic social responses to it; the two accounts address different mechanisms and are cited separately here rather than as joint evidence for a single claim. Coiera (2000) established that communication failures in technologically mediated clinical settings arise from mismatches between medium affordances and users' pragmatic expectations.

The present study treats this as one illustrative account of affordance-expectation mismatch rather than as a general theory of generative-AI miscommunication, since Coiera's evidence base is specific to clinical information systems. While HMC theory and NLP critique have advanced understanding of AI as a communicative agent in Western contexts, qualitative evidence on how Bangladeshi youth experience AI's co-communicator role within hybrid linguistic environments remains largely absent, a gap this study addresses through in-depth qualitative inquiry.

Meaning construction and the encoding-decoding process

Stuart Hall's (1980) encoding-decoding model provides the conceptual foundation for analysing meaning distortion in AI-generated communication. Hall argued that meaning is actively produced through distinct semiotic processes at each end of the communication chain, with dominant, negotiated, or oppositional readings depending on the decoder's social position and interpretive framework (Hall, 1980; Morley, 1992).

Applied to AI-generated text, this model suggests a potentially asymmetric encoding process: AI systems encode messages through statistical optimization of training data that skews toward Western, English-dominant communicative norms, while Bangladeshi youth decode these messages through culturally embedded frameworks shaped by collectivist values, high-context communication, and multilingual pragmatic repertoires (Androutsopoulos, 2013; Hofstede, 2001). This mismatch between AI encoding and culturally situated decoding is treated here as a recurring interpretive risk rather than a guaranteed outcome, since, as the findings show, participants frequently identify and correct it before a message reaches its receiver.

Research on automated text processing suggests that pragmatic features such as tone, social register, and relational implication are harder for such systems to preserve than propositional content (Danescu-Niculescu-Mizil et al., 2013, whose study of how individual language use shifts over a user's tenure in an online community illustrates, by extension, how sensitive pragmatic signals are to the processing context in which text is produced, though the study itself does not examine AI-generated text directly). Hutchby (2001) theorized that communication technologies shape interactional possibilities through their affordances, a framework this study applies to argue that AI's affordances can constrain reliable meaning encoding and decoding without determining it outright.

Spitzberg (2006) further established that communication competence requires pragmatic sensitivity to context, register, and relational positioning — sensitivity that current AI systems can only partially approximate. Hall's encoding-decoding model has not previously been applied empirically to AI-generated communication in non-Western multilingual contexts, and how Bangladeshi youth decode AI-generated messages has not been qualitatively examined — a gap this study addresses through systematic thematic analysis.

Miscommunication and meaning distortion in AI-mediated contexts

Miscommunication in AI-mediated contexts encompasses tone misalignment, pragmatic ambiguity, contextual inadequacy, and register failure as analytically distinct failure types (Coiera, 2000; Spitzberg, 2006; Jurafsky & Martin, 2023). Tone misalignment — the generation of semantically accurate but pragmatically inappropriate output — has been discussed as a recurring risk in large language model output (Bender et al., 2021).

Clark and Schaefer's (1989) grounding theory holds that successful communication depends on iterative mutual adjustment to achieve shared reference; current conversational AI systems can respond to feedback and revise output within a session, but they lack full access to shared history, established relationships, nonverbal cues, and

culturally embedded expectations, which limits how completely they can ground meaning the way human interlocutors do. Grice's (1975) cooperative principle offers additional analytical leverage: AI-generated messages can violate the maxim of relation by producing contextually plausible but situationally misjudged output, and the maxim of manner through unnecessary formality that diverges from users' contextual expectations.

Empirical research documents specific patterns of AI-related miscommunication with relevance to the Bangladeshi context, though the strength of individual claims varies and is represented accordingly here. Hancock et al. (2020) outline a research agenda showing how AI-mediated communication can produce misunderstandings of communicative intent among recipients unaware of a message's AI origin, without claiming that such misunderstanding is universal or inevitable. Zhou et al. (2020) describe the design of Xiaolce, a social chatbot built to sustain empathetic, culturally attuned conversation; read for what it actually demonstrates, Xiaolce's design choices illustrate how much deliberate cultural and affective engineering is required for a conversational system to avoid the kind of culturally inappropriate output this study documents — it is cited here as evidence of the engineering effort such calibration requires, not as a study measuring failure rates across cultural contexts.

A more precise argument, and the one this study adopts, is that general-purpose AI systems may have difficulty preserving locally meaningful pragmatic cues, and that this difficulty likely varies by language, platform, task, and context rather than applying uniformly.

Linguistic hybridity and cultural context in Bangladesh

Linguistic hybridity, the systematic mixing of two or more languages within communicative events, is a defining feature of Bangladeshi youth digital communication, where Bangla and English are fluidly combined in social media messaging, academic writing, and interpersonal exchange (Androutsopoulos, 2013; Pennycook, 2010).

Androutsopoulos (2013) theorized that digital code-switching is a sophisticated semiotic resource through which bilingual users construct identity, signal social affiliation, and calibrate relational proximity — functions that AI systems trained predominantly on monolingual English corpora are not well positioned to recognize or reproduce.

Myers-Scotton's (1993) Matrix Language Frame model offers a theoretical architecture for understanding how Bangla-English code-switching operates morphosyntactically; applied to the present data, it helps explain why participants' Banglish input — in which Bangla typically supplies the grammatical matrix while English contributes embedded lexical items — was frequently misread by AI systems that default to a monolingual English matrix, as in P9's and P11's accounts of failed translation and topic drift (Jurafsky & Martin, 2023; Romaine, 1995).

