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Communication Pattern Typologies in Human-AI Interaction: A Qualitative Thematic Analysis of Chatbot Conversational Dynamics

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Abstract
Artificial intelligence (AI)-powered chatbots have substantially reshaped the landscape of human-AI interaction, yet questions remain about the communicative behaviors users deploy in these exchanges and how they are

shaped by AI system characteristics. This study investigates communication pattern typologies in human-chatbot interactions through qualitative thematic analysis of 150 conversation transcripts across customer service, mental health, and educational contexts. Grounded in social presence theory and affordance theory, and employing reflexive thematic analysis (Braun & Clarke, 2022) with an interpretivist-constructivist epistemological stance, this study identified five typologies of communication patterns: adaptive mirroring (prevalent across the majority of transcripts, 78.7%), emotional scaffolding (frequently manifested, 65.3%), contextual anchoring (emergent in a substantial portion of conversations, 58.0%), conversational repair mechanisms (present in a considerable minority, 42.7%), and trust-building narratives (identified in over one-third of transcripts, 37.3%). These figures reflect descriptive frequency counts indicating the proportion of transcripts in which each pattern was observed; they serve as organizational summaries, not statistical evidence, and patterns are not mutually exclusive. The distribution of these patterns varied across demographic groups and interaction contexts, with younger participants showing comparatively greater communicative flexibility. Results suggest that users deploy socially patterned communicative behaviors in AI-mediated contexts that extend beyond purely task-oriented exchanges. These findings carry implications for designing AI systems that are attentive to the relational and contextual dimensions of user communication in healthcare, education, and customer service.

Keywords: *Interpersonal Communication, Chatbot Interaction, Deep Learning, Human-Machine Communication, Communication Patterns.*

1. Introduction

The rapid advancement of artificial intelligence has substantially reshaped the landscape of human-AI interaction, particularly through the emergence of sophisticated conversational agents and chatbots that increasingly mediate daily digital exchanges (Mariani et al., 2023). As these AI-powered systems become more prevalent across diverse domains, from customer service platforms to educational tools and mental health applications, understanding the intricate dynamics of human-machine communication has become paramount for both technological development and social integration (Al-Shafei, 2023; Mariani et al., 2023). Foundational scholarship in computer-mediated communication, including (Walther, 1996) hyperpersonal model and (Short et al., 1976) The social presence theory has long recognized that mediated communication carries distinct relational implications. More recent work on AI-mediated communication (Fischer et al., 2023; Luger & Flanagan, 2016; van Veen et al., 2022) has begun to address how these dynamics are reconfigured in interactions with artificial conversational agents.

Contemporary chatbot technologies have evolved far beyond simple rule-based systems to incorporate sophisticated neural architectures capable of understanding context, maintaining conversation history, and generating contextually appropriate responses (Mariani et al., 2023; Mundlamuri et al., 2022). Large language models and neural conversational agents have demonstrated remarkable abilities to engage in coherent, multi-turn conversations. However, this technological sophistication has introduced new complexities in human-AI interaction that require careful examination through qualitative research methodologies capable of capturing the nuanced dynamics of these communicative relationships.

Traditional approaches to evaluating chatbot effectiveness have predominantly focused on technical metrics such as accuracy, response time, and task completion rates (Rieke & Martins, 2023; Skjuve et al., 2021). This emphasis on technical metrics constitutes a specific research gap: the absence of qualitative research examining the interpersonal communicative processes, how users adapt, scaffold, repair, and build trust, that unfold within human-chatbot interactions across multiple domains. Several theoretical frameworks are particularly relevant: Communication Accommodation Theory (CAT; (Giles, 1973)), social presence theory (Short et al., 1976; Walther, 1996), affordance theory (Gibson, 1979; Hutchby, 2001), emotion regulation theory (Gross, 1998), and scaffolding theory (Vygotsky, 1978). Together, these frameworks offer a principled theoretical basis for examining why and how users develop specific communicative patterns in AI-mediated contexts.

