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The Rise of Thinking Machines: A Review of Artificial Intelligence in Contemporary Communication

Mohammad Javad Gholami[1*], Taqi Al Abdwani[2]
[1]Ferdowsi University of Mashhad, Iran, [2]Gulf College, Oman

Abstract Artificial intelligence (AI) capabilities in natural language processing are rapidly advancing and transforming communication practices across diverse contexts. This review provides a comprehensive analysis of AI's emerging roles in mediating and participating in direct communication to highlight key opportunities and research priorities around responsible innovation. The study surveys the extensive literature on major applications of AI, including virtual assistants, chatbots, smart replies, sentiment analysis tools, and automatic translation technologies. It also closely examines their current and potential usage and benefits across interpersonal, organizational, and societal communication. The analysis reveals these AI technologies promise enhanced efficiency, personalization, accessibility, and new modalities of expression in communication. The study found that if judiciously and ethically applied, they could incrementally improve communication speed, quality, relationships, and even therapists' capabilities over time. However, more rigorous research is still recommended to investigate longitudinal impacts on human well-being, increase accessibility for vulnerable demographic groups, advance multimodality AI systems, and develop tailored guidelines and user-centered studies to ensure ethical, socially responsible progress. Overall, this review synthesizes the current state of the science and pressing research needs in this rapidly emerging field.

Keywords: *AI, Human communication, Machine learning, NLP, Natural language processing*

[*]Corresponding Author:
Mohammad Javad Gholami
mjgholamihosseinabad@mail.um.ac.ir

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1. Introduction

Artificial intelligence (AI) systems are rapidly transforming communication and relationships between individuals and organizations, as well as the use of technology (Min et al., 2023). Following the advancements of machine-learning algorithms, AI agents are gaining the ability to analyze language, generate texts, and engage in dialogues, which raises significant questions regarding how AI may impact human communication in the coming years. From customized media recommendations to automated conversational agents, AI tools and techniques are so increasingly participating in and mediating communication

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that some predict that distinguishing them from human communicators may become a serious challenge over time (Mylrea & Robinson, 2023).

Gunkel (2012) narrates the story of a New Yorker cartoon by Peter Steiner, which depicts two dogs in front of an Internet-connected computer, with one of the dogs claiming that nobody on the other side of the computer knows their identity. This cartoon has been widely cited to address anonymity in computer-mediated communication (CMC). It also illustrates the indeterminacy of the identity of *others* in CMC, as well as the users' assumption that the other person they interact with is another human being, which is the standard operating assumption of mainstream communication theory and practice. Online identity is reconfigurable, but everyone assumes that the other person on the other end is another human user, despite minor variations in physical appearance and background. However, as Norbert Wiener anticipated in 1950, interactions would be mostly human-to-machine (H2M) or machine-to-machine (M2M) rather than human-to-human (H2H) exchanges. Therefore, communication studies must adapt to this shift and reorient theoretical frameworks to accommodate situations where the other person in communication is no longer a human. This will define the opportunities and challenges for communication research in the 21st century.

This study provides a comprehensive overview of the burgeoning applications of AI in human communication and their implications. Following an outline of the historical development of AI systems capable of analyzing language, generating texts and speech, and engaging in dialogues, current usages across diverse communication channels will be explored in depth. This review also aims to analyze virtual assistants, smart speakers, chatbots, automatic reply suggestions, sentiment and tone analysis tools, and AI translation mechanisms. Additionally, critical challenges posed by AI in communication systems, including issues of privacy, manipulation, transparency, and accountability, as well as the need for ongoing consideration of social and ethical responsibilities, provide another important focus of this study. Moreover, by surveying the current literature and applications in this rapidly evolving field, this review synthesizes understanding of multifaceted impacts across interpersonal, organizational, and societal communication through the emergence of intelligent algorithms.