Cultural communication norms in Bangladesh are characterized by high-context interaction, relational indirectness, elaborate face-saving politeness conventions, and context-dependent meaning-making that AI systems trained on low-context English data can struggle to reproduce (Hofstede, 2001; Hall, 1976; Brown & Levinson, 1987).

Edward T. Hall (1976) established the high-context/low-context distinction, demonstrating that high-context cultures rely on shared cultural knowledge, relational history, and situational embedding to convey meaning that algorithmic systems cannot encode without genuine cultural competence. This framework should not be confused with Stuart Hall's (1980) Encoding-Decoding Model, the two scholars share a surname but represent distinct theoretical traditions, and this study refers to them throughout by full name to avoid ambiguity. Pronoun choice offers a concrete illustration of how much cultural information Bangla carries beyond lexical content: Bangla distinguishes *tui* (intimate or, when used upward, deliberately disrespectful), *tumi* (familiar, used with peers, younger people, or close relations), and *apni* (formal and respectful, used with elders and in professional or unfamiliar contexts), and the choice among them encodes hierarchy, intimacy, and respect in ways that have no direct equivalent in English — which is why participants' reports of AI systems collapsing this distinction, carry particular pragmatic weight.

Well-documented barriers to digital learning and communication access among Bangladeshi students point to the broader infrastructural and pedagogical challenges this population faces in digitally mediated settings (Islam & Habib, 2021), even though that literature was not designed to test AI-specific pragmatic failure and is not cited here as direct evidence of it.

No qualitative study has yet examined how Bangladeshi youth experience, interpret, and communicatively respond to AI-generated messages that fail to accommodate Bangla-English hybridity and Bangladesh's high-context cultural norms — a gap this study fills by generating grounded qualitative evidence.

The reviewed literature suggests that AI-generated communication carries a recurring risk of meaning distortion linked to computationally constrained encoding, limited pragmatic awareness, cultural decontextualization, and NLP systems not designed to accommodate linguistic hybridity (Guzman & Lewis, 2020; Bender et al., 2021; Hall, 1980; Androutsopoulos, 2013).

Four interconnected gaps converge to justify this study: an absence of qualitative evidence on HMC dynamics in Bangladeshi youth contexts; no empirical encoding-decoding analysis of AI text in non-Western multilingual settings; undocumented AI-mediated miscommunication patterns in Bangladeshi digital practice; and no qualitative investigation of how code-switching and high-context cultural norms interact with AI-generated text to shape interpretation. The present study addresses all four gaps by centring Bangladeshi youth communicative experiences.

THEORETICAL FRAMEWORK

This study integrates Stuart Hall's (1980) Encoding-Decoding Model and Human-Machine Communication (HMC) Theory (Guzman, 2018) to examine AI-mediated miscommunication among Bangladeshi youth. These theories are selected because, together, they address both the structural process by which meaning is constructed and potentially misinterpreted across asymmetric contexts, and the distinctive relational dynamic introduced when AI functions as an active communicative participant rather than a neutral medium. Neither theory was developed to explain code-switching or

the social meanings of bilingual practice on its own terms; where the analysis turns specifically to Bangla-English hybridity (RQ3), it draws additionally on Androutsopoulos (2013) and Myers-Scotton's (1993) Matrix Language Frame model (Section 2.4) as a complementary sociolinguistic lens, rather than asking the encoding-decoding and HMC frameworks to carry that explanatory weight alone.

Encoding-decoding model

Stuart Hall (1980) reconceptualised communication as a structured production process in which meaning is constructed, not transparently transmitted. The model identifies encoding as the production of a message within specific institutional and ideological codes; the message as the textual form carrying a preferred reading; and decoding as the audience's active interpretation through their own cultural and experiential frameworks. Hall distinguished three decoding positions: dominant-hegemonic, in which the preferred meaning is accepted; negotiated, in which the meaning is partially modified; and oppositional, in which it is decoded through an entirely different framework (Morley, 1992). Miscommunication arises from what Hall (1980) termed the structural non-equivalence between encoding and decoding contexts. As in Section 2.4, this study refers to Stuart Hall by full name throughout this section to distinguish his Encoding-Decoding Model clearly from Edward T. Hall's high-context/low-context framework.

Adapting a model built for institutional mass-media producers to a generative AI system requires some justification, since AI is not an intentional encoder in the way a media producer or editorial board is: it has no communicative intent of its own, and the findings below show that a human user typically retains editorial control over what is ultimately sent. The adaptation made here is accordingly a qualified one. The AI system functions as a technological co-encoder whose outputs are structured by training corpora skewed toward English-language, Western-context data, generating a preferred reading that can be misaligned with Bangladeshi communicative norms (Bender et al., 2021), while the human sender remains the primary encoder and gatekeeper who drafts, edits, verifies, or rejects that output before it is sent (Section 5.1). The AI-generated text constitutes the message, whose surface-level linguistic naturalness can obscure cultural and contextual incongruence where it is not caught in editing (Guzman & Lewis, 2020).

Bangladeshi youth operate as decoders embedded in a context of pronounced linguistic hybridity, characterised by Bangla-English code-switching and culturally specific pragmatic conventions. Where a message's encoding and a decoder's interpretive framework diverge, and where human editorial gatekeeping has not caught the divergence beforehand, negotiated or oppositional readings become more likely and meaning distortion becomes a recurring risk rather than a guaranteed outcome.

Human-Machine Communication theory

Guzman (2018) argued that the proliferation of sophisticated AI systems requires communication scholars to reconceptualise AI not as a passive conduit but as an active communicative agent that produces, shapes, and co-constructs meaning within exchanges. This theoretical reorientation is substantive: communication occurs with AI, not merely through it (Guzman & Lewis, 2020).