The emergence of conversational AI in sensitive domains such as mental health support and educational assistance has highlighted the importance of understanding how users develop trust, maintain engagement, and navigate emotional disclosure in interactions with artificial agents (Adıgüzel et al., 2023; Lopes et al., 2023; Zhong et al., 2024). A qualitative approach is appropriate for this inquiry because the communicative dynamics of human-chatbot interaction are, by nature, processual, context-sensitive, and interpretively complex. Reflexive thematic analysis (Braun & Clarke, 2022) enables systematic identification of patterned communicative behaviors across a corpus of transcripts while preserving the interpretive richness required to understand how those patterns emerge and vary across contexts.

This study addresses the identified gap in understanding the communicative behaviors users deploy in human-AI interactions. Specifically, the following research questions guide the investigation: (RQ1) What distinct interpersonal communication pattern typologies emerge in human-chatbot interactions across customer service, mental health, and educational domains? (RQ2) How do chatbot system characteristics, including response style, perceived empathy, and interaction affordances, relate to the observed communicative patterns? (RQ3) What demographic and contextual variations exist in communication pattern deployment across different user groups and interaction contexts? (RQ4) What are the theoretical and practical implications of the identified patterns for understanding human-AI communication and for AI system design?

2. Method

2.1. Research Design and Theoretical Framework

This study employed a qualitative research design utilizing reflexive thematic analysis (Braun & Clarke, 2022) to examine communication pattern typologies in human-chatbot interactions. The epistemological stance adopted is interpretivist-constructivist, which recognizes that meaning is co-constructed between participants and their communicative contexts. The analytical framework is grounded in social presence theory (Short et al., 1976; Walther, 1996) and affordance theory (Gibson, 1979; Hutchby, 2001). The study was conducted in accordance with established ethical guidelines for digital research, with attention to privacy protection and informed consent procedures appropriate to each data domain (Řepová et al., 2024). The study does not adopt a phenomenological perspective, as the transcript-based data collection method does not meet the methodological requirements of phenomenology; instead, the interpretivist-constructivist epistemological stance underpinning reflexive thematic analysis guides the analysis throughout.

2.2. Participants and Data Collection Procedures

Data collection involved the systematic analysis of 150 human-chatbot conversation transcripts collected from three primary domains: customer service interactions (n=50), mental health support conversations (n=50), and educational assistance dialogues (n=50). The sample size of N=150 was determined by theoretical saturation principles, the need for balanced domain distribution, and 50 transcripts per domain to provide sufficient depth for pattern emergence. Transcripts were collected under formal data-sharing agreements with the respective platforms, with institutional ethical approval obtained prior to data collection.

Purposive sampling criteria were applied to ensure diversity in user demographics (age range 18–65, gender diversity, range of educational backgrounds), interaction contexts (3 to 50+ conversational turns), and chatbot types (rule-based customer service systems, neural language model-powered assistants, and specialized therapeutic AI systems including Woebot and Wysa). Inclusion criteria required transcripts to: (a) involve at least five conversational turns, (b) be conducted in English, (c) include the full conversation from opening to closing, and (d) originate from platforms using AI-driven rather than purely scripted chatbot systems. All personally identifying information was systematically removed and replaced with participant codes (CS-01 through CS-50, MH-01 through MH-50, EA-01 through EA-50). Conversations averaged 23.7 conversational turns across the full corpus.

2.3. Data Analysis Procedures

The analysis process followed a comprehensive six-phase reflexive thematic analysis approach (Braun & Clarke, 2022): (1) data familiarization through repeated reading and initial observation noting, (2) systematic initial coding using both inductive and deductive approaches, (3) theme construction through code collation and pattern identification, (4) theme review and refinement through peer consultation and member checking, (5) theme definition and labeling with attention to theoretical coherence, and (6) report production with illustrative extracts and theoretical integration. Intercoder reliability was assessed at the initial coding phase (Cohen's kappa $\kappa = 0.847$) and after thematic classification ($\kappa = 0.81$). NVivo 14 served as the qualitative data management tool. Trustworthiness was enhanced through peer debriefing and member checking with eight participants.