2. Artificial Intelligence and Communication

Alan 'Turing's seminal 1950 paper "Computing Machinery and Intelligence" introduced the concept of the "Imitation Game" as a way to assess whether machines can demonstrate human-like intelligence. This game involves an interrogator conversing with a human and a machine, attempting to determine which is which solely based on their responses. Turing argues that if the interrogator cannot reliably distinguish them, it would be reasonable to consider the machine intelligent. The Imitation Game sets up a CMC scenario where identity is concealed, similar to modern chat applications. It emphasizes communication ability as the deciding factor in assessing intelligence, effectively reformulating "Can machines think?" to "Can they demonstrate thought convincingly through conversation?". This connects to 'philosophy's "other minds problem", the difficulty in determining if an entity truly has an internal mental life just by observing its behavior. Since inner workings are opaque, behavioral tests become proxies.

When Turing wrote the paper in 1950, he predicted that by the year 2000, machines with enough computational storage and programming would be able to play the game successfully, fooling interrogators at least 70% of the time after five minutes of questioning. While seeming simplistic by modern standards, Joseph Weizenbaum's 1966 ELIZA program possessed a surprising facility in natural language conversations, leading some users to insist the program really understood them even when it performed relatively straightforward pattern matching.

In the decades that followed, Turing's emphasis on communicative ability became a standard by which AI progress was benchmarked. Programs have grown increasingly sophisticated in their linguistic processing and ability to simulate human conversational patterns (Gunkel, 2012). Yet capturing the full scope and nuance of human cognition through communication remains an ongoing ambition driving cutting-edge techniques like deep learning neural networks. The Imitation Game's question of whether, in unstructured dialogues machines can demonstrate human-level intelligence persists as a motivating vision.

Turing's proposal that communication ability implies intelligence rests on the assumption that language use stems from and demonstrates cognitive capacities like reasoning. However, this claim has been challenged, notably by John Searle's 1980 "Chinese Room" thought experiment. Searle argues that a computerized system could pass the Turing test by following symbol manipulation rules without any understanding of the symbols' meaning. This amounts to simulation without intelligence. Descartes (1988) likewise differentiated humans from animals and machines via their rational use of meaningful language. The debate continues around whether conversational ability alone equates to intelligence or if the comprehension of linguistic meaning is also necessary. Turing's test intends to bypass the problem of determining internal states by using external communication as proof of thought. However, theorists like Searle counter that symbolic processing alone falls short. Therefore, subsequent AI systems have aimed to move beyond mechanical symbol manipulation toward contextual understanding.

Notably, the computer in Turing's scenario serves as both the medium enabling human-computer communication tests and as an agent participating actively in conversations. This presaged the development of CMC as an area of social scientific inquiry, as characterized in a 1968 essay by Licklider and Taylor. They highlighted interactive communication functions in early networking, predicting the computer's evolution into a platform for interpersonal exchanges and not just data processing. The subsequent creation of ARPANET and the Internet bore out this vision. Considering machine intelligence, Turing focused more on responsive conversation than strict rational thought. This interactive standard persists in modern social media bots aiming to simulate personas. However, the debate still continues around the criteria: whether conversational ability alone satisfies a "thinking" determination or if understanding the significance of exchanged symbols is essential as well. Either way, Turing's lasting influence was in centering communication as AI's definitive test case, proposing an empirical, observable metric against which progress could be demonstrated and judged.

The term "computer-mediated communication" (CMC) was introduced by Hiltz and Turoff in 1978 to refer to human communication facilitated by computers. They highlighted emerging computer conferencing systems that enabled communication and information exchange among large groups of people. The field of communication studies initially focused on the computer as a medium through which humans interact (Gunkel, 2012). However, Cathcart and Gumpert (1985) differentiated between humans communicating "through" versus "with" computers. The latter constitutes an interpersonal relationship where the computer actively responds in an ongoing exchange. Therefore, computers should not be viewed solely as message transmission instruments. They can participate in exchanges as additional conversational agents beyond just mediating communication between human users. These challenge the definitions of computers as passive mediums since they demonstrate capacities for interactivity and autonomy in communication. The passage traces an evolution in conceptualizing computers from mediums of human interaction to entities that humans can interact with in two-way interpersonal exchanges as active participants. This laid the groundwork for approaching computers as collaborative partners and quasi-conversational agents, foreshadowing developments in human-AI interactions.