Nass and Moon's (2000) mindlessness account is relevant here in a specific way: they show that people apply social scripts to computer-generated output automatically, through superficial cues, independent of what they consciously believe about the machine's nature. This supports Guzman's (2018) reorientation by suggesting that AI's communicative agency can shape user response even without users treating the system as human-like, which is a narrower and more precise claim than an anthropomorphism account would make.

It also raises a genuine question this study is positioned to examine whether the same automatic social response Nass and Moon documented persists once a user consciously distrusts or verifies AI output, or whether — as the calibrated conscious verification habits can coexist with, rather than override, an automatic social response. The findings do not settle this question, and it is presented here as a possibility the data raise rather than a confirmed divergence from Nass and Moon's account.

In the Bangladeshi context, youth increasingly rely on AI-assisted messaging, automated translation, and chatbot interaction as integrated communicative practices (Hancock et al., 2020). HMC theory suggests that this reliance generates a co-construction of meaning in which the AI's output shapes the user's interpretive process, even as the user retains editorial authority over the final message. Because Bangladeshi youth engage AI outputs as communicative acts, they bring attributional frameworks that are not always calibrated to detect algorithmically produced cultural incongruence, which is one reason careful human review before sending remains consequential.

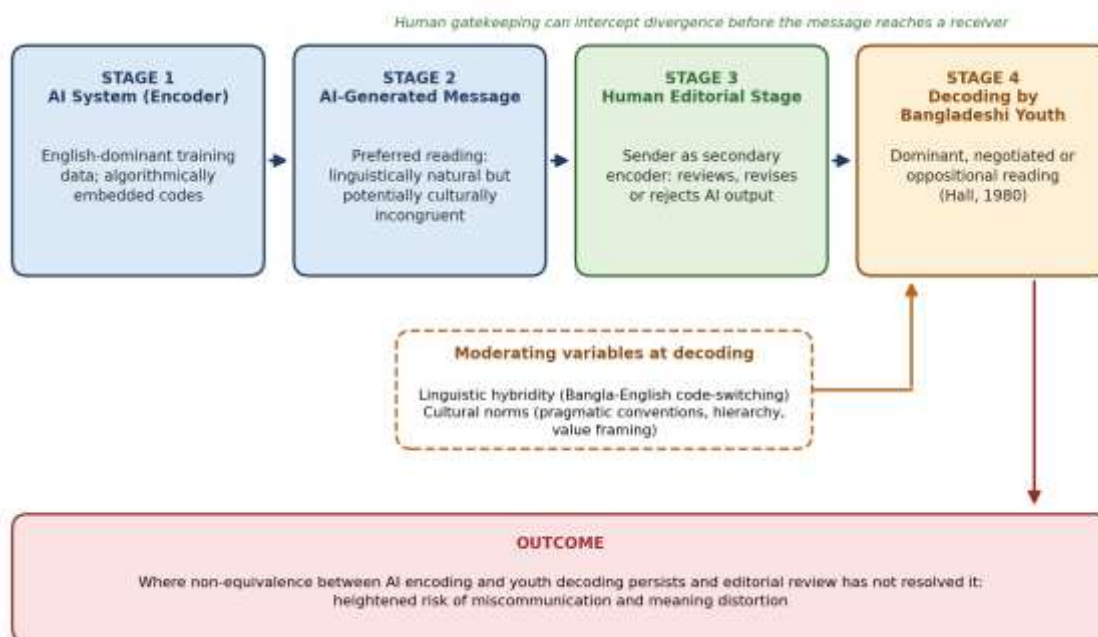
The two theories are analytically complementary. The Encoding-Decoding Model addresses the structural mechanism of miscommunication: non-equivalence between AI encoding and Bangladeshi decoding frameworks can produce interpretive gaps where human gatekeeping does not intervene (Hall, 1980). HMC theory specifies why this gap matters in practice: users' social response to AI output can amplify encoding-decoding misalignment, even as the same users retain and exercise editorial control (Guzman, 2018). Neither theory alone is sufficient: Hall's model does not on its own address AI's distinctive communicative agency or the human user's role as co-encoder, while HMC theory does not systematically theorise interpretive gaps at decoding. Combined, and read alongside the sociolinguistic literature on code-switching, they provide a framework for examining AI-mediated meaning distortion among Bangladeshi youth as a negotiated, human-moderated process rather than a one-directional technological effect.

Conceptual framework model

Figure 1 illustrates the study's directional process model in four stages. The AI System (Encoder) produces outputs shaped by algorithmically embedded codes reflecting English-dominant training data, positioning AI as an active communicative agent per HMC theory (Guzman, 2018). The resulting AI-Generated Message carries a preferred reading that may appear linguistically natural while remaining culturally incongruent. Before that message reaches a receiver, it typically passes through a human editorial stage in which the sender acts as a secondary encoder — reviewing, revising, or rejecting the AI's output.

Figure 1

Conceptual Framework of AI-Mediated Meaning Construction and Distortion among Bangladeshi Youth



Note. Developed by the authors from Hall (1980) and Guzman (2018).

Two moderating variables intervene at decoding: linguistic hybridity, reflecting Bangla-English code-switching, and cultural norms, encompassing pragmatic conventions, hierarchical address, and value-level framing specific to Bangladesh. These variables shape the interpretive framework through which Bangladeshi youth decode the message, producing dominant, negotiated, or oppositional readings (Hall, 1980). Where non-equivalence persists between the AI's encoding and the youth's decoding — and where human editorial review has not resolved it — the outcome is a heightened risk of miscommunication and meaning distortion.