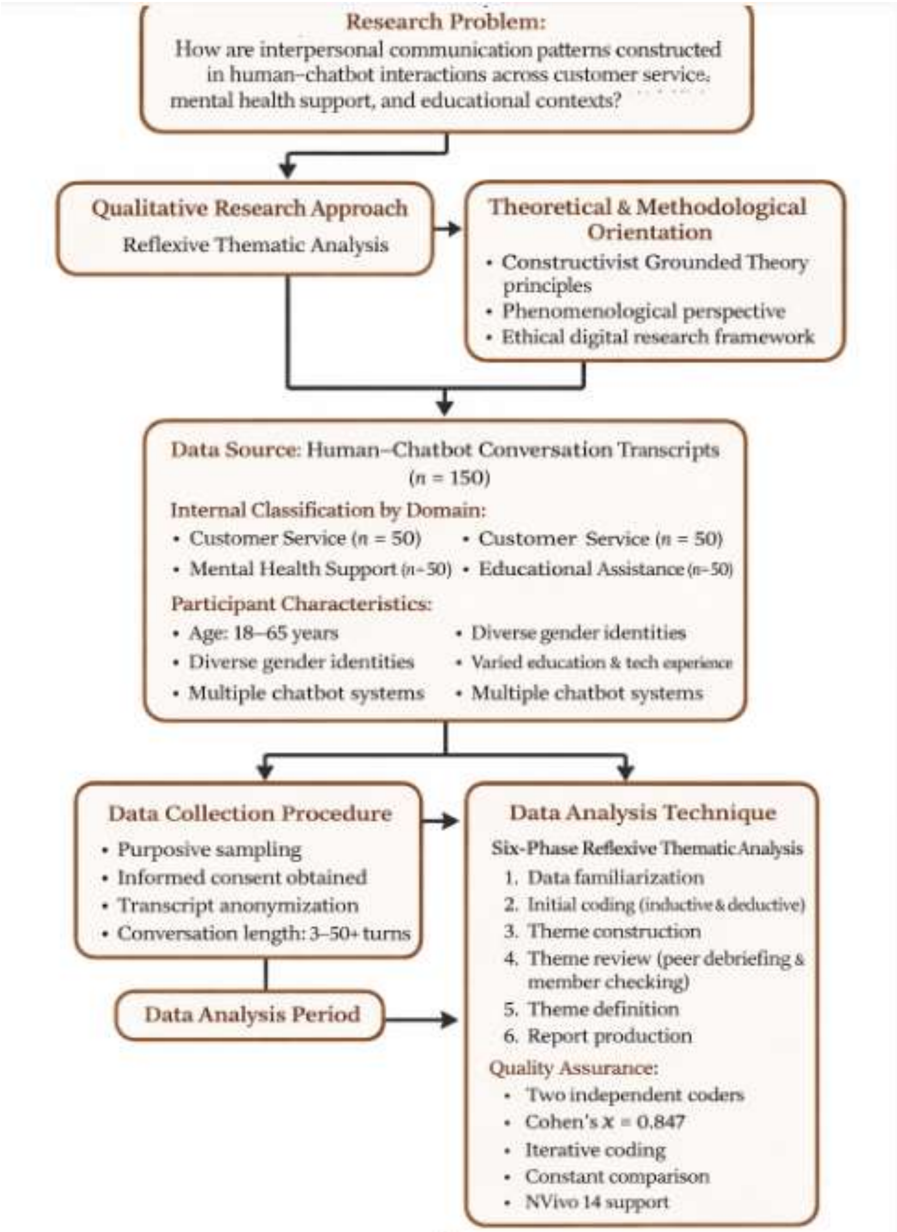

Figure 1. Research Flow Diagram

3. Results

The reflexive thematic analysis of 150 human-chatbot conversation transcripts identified five communication pattern typologies across the three interaction domains. These patterns are not mutually exclusive and frequently co-occur within individual conversations. Table 1 summarizes all five typologies, their descriptive frequencies, and primary contexts of occurrence.