3. The Applications and Implications of AI in Communication

Artificial intelligence has moved beyond experimental research and narrow applications, now playing a pervasive role in communication systems and media that touches many aspects of human connection. A range of AI tools and techniques are transforming communication practices across diverse contexts, with important philosophical and practical implications. This section provides an overview of the leading applications, outlining current usage and analyzing the resultant impacts. The developments considered most transformative thus far involve virtual assistants and smart speakers, chatbots, automatic reply suggestions, sentiment and tone analysis, and AI translation mechanisms.

3.1. Voice Assistants and Smart Speakers

AI has significantly improved user interaction with computers, leading to a sense of belonging and enhanced positive feelings. The integration of AI-enabled voice assistants, such as Apple's Siri, Google's Assistant, Microsoft's Cortana, and Amazon's Alexa, or smart speakers, like Amazon Echo, Apple Homepod, and Google Home, into daily lives has gained popularity (Hwang et al., 2020; Kim et al., 2021). AI-enabled voice assistants use natural language processing and machine learning to recognize and interpret users' language, providing real-time responses via synthesized voices (Cardon et al., 2023).

As Terzopoulos and Satratzemi (2020) explain, smart speakers, equipped with microphones and speakers, are now incorporating voice assistants into devices that communicate with users. Cloud platforms enable voice assistants in millions of homes, relying on a cloud-based architecture. The basic idea is that the user makes a request through the voice-activated device, and the voice request is streamed through the cloud, where the voice gets converted into text. The text request goes to the backend, which replies with a text response, and the text response then goes through the cloud and gets transformed into voice, which is streamed back to the user.

These devices are used for various tasks, such as controlling home automation systems, setting reminders, booking cabs, purchasing items, listening to news, playing music, and asking doubts (Malodia et al., 2022). With rapid changes in AI technology and natural language processing advancements, voice assistants' capabilities are continuously expanding.

Research on smart speaker usage in homes has uncovered patterns in device interactions and user satisfaction. Bunyard (2019) and Purington et al. (2017) found entertainment and information retrieval to be the primary use cases, though they also considered them useful in scheduling, shopping, and device commands. Sciuto et al. (2018) analyzed logs from 75 Alexa households, finding parents reported children interacting with ease, even before smartphones. McLean and Osei-Frimpong (2019) surveyed over 700 Echo users, showing predominately utilitarian usages such as information search and task support. Rzepka (2019) highlighted efficiency, enjoyment, and cognitive ease as objectives that maximize user value with voice assistants. Survey data from Song (2019) reinforced usefulness and ease of use as significant factors in driving adoption. Overall, convenience and hands-free operation appear valued in smart speakers, though further research must continue investigating patterns of domestic integration and family use.

Recent studies indicate that voice assistants can be used as efficient tutors to assist multiple users in solving complex problems (Winkler et al., 2021). For instance, meta-analytic studies of computer-mediated tutoring among children have demonstrated that computer tutors can facilitate learning gains similar to human tutors (Kulik & Fletcher, 2016). Several studies have also examined how children interact with voice assistants and their perceptions of these systems. Druga et al. (2017) found that with facilitating guidance, children were able to improve their voice interaction strategies when playing with assistants such as Alexa, Google Home, and chatbots. In another study, Yuan et al. (2019) observed that personified interfaces were preferred, and age had an impact on performance in that older children needed less support in getting answers from speech agents. Lovato et al. (2019) analyzed smart speaker use in households, showing high transcription accuracy for child questions, but only 50% of those who were often about the world around them received full answers. While voice assistants have the potential to aid children's learning, interaction difficulties may arise for those who are still developing conversational abilities (Terzopoulos & Satratzemi, 2020). These studies highlight the opportunities and challenges embedded in the use of voice assistants by the youth; however, ongoing research is required to offer ways to engage the youth more and add to the positivity of their interaction with voice assistants.