METHODOLOGY

This study employed a qualitative research design using semi-structured in-depth interviews (IDIs) with Bangladeshi youth and key informant interviews (KIIs) with experts to examine AI-mediated miscommunication and meaning distortion. The design was selected because the study sought to understand participants' experiences, interpretations, and contextual explanations rather than measure the frequency of predefined phenomena.

The study sample included 12 youth participants and four expert informants, with gender balanced across both groups: 50% of IDI participants and 50% of KII participants were male, and the remaining 50% in each group were female. Youth participants were purposively selected because they possessed direct experience of using AI-generated communication tools in everyday digital communication. Expert informants were selected purposively based on their relevant expertise in communication, artificial intelligence, digital media, or linguistics, and their role in teaching related courses at the

tertiary level; experts were engaged primarily to illuminate the institutional and academic context of AI usage in higher education, and their accounts are triangulated in Section 5 with the everyday, cross-domain experiences reported by youth participants.

Given the exploratory nature of this qualitative inquiry into a largely unexamined context, a sample of 12 youth participants and four expert informants was considered appropriate for generating in-depth, information-rich accounts of participants' experiences and interpretations rather than population-level estimates; the sample is not intended to be statistically representative of Bangladeshi youth as a whole. see the Limitations Paragraph of the Discussion and the Conclusion.

The four experts were selected to provide complementary disciplinary perspectives on AI-mediated communication, spanning communication studies, linguistics and translation, AI and digital media, and information and communication technology (Table 1, Panel B), rather than expertise concentrated in any single specialization. None were selected specifically for expertise in cultural translation as a distinct field; we note this as a boundary of the present expert sample and a direction for future expert-informant selection in this line of research.

Youth participants were eligible if they: (1) were Bangladeshi youth aged 15 to 24 years, following the United Nations' definition of youth, with the achieved sample ultimately comprising participants aged 18 to 24 (Table 1), (2) regularly used AI-based tools capable of generating, translating, or modifying text; (3) had combined experience using AI-generated messages across personal, social, academic, and professional communication; and (4) were willing and able to describe their experiences in an interview. Participants were primarily tertiary-level students from diverse academic backgrounds — including the social sciences, arts and law, and science and business studies — as well as individuals who had recently begun internships or held entry-level professional positions. Individuals who had no direct experience with AI-assisted personal, social, academic, or professional communication, could not provide informed consent, or were unable to participate in the interview were excluded.

Expert informants were eligible if they had relevant professional, academic, or research expertise concerning AI, communication, digital media, or linguistics, and taught related courses at tertiary-level educational institutions in Bangladesh. Individuals without relevant expertise or without direct knowledge of the phenomenon were excluded.

Purposive sampling was used to identify information-rich participants. Recruitment and interviewing proceeded iteratively alongside preliminary analysis to assess the adequacy of the emerging data. Data collection continued until thematic saturation was reached, defined in this study as the point at which successive interviews no longer generated substantively new codes, meanings, or dimensions relevant to the research questions. Saturation was reached after the 12th youth interview and the 4th expert interview. Concretely, transcripts were reviewed and provisionally coded as they were collected, and the codes generated by each new interview were compared against the developing codebook for that participant stream (youth or expert); saturation was judged to have been reached within a stream once its final interviews no longer produced codes, meanings, or dimensions beyond those already documented from earlier

interviews in the same stream. The decision was further supported by the focused research questions, relatively specific participant groups, established theoretical framework, and in-depth semi-structured interview format. The final sample therefore comprised 12 youth participants and four expert informants.

Semi-structured interviews were conducted in person between 15 April 2026 and 30 May 2026, in Bangla, allowing participants to articulate culturally and linguistically situated experiences without the constraints of conducting interviews in a second language. Interviews were transcribed verbatim and manually translated into English for analysis by the interviewing researcher. Translated transcripts were subsequently reviewed by participants against the original Bangla transcripts, a member-checking step intended to confirm that intended meaning, contextual expressions, and culturally specific nuances had been preserved in translation. Participant identities were anonymized during transcription and analysis. Participants reported using a range of large language model (LLM)-based tools in their everyday practice, most commonly ChatGPT, Gemini, Grammarly, Claude, and Perplexity, among others. Standardized measures of AI-use frequency (e.g., daily, weekly, or monthly use) were not collected, as the study was designed to elicit participants' communicative experiences and uses of AI-generated messages rather than to quantify usage frequency. Table 1 instead reports each participant's primary AI-use context.

Table 1

Characteristics of Study Participants

Panel A. Youth Participants (n = 12)

Participant ID	Age	Gender	Educational/Professional Status	Academic/Professional Background	Primary AI-Use Context
P1	21	Male	Undergraduate student	Social Sciences	Academic and interpersonal communication
P2	22	Female	Undergraduate student	Business Studies	Academic writing and professional communication
P3	20	Male	Undergraduate student	Science and Technology	Academic and digital communication
P4	23	Female	Undergraduate student	Law	Academic and formal communication
P5	19	Male	Undergraduate student	Arts and Humanities	Academic and social communication
P6	21	Female	Undergraduate student	Social Sciences	Academic writing and interpersonal communication
P7	24	Male	Recent graduate / Entry-level professional	Business and Management	Workplace and professional communication

Participant ID	Age	Gender	Educational/Professional Status	Academic/Professional Background	Primary AI-Use Context
P8	20	Female	Undergraduate student	Arts and Humanities	Academic and interpersonal communication
P9	22	Male	Undergraduate student	Science and Business	Academic and multilingual communication
P10	19	Female	Undergraduate student	Social Sciences	Academic writing and digital communication
P11	23	Male	Recent graduate / Intern	Law and Social Sciences	Professional and interpersonal communication
P12	21	Female	Undergraduate student	Science and Technology	Academic and social communication