Table 1. Communication Pattern Typologies In Human-Chatbot Interactions

Pattern Type	Description	Descriptive Frequency	Primary Context
Adaptive Mirroring	Users progressively align their communicative style, formality, length, vocabulary, with the chatbot's response patterns	78.7%	Customer Service & Educational
Emotional Scaffolding	Progressive emotional disclosure facilitated by the chatbot's consistent empathetic responses	65.3%	Mental Health
Contextual Anchoring	Users establish conversational context through references to previous interactions and shared knowledge	58.0%	Educational Assistance
Repair Mechanisms	Collaborative correction of misunderstandings through clarification and reformulation strategies	42.7%	All Contexts
Trust-Building Narratives	Users share personal experiences and seek validation to establish relational bonds with the chatbot	37.3%	Mental Health & Customer Service

Note: Frequencies reflect the proportion of transcripts in which each pattern was identified. Patterns are not mutually exclusive. Figures serve as descriptive organizational summaries, not statistical evidence.

3.1. Communication Pattern Typologies (RQ1)

Five communication pattern typologies were identified through reflexive thematic analysis. The following sub-sections present each pattern with its defining linguistic markers, behavioral indicators, and illustrative transcript excerpts.

3.1.1. Adaptive Mirroring (78.7%)

Adaptive mirroring was the most prevalent pattern, observed across 78.7% of transcripts, particularly in customer service and educational contexts. This pattern is characterized by users progressively matching the chatbot's level of formality, response length, and linguistic complexity over the course of an interaction. Illustrative excerpt (Transcript CS-17): The user opened with abbreviated, informal phrasing ("need help w/ my order") but by the third exchange had shifted to complete, formally structured sentences ("I would like to request a refund for the above order, as it has not arrived within the stated delivery window"), mirroring the chatbot's formal response style.

3.1.2. Emotional Scaffolding (65.3%)

Emotional scaffolding was observed in 65.3% of transcripts, manifesting most frequently in mental health support interactions. This pattern reflects a co-occurrence of progressively more emotionally expressive disclosures with chatbot responses characterized by consistent empathy and non-judgment. Illustrative excerpt (Transcript MH-23): The user's early turns contained brief, guarded expressions ("I've just been feeling off lately"), which across subsequent exchanges became increasingly specific and emotionally detailed as the chatbot maintained consistent non-judgmental responses. This co-occurrence does not establish causality; rather, it reflects an observable tendency for emotional content depth and empathetic responses to co-occur across turn sequences.

3.1.3. Contextual Anchoring (58.0%)

Contextual anchoring emerged in 58.0% of the corpus overall, most prominently in educational assistance contexts. Users attempted to establish continuity across and within interactions by referencing prior exchanges, building on earlier discussion points, and developing shared contextual references with their AI interlocutor. Illustrative excerpt (Transcript EA-31): A student began each session with a brief summary of the previous conversation ("Last time we were working on hypothesis testing, I want to continue from there"), constructing an ongoing knowledge-building frame. Users frequently attributed more sophisticated memory functions to chatbots than they actually possess (Nißen et al., 2022).

3.1.4. Conversational Repair Mechanisms (42.7%)

Conversational repair mechanisms were present in 42.7% of interactions, appearing across all three domains. These sequences involved clarification requests, reformulation of queries, and explicit negotiation of understanding when communication breakdowns occurred. Users employed both self-initiated and other-prompted repair strategies. Illustrative excerpt (Transcript CS-34): After a chatbot response that misidentified the nature of a billing query, the user produced an explicit reformulation: "Sorry, I should clarify, I'm not asking about my balance, I'm asking about an incorrect charge from last month," followed by meta-commentary on the communication breakdown.