Apart from children, research has also uncovered distinct usage patterns and needs for voice assistants among older adults and those with disabilities. Kowalski et al. (2019) found that older adults enjoyed voice-only interactions for certain tasks; however, further research is required to explain the reasons underlying adults' satisfaction with this form of interaction. Baldauf et al. (2018) pinpointed the scarcity of voice assistant applications designed for the cognitively impaired, though users expressed strong interest in alleviating loneliness. Smart speakers have also achieved popularity among those with visual or mobility impairments, as Abdolrahmani et al. (2018) showed that they make daily tasks more convenient for blind individuals. Comparing screen readers to voice assistants, Vtyurina et al. (2019) developed a system called VERSE, combining functionalities that were positively evaluated by blind testers. Overall, while preliminary findings show promise and excitement around voice assistants for older and disabled groups, there remain open questions about customized deployments. Continued research must address key accessibility barriers, use cases, and design requirements to facilitate broader adoption while meeting their unique needs.

In addition to studies investigating the use of voice assistants by children and adults, a range of studies have developed ways and tools to integrate voice assistants in the classroom and facilitate student learning. Ilhan et al. (2017) proposed an AI teaching assistant called Scarlet to provide information to students, while Mulyana and Hakimi (2018) developed an assistant for course management tasks. Trivedi (2018) created ProblemPal, an Alexa skill that allows teachers to automatically generate practice questions using Wikipedia and other APIs. Horn (2018) suggested that assistants could provide personalized answers to students in real-time as an “amplifier” for teachers. Beyond core subjects, Kloos et al. (2019) designed a voice app to teach Java programming concepts. Selak (2017) observed that these assistants enabled elementary students to consistently ask mathematical confirmation-checking questions. For special education, Porayska-Pomsta et al. (2018) found positive outcomes with an AI environment for autistic students. Despite students’ and teachers’ interest in the use of voice assistants, as well as their promising results in enhancing education outcomes, key challenges exist in terms of language limitations, security/privacy, and the need for training teachers, all of which require further research so that these AI-based tools can be adopted more efficiently (Lau et al., 2018; Lovato et al., 2019).

3.2. Chatbots

The idea of computers engaging in conversational dialogue with humans emerged with the first chatbot, ELIZA, created by Joseph Weizenbaum in 1966. Touted as a virtual psychotherapist, ELIZA used pattern matching and a response template system of pre-set scripts to simulate interaction with a Rogerian therapist, with users typing statements and ELIZA responding through prompting questions. While ELIZA’s capabilities were quite limited, and its responses were generated with little context or variation, it sparked the future development of conversation systems that could genuinely converse with humans to fulfill meaningful needs beyond entertainment (Adamopoulou & Moussiades, 2020). ELIZA’s approach laid the foundation for techniques like procedural response schemes, textual pattern matching, and more open-domain discussions online, though modern research ultimately requires much more sophisticated abilities in understanding language, reasoning, empathy, and self-awareness (Wallace, 2009).

Other important early steps included PARRY, built by Dr. Kenneth Colby in 1972 to mimic a patient with paranoid schizophrenia, and “Jabberwacky” in 1988, which applied more extensive contextual analysis of prior chat content to determine bot responses in a more natural and human-like manner. The term “chatterbot” also emerged in 1991 for artificial entities focused purely on open-ended social conversation (Mauldin, 1994), while industrial applications like SmarterChild came about in 2001 for practical task support like news and weather updates (Bastos et al., 2012). As AI and language processing matured in the 2000s and 2010s, chatbots transitioned to new modalities like speech through digital voice assistants embedded into smartphones and home devices. Apple Siri, IBM Watson, Google Assistant, Microsoft Cortana, and Amazon Alexa enabled information search and task management through conversational voice commands, understanding natural language requests to control integrated apps and Internet of Things devices.

The latest wave of chatbots aims for deeper levels of contextual understanding across long, coherent dialogues by focusing on users’ needs and preferences rather than canned responses. Microsoft’s XiaoIce has pioneered efforts in this direction, with nearly 6 billion conversations logged, leveraging emotional and conversational intelligence to establish genuine connections and relationships with users (Zhou et al., 2019). Commercial products like Claude from Anthropic represent a philosophical commitment to safety and transparency through self-supervision techniques while discussing diverse topics meaningfully. Most recently, in late 2022, OpenAI’s launch of ChatGPT also spurred tremendous public interest in and debates around the societal impacts of conversational AI writing fluently across contexts (OpenAI, 2022). As capabilities continue to advance, emerging challenges require cross-disciplinary collaboration on the ethical development and deployment of increasingly autonomous chatbot systems. Considering the applications of chatbots, it is noteworthy that they are increasingly being used to support customers in a variety of industries. Studies have examined the use of chatbots in areas like banking (Venkatesh et al., 2021), healthcare (Montenegro et al., 2019), education (Shukla & Mishra, 2020), and customer service (Johannsen et al., 2018). For example, Venkatesh et al. (2021) developed a chatbot to help bank customers complete transactions and access account information. They reported that the chatbot improved perceived service quality and customer satisfaction compared to the traditional website. In healthcare, Montenegro et al. (2019) systematically reviewed studies on conversational agents. They found chatbots facilitated tasks like appointment booking while reducing administrative burdens on medical staff. However, physicians expressed concerns about the diagnostic accuracy of chatbots.