Panel B. Expert Informants (n = 4)

Expert ID	Gender	Academic/Professional Field	Relevant Expertise	Institutional/Professional Role
E1	Male	Communication Studies	Health/Interpersonal Communication and Digital Media	University faculty member
E2	Female	Linguistics	Language, Translation and Multilingual Communication	University faculty member
E3	Male	Communication and Media Studies	AI-mediated communication and Digital Media	University faculty member/researcher
E4	Female	Information and Communication Technology	Artificial Intelligence and Digital Communication	University faculty member/researcher

Data analysis

Data were analysed using a hybrid approach combining deductive, theory-driven coding with inductive, data-driven coding (Fereday & Muir-Cochrane, 2006). Analysis began with an initial deductive coding framework structured around analytical categories derived from Hall's (1980) Encoding-Decoding Model and Human-Machine Communication (HMC) theory (Guzman, 2018); these theoretical lenses guided examination of how AI-generated text functions as an encoded communicative product, how Bangladeshi youth interpret and negotiate these messages, and how linguistic hybridity, cultural nuance, and AI's communicative agency contribute to meaning distortion.

Concurrently, an inductive process allowed empirically grounded subthemes and contextual codes to emerge directly from the data where they were not anticipated by the initial framework, consistent with the theory-driven analysis that nonetheless allowed data-driven subthemes to emerge, as reported in the abstract.

To strengthen analytical rigor, coding was conducted independently by two researchers, who maintained a neutral, non-evaluative stance throughout to limit researcher bias given their position as academic observers. Following independent initial coding, the two researchers met to compare codebooks, cross-check code applications, and refine thematic definitions; analytical discrepancies or coding disagreements were discussed until full consensus was reached.

Expert accounts were analysed using the same hybrid framework and systematically compared with youth narratives to identify convergence, divergence, and complementary perspectives, providing a form of respondent-type triangulation between the institutional/academic perspective captured in the KIIs and the everyday communicative experience captured in the IDIs. The themes reported in Section 5 were not read directly off the initial theoretical categories; rather, they were developed through iterative comparison and consolidation of the deductive, theory-derived codes with the inductive, data-driven codes across the full dataset, retaining subthemes and participant meanings that fell outside the original Hall/HMC categories where the data supported them (e.g., the sender-provenance pattern in Section 5.5). Hall's Encoding-Decoding Model and HMC theory accordingly functioned as sensitizing frameworks that oriented the initial coding rather than as a fixed template that predetermined the final themes.

FINDINGS

The findings of this study reveal that Bangladeshi youth engage with AI-generated communication in a deliberately bounded, self-regulated manner, yet still encounter recurrent and often consequential episodes of miscommunication rooted in tone misalignment, linguistic hybridity, and cultural incongruence.

Hybrid deductive-inductive thematic analysis of the twelve in-depth interviews (IDIs) with youth participants — identified below as P1 through P12 — and four key informant interviews (KIIs) with communication and education experts — identified as Expert P-1 through Expert P-4 — generated six interconnected themes: instrumental, purpose-bounded AI use; identity, authenticity, and impression management; tone and emotional misalignment; linguistic hybridity and translation breakdown; cultural incongruence and Western-centric framing; and calibrated trust and critical reliance.

Read together through Hall's (1980) Encoding-Decoding Model and Human-Machine Communication theory (Guzman, 2018), these themes demonstrate that AI functions as an active but culturally under-equipped co-encoder whose English-dominant, low-context outputs are persistently renegotiated, corrected, or rejected by Bangladeshi decoders. One methodological caveat must be reported transparently before the thematic evidence is presented: because the KII protocol was scoped specifically to AI in higher education, expert accounts provide rich triangulating evidence for Themes 1, 2, and 6, but offer no direct evidence on tone, code-switching, or cultural norms discussed under Themes 3 to 5. This asymmetry is treated as a genuine finding about the dataset rather than smoothed over with inferred expert opinion.

1. Instrumental, purpose-bounded AI use

RQ1, participants across the sample described AI as a bounded instrument confined largely to formal, academic, and professional communication rather than a full communicative substitute. At least four of the twelve youth participants (P1, P2, P3, and P4) reported restricting AI use to narrow, editable functions, including grammar polishing, tone checking, and translation, while retaining ownership of the message's substance. As P1 explained:

I keep the main blueprint in my head and just use AI to enhance the message... AI cannot set the tone well, so I take the words or paragraphs it suggests and edit the message myself.

P2 similarly noted, "I don't use them all the time, only in certain situations... For communication, I don't use it for interpersonal chats," while P3 stated flatly, "I never use AI for chatting with friends or relatives." Editing AI output before sending it was reported by 10 of the twelve youth participants, illustrated by P4's practice of drafting a message first and asking AI only "to refine it and fix grammatical mistakes."

This pattern of draft-then-refine use, sustained across a diverse set of tools including ChatGPT, Gemini, Claude, and Perplexity, suggests that youth exercise active gatekeeping over the encoding process rather than ceding authorship to AI — direct empirical support for the co-encoder framing set out in Section 3.1, and a pattern that qualifies Guzman's (2018) framing of AI as a fully autonomous communicative agent. Expert accounts converge with this instrumental framing but articulate the boundary in institutional rather than practical terms.