3.1.5. Trust-Building Narratives (37.3%)

Trust-building narratives were identified in 37.3% of transcripts, appearing most prominently in mental health and extended educational interactions. The narrative structure of trust development was observable across turns: users gradually disclosed personal experiences, sought validation, and tested the chatbot's consistency. Users exhibiting this pattern often anthropomorphized their AI interlocutors (Keijsers et al., 2021). Illustrative excerpt (Transcript MH-41): "Can I ask you something personal? I'm not sure if I should be telling a chatbot this, but I've been struggling with sleep…" followed by the user's monitoring of the chatbot's response before continuing.

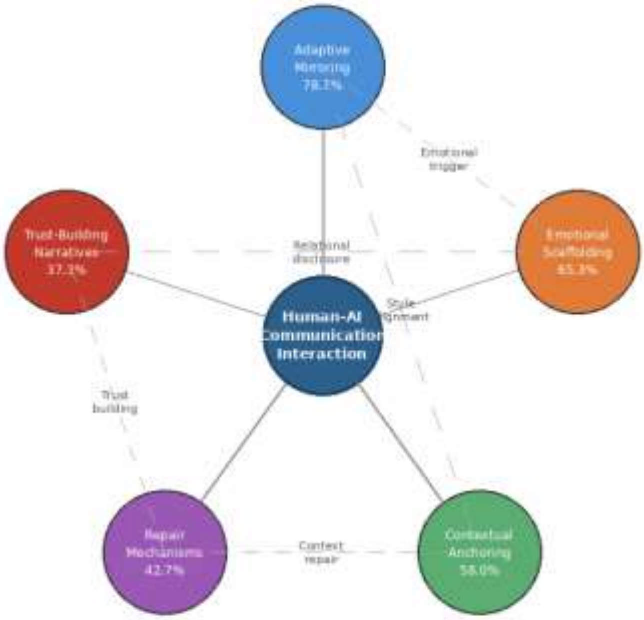

Figure 2. Relational Diagram of Five Communication Pattern Typologies and Their Interconnections in Human-Chatbot Interactions

3.2. Demographic and Contextual Variations in Pattern Distribution (RQ3)

Qualitative comparison of subgroup patterns revealed meaningful variation in how communication patterns were deployed across age groups, educational backgrounds, and technological experience levels. These differences are interpreted as qualitative patterns reflecting variation in communicative style and digital interaction experience, not as statistically validated group differences.

Table 2. Demographic Variations in Communication Patterns

Age Group	Primary Pattern	Pattern Flexibility	Qualitative Observation
18–35 years	Adaptive Mirroring	High	Readily shifted between pattern types within a single conversation (e.g., CS-12: adaptive mirroring → repair → contextual anchoring)
36–50 years	Contextual Anchoring	Medium	Moderate communicative flexibility; the highest proportion of contextual anchoring among all age groups
51–65 years	Trust-Building Narratives	Low	More deliberate, sequential relational approach; e.g., MH-38 developed a sustained trust-building narrative across 32 turns

Table 3. Communication Patterns by Interaction Domain

Communication Pattern	Customer Service	Mental Health	Educational Assistance
Adaptive Mirroring	High (dominant)	Moderate	High
Emotional Scaffolding	Low–Moderate	High (dominant)	Low
Contextual Anchoring	Moderate	Moderate	High (dominant)
Repair Mechanisms	High	Moderate	Moderate
Trust-Building Narratives	Moderate	High	Low–Moderate

Younger participants (18–35) demonstrated greater communicative flexibility, readily shifting between pattern types within a single conversation. In contrast, older participants (51–65) tended toward consistency within a primary pattern, with trust-building narratives emerging more prominently in extended interactions. Educational background influenced pattern sophistication: participants holding advanced degrees exhibited more complex pattern combinations and greater meta-communicative awareness. High-tech-experience users showed faster adaptation to chatbot communication norms but lower levels of emotional engagement, while users with limited technological experience showed longer adaptation periods but higher levels of social and emotional engagement once rapport was established. Cultural background analysis revealed that participants from collectivistic backgrounds showed higher frequencies of contextual anchoring and trust-building narratives, while those from individualistic cultures demonstrated more frequent use of adaptive mirroring and repair mechanisms (Tsai et al., 2021).