The impact of chatbot design factors on user perceptions has also been a major research focus. Anthropomorphism, or human-like features, can increase trust and emotional connection but may backfire in some contexts (Mori et al., 2012). Go and Sundar (2019) manipulated the visual appearance, identity cues, and interactivity of a chatbot. They found that a more human-like appearance increased feelings of psychological closeness. In contrast, Crolic et al. (2022) showed anthropomorphic chatbots elicited more negative reactions from angry customers. The authors argue that designers should consider situational and individual differences when developing chatbots.

Other studies have analyzed the conversational content of chatbots. Jiang et al. (2022) proposed the COM-B model, which links chatbot communication styles to customer behavioral outcomes. More socially-present chatbots increased retailer innovativeness and intimacy, thereby boosting purchase intentions. However, perceived privacy risks can hinder commercial chatbot adoption despite its usefulness (Mostafa & Kasamani, 2021). To overcome this challenge, providing transparency around data collection and allowing user customization are essential (Wirtz et al., 2018).

The use of chatbots in specialized domains has expanded following natural language processing advancements. Shukla and Mishra (2020) reported that playfulness, visual appeal, and anthropomorphism predicted utilitarian and hedonic attitudes toward voice assistants, which influenced satisfaction and word-of-mouth intentions. In education, Porayska-Pomsta et al. (2018) developed a social, game-based learning environment incorporating a chatbot peer. Trials with autistic children showed improved social and communication skills. The authors argue chatbots' predictable, emotionless, and tireless nature facilitates positive learning outcomes.

As chatbots proliferate, emerging issues involve evaluating quality and preventing harmful AI behaviors like providing dangerous advice to vulnerable populations. Developing standards for testing chatbot safety and effectiveness across different situations would thus enable accountable, ethical design (Hengstler et al., 2016). Overall, research illustrates chatbots' expanding potential while highlighting the need for evidence-based guidelines tailored to specific users and contexts.

3.3. Smart Replies

Generative AI is increasingly being used to mediate human communication through applications like smart replies, which now generate billions of emails daily (Mairesse et al., 2007). Research has found that while exposure to smart replies does not directly impact social perceptions, their actual use in conversation increases communication speed and positive emotional language (Hohenstein et al., 2023). However, people suspected of overusing smart replies face backlash, being rated as less cooperative and affiliative. The negative reaction stems from assumptions that AI interferes with quality communication, though its real impacts can be positive (Hohenstein et al., 2023). Specifically, experiments reveal that when participants use more smart replies, their partner views them as more cooperative and feels greater affiliation towards them (Hohenstein et al., 2023). This demonstrates a mismatch between perceptions and reality regarding AI. The positive effects may arise from changes in emotional language caused by smart replies; for instance, the use of positive, smart replies has given conversations a more positive vibe (Hohenstein et al., 2023).

Research also has implications for communication theory and AI design. Evidence shows that AI can shape language production and interpersonal perceptions, which is noteworthy as language informs judgments of others (Mairesse et al., 2007). Additionally, developers could leverage smart replies' subtle impacts on conversations but must weigh social risks (Hohenstein et al., 2023). Another area of concern is AI's long-term influence as its roles expand, as we lack insight into the regularity of use and possible homogenization of expression over time. More investigation into longitudinal impacts is thus needed. Nonetheless, judicious AI mediation could enhance communication speed and quality (Hohenstein et al., 2023).