Expert P-2 compared AI to "Wikipedia as a source of preliminary knowledge," positioning it as an assistive rather than authorial tool, while Expert P-4 distinguished between students who use AI "as a learning assistant" and those who use it "as a shortcut," a distinction echoed by P3's own account that reliance on AI "hinders my thinking and creates dependency" as they themselves experienced it.

Taken together, this theme indicates that Bangladeshi youth intuitively contain AI's role to lower-stakes, higher-formality contexts, precisely where misalignment is easiest to correct, an implicit form of pre-emptive risk management that anticipates the miscommunication documented in the subsequent themes.

2. Identity, authenticity, and impression management

A closely related theme concerns how AI-mediated text reshapes participants' sense of voice and how they believe they are perceived by receivers. Ten of the twelve youth participants explicitly stated that AI output does not sound like them. P10 described the sensation vividly: AI writing "doesn't sound like me; it feels like the AI is providing its own perspective," while P1 observed that AI's answers are "a weighted summation" drawn from "thousands of people's data," rendering the resulting text emotionally generic. For several participants, this loss of authenticity was accompanied by an unexpected confidence gain from AI's polished vocabulary; P1 noted that although AI use "makes me feel less authentic," the richness of its vocabulary "makes me feel confident," a tension echoed in P12's account of feeling more confident because AI "gives me angles and ideas I wouldn't have thought of on my own."

Detection by receivers emerged as a concrete relational rupture. P9 recounted sending an AI-generated reply to a friend "in a rush," who then asked, "Why are you talking so professionally?", after which P9 "stopped using it for texting." P2 reported being able to identify AI-authored messages from friends "based on their patterns and vocabulary," a decoding practice in which the receiver interprets not merely the content of a message but the fact of its non-human origin, extending Hall's (1980) decoding process beyond its original scope.

Not all outcomes were negative, however: P4 described a genuine positive case in which AI-assisted refinement made the receiver perceive the sender “as someone who communicates perfectly,” illustrating that AI can succeed as encoder when human editorial oversight remains tight. Institutionally, experts voiced a parallel concern about authenticity at the level of the cohort rather than the individual.

Expert P-4 worried about “uniformity because many students may rely on similar AI-generated language and structures, which can reduce originality.” Together, these accounts show that AI's role as co-encoder is experienced ambivalently, simultaneously eroding authorial voice and bolstering linguistic confidence within the same individuals.

3. Tone and emotional misalignment

Addressing RQ2, tone and emotional misalignment emerged as the most frequently and concretely reported form of miscommunication, raised by nine of the twelve youth participants, often with named social consequences. P1 recalled sending an AI-drafted formal application to a teacher requesting a retest: “The tone sounded a bit rude, and he thought I was forcing him to take the retake,” an incident that damaged the relationship until P1 wrote an apology “entirely without AI.” P10 described an even starker outcome when messaging a student's guardian: the AI-generated text “sounded very rude and lacked politeness. The guardian didn't even reply.” P8 reported that AI “misinterpreted the tone and cultural respect” in a formal message, while P9 offered the theme's clearest statement of the underlying concern: “AI has no emotion. Only humans can express true emotions.”

These incidents constitute the clearest empirical instances of what Hall (1980) termed the structural non-equivalence between encoding and decoding: the AI's optimization toward maximal formality and grammatical correctness produces a preferred reading that human receivers, embedded in hierarchical and relational contexts, decode as cold, blunt, or disrespectful.

This pattern also sits alongside, rather than simply confirming, the mindlessness account discussed in Section 3.2: rather than automatically attributing warmth or intentionality to AI output, Bangladeshi youth consistently describe it as emotionally robotic and actively compensate by editing it before it reaches a receiver, suggesting that conscious editorial vigilance can coexist with, and in these cases outweigh, an automatic social response to computer-generated text. Because the KII protocol did not probe tone or emotion directly, no expert data speaks to this theme, and this gap is reported honestly as a limitation of triangulation rather than papered over.

4. Linguistic hybridity and translation breakdown

This theme, addressing RQ2 and RQ3, captures mechanical failures specific to Bangla-English code-switching. Ten of twelve youth participants, all except P4 and P6, reported that AI struggled with hybrid “Banglish” input — the informal mixing of Bangla and English within a single message or sentence, introduced in Section 1 — or systematically defaulted to English regardless of prompt language.

P2 stated that Bangla translation “isn't natural; it creates awkward tones and heavily prefers English,” a pattern P5 corroborated: “It heavily prioritizes English. If I ask in

Bangla, it feels like it answers in English first and then translates it to Bangla, making it hard to understand.” P9 offered the theme’s most concrete institutional consequence, describing how AI could not translate the word “Fix” and instead rendered the English word in Bengali script, causing a formal application to be rejected. P11 similarly described asking, in Banglish, about “The African Rights of Passage” and receiving information about a different topic entirely, while P3 noted that AI frequently “mixes up the pronouns (Tui, Tumi, Apni)” — the hierarchy- and intimacy-marking pronoun system introduced in Section 2.4 — collapsing a distinction that carries real social weight into an undifferentiated register.

The consistency of the English-bias finding across participants using different platforms and task types, rather than being an isolated glitch, suggests that English dominance may be an important factor in the observed translation and code-switching difficulties, consistent with the theoretical framework’s treatment of linguistic hybridity as a moderating variable shaping decoding outcomes.

However, the qualitative data cannot establish the underlying computational cause, which may vary across systems, model versions, prompts, and tasks. Two negative cases qualify this pattern: P4, who uses AI only for formal English-language writing, and P6, who primarily uses AI for mathematics and coding, both reported largely trouble-free experiences, suggesting that the severity of translation breakdown is partly a function of use-context and platform version rather than a uniform property of all AI-mediated communication.