3.3. Chatbot System Characteristics and Communicative Patterns (RQ2)

Customer service interactions exhibited distinct patterns characterized by goal-oriented communication, frequent use of repair mechanisms when initial queries were misunderstood, and adaptive mirroring of the chatbot's professional communication style. Mental health support conversations demonstrated the richest pattern complexity, with all five communication patterns frequently co-occurring within single interactions. These conversations were characterized by careful emotional scaffolding, extensive trust-building narratives, and sophisticated contextual anchoring; consistent response style, predictable interaction patterns, and continuous availability were plausibly associated with users' progressive emotional disclosure, though causal attribution is beyond the scope of transcript analysis (Maurya, 2024; Prescott et al., 2024). Educational assistance dialogues showed high frequencies of contextual anchoring and adaptive mirroring as students worked to establish productive learning relationships with AI tutors, often displaying meta-cognitive awareness about their own learning processes (Cheng et al., 2024).

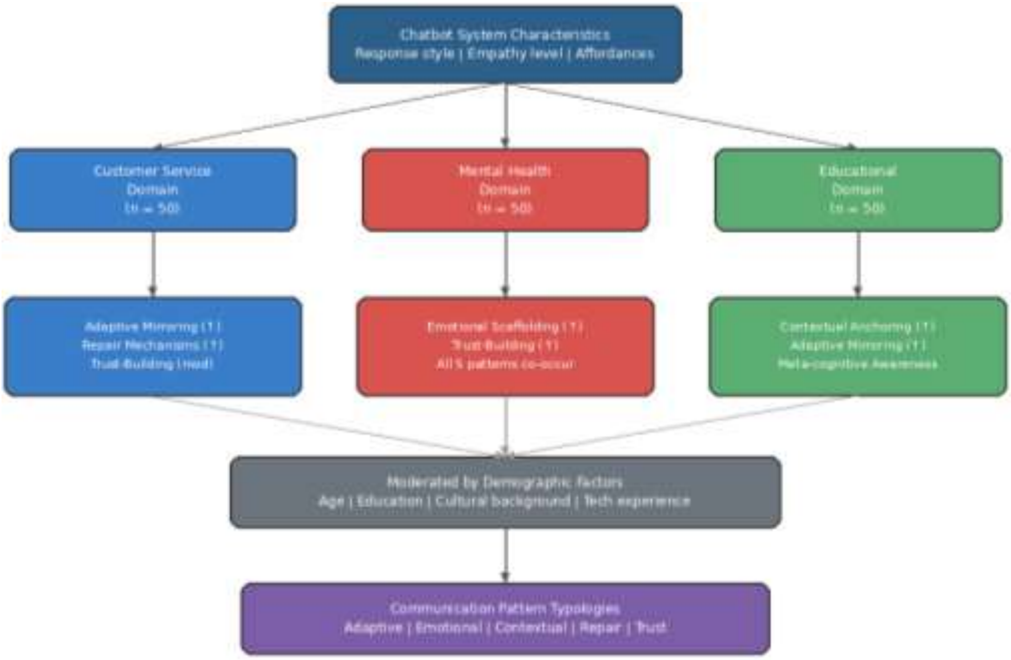

Figure 3. Process Flow: Chatbot System Characteristics and Communication Pattern Emergence Across Interaction Domains

4. Discussion

4.1. Theoretical Implications and Comparison with Prior Research

The identification of five communication pattern typologies in human-chatbot interactions provides evidence for the complexity of communicative behaviors users deploy in AI-mediated contexts. These findings contribute to ongoing scholarly debate about the nature of human-AI interaction, which has traditionally emphasized functional efficiency and task completion over the communicative and contextual dimensions of these exchanges (Ahmed & Chen, 2024; Markowitz, 2024).