In conclusion, deploying AI in communication technologies holds both opportunities, like improving the perceptions of conversants, and risks, like emotional and relational effects from altered language. Therefore, research indicates the need to balance utility and unintended consequences (Hohenstein et al., 2023).

3.4. Sentiment and Tone Analysis

Sentiment analysis has become a vital competitive intelligence tool due to the wealth of subjective opinion data available online from consumer reviews, social media, forums, and more. It employs natural language processing techniques to computationally identify and extract affective information on the emotions, attitudes, and opinions expressed towards certain products, services, individuals, organizations, or topics (Cambria et al., 2017). Machine learning algorithms automatically classify sentiment polarity as positive, negative, or neutral, quantifying the prevalence of different leanings. Granular, aspect-based sentiment analysis provides additional insights by detecting sentiments toward specific attributes rather than a whole item (Nandal et al., 2020).

Key applications of sentiment analysis include understanding public perceptions of marketing campaigns, gauging reactions to product launches based on online buzz, and highlighting areas in need of improvement from mining user reviews. For example, if multiple customer complaints focus on a certain smartphone feature not working properly, sentiment analysis can rapidly surface this for the manufacturer to address. It serves an important listening function for brands alongside more overt customer outreach. From a competitive angle, companies utilize sentiment analytics to benchmark their brand sentiment against rivals and analyze competitor messaging/positioning strategies revealed through the tones used in communication (Taherdoost & Madanchian, 2023).

While early sentiment analysis relied on lexicon-based methods, modern approaches employ far more sophisticated natural language and deep learning procedures. This allows the handling of linguistic complexities like sarcasm, ambiguity, and context-dependence, which impact opinion interpretations (Poria et al., 2015). Nonetheless, challenges remain, from the need for large training datasets in each domain for accuracy to multilingual and cultural variances in how sentiments manifest. Ongoing advances target these issues through techniques like semi-supervised learning, multimodal fusion, and dynamic adaptation of models (Cambria et al., 2017).

Tone analysis examines writing style instead of subjective opinions, seeking to profile the underlying imprint of a text via attributes like its vocabulary complexity, cohesion, confidence, and emotional affect (Brooke, 2009). Combined with the metadata of the author and recipient, as well as the document type. For competitive analysis, tone analytics could uncover differences or changes in the tone of a rival company's earnings reports over time. Marketers can also apply it to track brand sentiment shifts across demographics (Dwivedi, 2021).

Several studies have been conducted over the past few years applying advanced machine learning techniques to detect emotions from text data. Chatterjee et al. (2019) evaluated various deep learning methods, like CNNs, LSTMs, and traditional ML algorithms, on a dataset of over 17 million Twitter conversation pairs. Their proposed SS-LSTM model, combining semantic understanding with sentiment analysis, achieved state-of-the-art performance in classifying texts across four emotions, namely joy, sadness, anger, and disgust. Khanpour and Caragea (2018) focused specifically on emotion detection in the health domain. They annotated medical forum posts for 6 Ekman emotions and developed a model combining CNN, LSTMs, and lexical features. Their approach could effectively identify emotions like joy, fear, and anger in medical text data. Kratzwald et al. (2018) introduced a bi-directional LSTM network architecture for variable text length classifications. Their transfer learning approach first trained the model for sentiment analysis before adapting it to emotion detection across seven categories. This method produced accuracy comparable to traditional ML techniques.

These studies demonstrate the potential of deep neural networks for understanding emotion semantics in written text. With access to labeled-quality data and sufficient computing, deep learning models have now approached human-level performance in emotion classification across different domains.

3.5. Translation Tools

The origins of machine translation date back to the late 17th century, but major advancements began in the 1950s with the Georgetown experiment and the first machine translation conference in 1952. This marked the beginning of decades of research into rule-based and dictionary-based approaches (Hutchins, 2010). However, these early systems were limited by strict syntax rules and lacked semantic analysis capabilities. A breakthrough came in the late 1980s and early 1990s with the rise of statistical machine translation (SMT). SMT leveraged statistical models trained on large bilingual text corpora to translate between languages, achieving much greater coverage and scalability compared to rule-based systems. The emergence of SMT aligned with rapidly increasing computational power and the advent of the Internet as a source of vast multilingual datasets (Lopez, 2008).