5. Cultural incongruence and Western-centric framing

Directly addressing RQ3, this theme captures failures rooted in cultural values and social hierarchy rather than language mechanics. P5 offered the study’s most vivid instance of oppositional decoding: when consulting AI about attire for Pahela Baishakh, “it told me wearing all red would look bad and violate fashion rules,” directly contradicting Bengali New Year custom and prompting her to conclude that she must “double-check AI advice with friends because AI can be culturally disconnected.” The same participant reported that AI interpreted eating with one’s hands as “rude” or “bad family manners” based on Western norms, describing the resulting interaction as akin to talking to “a Westernized friend.” As P12 put it, from their own perspective, AI “might support LGBTQ+ concepts which do not align with my cultural values” — a framing reported here as this participant’s personal view rather than a position the authors endorse — while P1 and P4 both reported that AI’s advice failed to differentiate respect or formality by age and seniority, with P4 observing that AI “gives generalized answers without specifically differentiating between elders and younger people”.

A particularly notable pattern, volunteered independently by five participants (P2, P4, P8, P11, and P12) without being directly asked, was sender-dependent interpretation: the same AI-polished text was read differently depending on who the human sender was believed to be. P2 explained that a formal message from a friend was read as a joke, while the identical register from a faculty member was taken seriously; P8 reported that “perfect English” from a friend “feels different” and prompts suspicion of AI authorship. This finding extends Hall’s (1980) model, originally developed for mass-

media broadcasting with a single known institutional sender, to show that in AI-mediated contexts decoding operates on perceived provenance as much as on textual content, a complication that HMC theory's attention to perceived communicative agency helps to explain. As with the two preceding themes, the KII protocol generated no direct expert evidence on cultural framing, and this gap is again reported as a dataset limitation rather than inferred.

6. Calibrated trust and critical reliance

The sixth theme, relevant to RQ1, provided the strongest youth-expert triangulation in the dataset. Rather than uncritically trusting AI output, ten of twelve youth participants offered explicit, often numerical, trust ratings: P1 rated AI "7 out of 10... I cannot blindly trust it"; P5 reported finding it "about 40% reliable... I always double-check"; P6 was more confident at "80% reliable," while P9 and P12 each settled near "50%." P10 described a specific lesson learned from experience: "I have suffered from blindly trusting it in the past." Verification, understood as cross-checking AI output against other sources before use, was reported as routine practice by more than half the sample, and P12 illustrated a decoder-side repair strategy following a detected-AI incident by "admitting I used AI due to a lack of time" rather than concealing it.

As these are participants' own accounts of their behaviour rather than observed behaviour, they are reported here as self-reported practice; participants may, understandably, describe their AI use in more careful or conservative terms than their actual day-to-day reliance, particularly regarding academic work, and this possibility is treated in Section 6 as a limitation rather than resolved by the interview data alone.

Overreliance concern was less prominent among youth, echoed mainly by P3, who described AI use as something that "hinders my thinking and creates dependency," and P10, but was the dominant and most emphatic theme across all four expert interviews. Expert P-1 stated plainly that "if we become too dependent on it, it can harm our creativity, critical thinking, and originality," a concern echoed by Expert P-3's observation that dependence "creates a gap between academic performance and actual understanding," and Expert P-4's worry that reliance produces "uniformity" and erodes originality.

This convergence — youth describing calibrated, verification-based engagement with AI, and experts calling for the same caution at an institutional and policy level — sits alongside the mindlessness account discussed in Section 3.2 as a further indication that conscious verification habits and automatic social response to AI output are not mutually exclusive and suggests that both groups have already begun to internalize a "trust but verify" posture toward AI as an imperfect encoder.

DISCUSSION

AI-mediated miscommunication among Bangladeshi youth is best understood not as a failure of linguistic accuracy but as a problem of contextual and pragmatic non-equivalence: AI systems can produce grammatically correct, semantically coherent Bangla-English text while still misjudging whose meaning is being made, for whom, and under what social conditions.

Across the six themes, breakdown consistently occurred not where translation failed lexically but where tone, register, hierarchy, or provenance were misjudged, suggesting that pragmatic calibration, more than linguistic competence, is the critical bottleneck in AI-mediated communication for hybrid-language users in this sample. This is the study's central contribution: demonstrating that AI-mediated miscommunication in this context is not reducible to lexical or grammatical error, but extends to tone, register, emotional meaning, social hierarchy, cultural expectations, linguistic hybridity, and the perceived source of a message. Given the study's twelve-participant qualitative design, this is presented as a pattern observed within the sample rather than a claim generalizable to AI-mediated communication.

This pattern is clarified by the co-occurrence of instrumental, bounded AI use with authenticity and tone concerns. Participants treated AI as an editing and refinement aid for their own messages rather than a communicative substitute, actively revising outputs to restore voice and appropriateness, a finding that supports Guzman and Lewis's (2020) framing of human-machine communication as a negotiated, agentic process rather than passive reception, while qualifying more optimistic claims about AI's communicative fluency. Where linguistic polish increased, perceived authenticity often decreased, and grammatically correct AI phrasing was frequently read as cold or presumptuous. This extends Brown and Levinson's (1987) politeness framework into AI-mediated contexts, suggesting that face-threat here was triggered less by propositional content than by the socially "unplaced" quality of AI-generated register — a pattern consistent with, and extending, prior findings on AI-mediated interpersonal misunderstanding (Hancock et al., 2020).