The prevalence of adaptive mirroring (78.7%) aligns with and extends Communication Accommodation Theory (Giles, 1973), which predicts convergence behaviors in social interaction. This finding is consistent with (van Veen et al., 2022), who documented user accommodation behaviors in AI-mediated contexts, and with (Fischer et al., 2023), who noted patterns of user adaptation in conversational AI research. However, the present study diverges from (Drouin et al., 2022), who found that users maintained relatively stable communicative styles across chatbot interactions. This difference is attributable to methodological distinctions: Drouin et al. examined shorter interactions (average 8 turns) using a controlled experimental paradigm, whereas the present study analyzed naturally occurring conversations averaging 23.7 turns across diverse real-world platforms. Extended interaction length appears to create the temporal conditions necessary for convergence patterns to become observable.

The emotional scaffolding pattern (65.3%) aligns with (Wilson & Lee, 2022) evidence from digital mental health platforms that empathetic AI responses co-occur with progressive emotional disclosure. Zhong et al., (2024) Meta-analysis similarly documented the therapeutic effectiveness of chatbot interactions, suggesting that the emotional scaffolding pattern identified here may have functional significance beyond mere communicative behavior. In contrast, (Seitz, 2024) reported more equivocal findings regarding the authenticity of AI empathy in healthcare, with some users questioning whether chatbot empathy felt genuine. This divergence may reflect differences in chatbot type: Seitz examined general-purpose healthcare chatbots, whereas the present study included specialized therapeutic platforms (Woebot, Wysa) specifically designed to facilitate emotional expression. Specialized therapeutic design may produce more sustained scaffolding conditions.

The contextual anchoring pattern (58.0%) resonates with (Nißen et al., 2022) taxonomy of user-chatbot relationships, which identified continuity-seeking behaviors as characteristic of users engaging in longer-term chatbot relationships. Hassan & Kim (2024) similarly noted that users develop expectations of conversational continuity analogous to human relationship norms. The present findings extend these observations by demonstrating that anchoring behaviors are particularly pronounced in educational contexts, where Vygotsky's (scaffolding theory provides a complementary theoretical explanation.

Conversational repair mechanisms (42.7%) are theoretically grounded in conversation analysis (Schegloff et al., 1977), and the present findings align with (Lew & Walther, 2023), who observed self-initiated and other-initiated repair sequences in human-chatbot dialogue. The present study confirms these patterns across three distinct domains, suggesting that repair mechanisms are a generalizable feature of human-AI communicative competence. Trust-building narratives (37.3%) are consistent with relational maintenance theory (Dindia & Canary, 1993) and with (Skjuve et al., 2021, 2022) longitudinal studies of human-chatbot relationships. Croes & Antheunis (2021) Similarly, identified trust formation processes in human-chatbot interactions. The relatively lower frequency of this pattern may reflect the demands of extended interaction required for trust narratives to develop, a condition more prevalent in mental health contexts than in brief customer service exchanges.

4.2. Explaining Demographic and Contextual Differences

The age-related differences in pattern flexibility, with younger participants (18–35) showing greater communicative adaptability, likely reflect differences in digital interaction experience and prior exposure to conversational AI systems. Younger users' familiarity with diverse digital communication norms may equip them with broader communicative repertoires that they deploy strategically in chatbot interactions, consistent with (Řepová et al., 2024), who found that prior chatbot experience significantly shaped interaction behaviors.

The higher prevalence of trust-building narratives among older participants (51–65) may reflect a more deliberate, sequential approach to relational engagement. This aligns with (Keijsers et al., 2021), who noted that users with lower AI familiarity tend to approach chatbot relationships more relationally and with greater anthropomorphic attribution. The educational background finding that users with advanced degrees demonstrate more complex pattern combinations is consistent with (Maurya, 2024) observation that meta-cognitive awareness influences human-AI interaction quality.

The domain-specific pattern profiles (Table 3) reflect the distinct communicative demands of each interaction context. Customer service interactions are primarily task-oriented, explaining the dominance of adaptive mirroring and repair mechanisms. Mental health contexts prioritize relational and emotional dimensions, creating conditions for emotional scaffolding and trust-building to emerge. Educational contexts, involving extended knowledge co-construction, naturally elicit contextual anchoring behaviors. These contextual differences are consistent with affordance theory (Gibson, 1979; Hutchby, 2001): different interaction contexts afford different communicative possibilities, shaping the patterns users deploy.

4.3. Practical Implications for AI System Design (RQ4)

The findings suggest several design considerations for conversational AI systems, framed as directions for further investigation rather than prescriptive conclusions. The prevalence of adaptive mirroring indicates that users adjust their communicative style in response to chatbot behavior, suggesting that attention to response style consistency may be relevant in system design. However, implementing dynamic style adaptation would require advances in user modeling and response generation, carrying both technical and privacy trade-offs (Heppner et al., 2024; Jiang et al., 2023).

The importance of emotional scaffolding in therapeutic contexts highlights the need for AI systems equipped with sophisticated emotional intelligence capabilities, including recognizing emotional states, responding empathetically, and facilitating appropriate levels of emotional disclosure over time. Such systems require careful integration of sentiment analysis, empathy modeling, and safety mechanisms to identify when human professional intervention may be necessary (Franklin & Moore, 2024; Seitz, 2024). The frequency of contextual anchoring behaviors raises questions about whether enhanced context management would support users' naturally occurring anchoring behaviors, though such features carry significant privacy trade-offs requiring careful attention to user control over data retention (Markowitz, 2024; Newstead et al., 2023).

The ethical implications of emotional AI engagement require broader consideration. Three critical concerns are identified: (1) sensitive personal data generated through emotionally disclosive AI conversations raises risks of data exploitation (Selbst et al., 2019)(2) demographic variations in pattern deployment may be encoded or amplified in training data, carrying risks of algorithmic bias (Mohamed et al., 2020)And (3) business incentives of platform operators may prioritize user engagement metrics over user well-being. These concerns call for robust regulatory frameworks, transparent disclosure of AI system capabilities, and genuine human professional oversight in high-stakes domains such as mental health (Lopes et al., 2023).

4.4. Limitations and Future Research

While this research provides valuable insights into human-chatbot communication patterns, several limitations should be acknowledged. The study focused on text-based interactions and did not examine voice-based or multimodal chatbot systems, which may exhibit different communication dynamics (Young & Harris, 2024). The sample was limited to English-language interactions primarily from Western cultural contexts, limiting cross-linguistic and cross-cultural generalizability (Liu & Yao, 2023; Tsai et al., 2021). The qualitative methodology, while appropriate for exploratory pattern identification, limits the ability to establish causal relationships between communication patterns and user outcomes. Future research directions include: (1) longitudinal qualitative studies tracking the same users across multiple interactions; (2) cross-cultural qualitative analysis; (3) mixed-methods studies combining qualitative pattern analysis with user interviews; (4) experimental studies manipulating chatbot response characteristics to enable causal claims; and (5) research specifically addressing the ethical implications of emotional scaffolding in mental health contexts.

5. Conclusion

This qualitative analysis of 150 human-chatbot conversation transcripts indicates that users deploy socially patterned communicative behaviors in AI-mediated contexts that extend beyond purely task-oriented exchanges. Five communication pattern typologies were identified: adaptive mirroring, emotional scaffolding, contextual anchoring, conversational repair mechanisms, and trust-building narratives. To synthesize these findings theoretically, the study proposes a preliminary AI-Mediated Communication Pattern (AMCP) model, which maps the five typologies onto two dimensions: relational orientation (low to high) and interactional complexity (low to high). Theoretical contributions include: (1) articulating communication patterns not previously described systematically in human-chatbot interaction research; (2) demonstrating that Communication Accommodation Theory and scaffolding theory apply meaningfully to human-AI contexts; and (3) highlighting interpersonal dimensions that extend beyond technical functionality. Communication patterns varied across demographic groups and interaction domains, indicating that AI system design should be attentive to this diversity. As conversational AI becomes increasingly integrated into sensitive domains, qualitative research examining interpersonal dimensions remains essential, maintaining methodological clarity and appropriately bounded claims grounded in empirical evidence.

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