The Bangla-English hybridity findings extend this point: breakdowns centred on pronoun choice, register-shifting, and implicit relational cues rather than vocabulary, meaning AI-mediated Banglish communication is a sociolinguistic and pragmatic phenomenon as much as a translation task. This is consistent with, and extends into a multilingual South Asian setting, prior sociolinguistic accounts of code-switching as an identity- and relationship-signalling resource (Androutsopoulos, 2013; Myers-Scotton, 1993), and it complicates optimistic assumptions in multilingual NLP scholarship that treat code-switching primarily as a parsing problem rather than a pragmatic one. It also helps explain why culturally situated hierarchy and indirectness were frequently flattened in AI output: large language models trained predominantly on English-centric data default toward Anglo-centric pragmatic and politeness conventions, a pattern consistent with Bender et al.'s (2021) caution about the limits of form-only fluency.

The finding that users actively verify and revise AI output, summarized in Theme 6, is particularly important for how it relates to Nass and Moon's (2000) mindlessness account. Rather than showing that Bangladeshi youth simply apply automatic social scripts to AI, as a strict reading of that account might predict, the data show users layering deliberate verification on top of whatever automatic response may be occurring — they do not merely trust or anthropomorphize AI; they also monitor and correct it. This qualifies, rather than contradicts, the mindlessness thesis: it suggests conscious verification and automatic social response can coexist, which is a question the present qualitative design can surface but not resolve experimentally.

Theoretically, these findings illustrate and refine Hall's (1980) encoding-decoding model by positioning AI as an active, culturally constrained co-encoder whose outputs still require human gatekeeping before circulation, while users function as secondary encoders who repair, contextualize, or reject AI meaning prior to reception. Within HMC theory, perceived message provenance emerged as a decisive input into decoding: identical AI-polished text was read differently depending on assumed authorship, extending machine-heuristic accounts of AI trust into interpersonal, culturally embedded exchanges.

Practically, these findings suggest AI developers and AI-literacy initiatives should prioritize register- and hierarchy-sensitive design for multilingual, low-resource contexts rather than uniform politeness defaults. Limitations include a small purposive qualitative sample, self-reported accounts that may understate actual reliance on AI (Section 6), Bangla-to-English translation of data, variation across AI platforms and versions, and an expert protocol scoped narrowly to higher education, which limited triangulation for three of the six themes (Sections 3 to 5) and should be read as a boundary on what the expert data can and cannot corroborate rather than a general limitation of the youth interview data. Future research should pursue receiver-focused, comparative Bangla-English-Banglish designs and experimental comparisons of AI-generated versus human-written messages, since the negative cases reported here (P4, P6) indicate miscommunication risk intensifies with relational and cultural complexity rather than occurring uniformly, underscoring that culturally responsive pragmatic calibration, not translation accuracy alone, should anchor future AI-mediated communication research.

CONCLUSION

This study finds that AI-generated communication among Bangladeshi youth produces recurrent miscommunication risk rooted not in lexical error but in tone misalignment, linguistic hybridity, and cultural incongruence. Framed through Hall's Encoding-Decoding Model and Human-Machine Communication theory, the findings show that AI functions as an active yet culturally under-equipped co-encoder whose English-dominant, low-context outputs are frequently renegotiated, corrected, or rejected by Bangladeshi decoders acting as the primary encoder and gatekeeper of what is ultimately sent.

Youth respond by treating AI as a bounded editorial instrument rather than a communicative substitute, exercising calibrated trust and verifying outputs before reliance, while experts express stronger concern about long-term overreliance and its effects on originality and critical thinking. Meaning distortion concentrated in pragmatic and relational dimensions — tone, register, hierarchy, and sender provenance — rather than in translation accuracy, indicating that culturally responsive pragmatic calibration should guide future AI design at least as much as linguistic precision alone.

Theoretically, the study illustrates and refines Hall's model beyond its original mass-media scope and extends HMC theory by showing that perceived message provenance shapes decoding as much as textual content. Practically, the findings call for register- and hierarchy-sensitive AI design and expanded digital-literacy initiatives tailored to multilingual, high-context, low-resource communication settings such as Bangladesh.

Given the study's small purposive sample and narrowly scoped expert protocol, findings should be read as context-generative rather than statistically representative, and as identifying a recurring risk that users actively manage rather than a systematic or inevitable communication failure. Future comparative and experimental research across Bangla-English-Banglish communication would further clarify how cultural and relational complexity moderates AI-mediated miscommunication, extending this study's contribution to communication theory and AI ethics scholarship in non-Western digital contexts.

DECLARATIONS

Author contributions

Author 1 contributed to the study conceptualization, research design, data collection, data analysis, and manuscript preparation. Author 2 contributed to the literature review, data collection, data analysis, and critical revision of the manuscript. Author 3 contributed to the study design, interpretation of findings, critical review, and final revision of the manuscript. All authors reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Conflict of interest

The Author(s) declare(s) that there is no conflict of interest.

Data availability statement

The interview data generated and/or analyzed during this study are not publicly available due to ethical and confidentiality considerations, including the protection of participants' anonymity. The data may be available from the corresponding author upon reasonable request, subject to ethical approval and applicable data-protection requirements.

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Ethics statement

Ethical approval for the study was obtained from the Research Centre of Bangladesh University of Professionals (BUP). Informed consent was obtained from all participants before participation in the interviews. Participants were informed about the purpose of the study, the voluntary nature of participation, their right to withdraw, and the confidentiality and anonymization of their responses. All participants were adults over 18 years old, consistent with the achieved sample age range reported in Table 1.

Artificial intelligence use declaration

The authors used ChatGPT (OpenAI) for language editing and refinement of the manuscript. The authors reviewed and edited the content as necessary and take full responsibility for the integrity and accuracy of the work.

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