In the 2000s and 2010s, neural machine translation (NMT) emerged as a new paradigm powered by neural networks and deep learning. Encouraged by the successes of deep learning in computer vision and speech recognition, researchers began exploring recurrent neural networks and sequence-to-sequence models for translation. NMT offers capabilities to model entire sentences and longer-range context, overcoming the limitations of SMT's dependence on shorter-phrase patterns (Bahdanau et al., 2014). In the 2010s and 2020s, there were dramatic improvements in translation quality and capabilities driven by advances in NMT, from better training algorithms to enormous multilingual models pre-trained on web-scale data. State-of-the-art systems can now translate between hundreds of languages. However, challenges still remain in accurately translating niche domains and low-resource languages and capturing nuanced semantics and pragmatics (Koehn & Knowles, 2017).

Recent advances in artificial intelligence and machine translation have led to unprecedented accuracy and capabilities in automated translation. Neural machine translation utilizing deep learning methods can now quickly process massive amounts of language data, enabling highly accurate translations (Das, 2018). Major technology companies like Google and Microsoft now offer neural machine translation services through APIs that allow users to translate languages using pre-trained machine learning models (Kolhar & Alameen, 2021). Despite improvements in accuracy, machine translation still relies on rigid grammatical rules and often struggles to fully capture semantic meaning and nuance (Li & Hao, 2021). As a result, human involvement through post-editing can help refine and adapt machine translation output (Massey & Ehrensberger-Dow, 2017). There is also evidence that combining machine translation with human teaching and learning can be beneficial (He, 2021). Integrating media materials and multimodal content into the translation curriculum has been found to increase student engagement and learning outcomes (Liu, 2023).

Rapid progress continues to be made towards real-time speech translation, cross-lingual information retrieval, visual translation interfaces, and augmented writing technologies leveraging translation (Massey & Ehrensberger-Dow, 2017). Translation ability is also increasingly being integrated with multilingual virtual assistants and chatbots. As networks grow ever larger and translation models become more capable, ethical considerations around transparency, bias, and fairness have taken on more prominence as well. Moreover, overreliance on technology can negatively impact translation. Machine translation has limitations in fully conveying linguistic and cultural complexity (Urlaub & Dessein, 2022). Therefore, educators must help students become aware of these technological constraints and provide opportunities to learn about the richness of authentic human interaction and communication (Huang, 2022). Ultimately, a balanced approach leveraging the efficiency of AI alongside human creativity and critical thinking is needed in its application in translation (Jiang, 2022).

4. Current Issues and Challenges in AI and Communication

The rapid advancement of AI capabilities in facilitating and participating in communication raises critical societal challenges that necessitate ongoing consideration. Key issues include threats to privacy, vulnerabilities to manipulation, a lack of transparency, and the need for accountability (Ray, 2022). As

Hernández Acosta and Reinhardt (2022) analyze, the datafication of everyday conversation into machine-readable inputs for training algorithms or generating responses presents significant privacy risks. Voice assistants and smartphone keyboard logging capture extensive personal details, while facial analysis may expose emotions without consent. Legal scholars argue this exponentially expands surveillance while evading notice through diffusion across platforms (Zuboff, 2021). That is why developing mitigation standards around data minimization and allowing user control have become urgent priorities (Wirtz et al., 2018).

An additional concern is the potential to leverage conversational AI at scale to manipulate public opinion or target vulnerable groups (Hegelich & Janetzko, 2021). The computational identification of communication style patterns combined with generative text synthesis could enable highly customized disinformation campaigns or social engineering attacks (Goldstein et al., 2023). While research characterizing these dangers remains limited, evidence of risks has emerged around emotionally targeted chatbots generating social media content or fake restaurant reviews (Araujo, 2018). Further challenges revolve around the inherent opacity of machine learning systems underlying much AI communication functionality (Rudin et al., 2021). The lack of model interpretability impedes evaluating reasoning chains or fairness across identities and cultures. This has spurred research into areas like explainable AI to enhance accountability and identify harm (Wang et al., 2019). Standards must also be developed to assess chatbot quality and safety across contexts before irresponsible release (Hengstler et al., 2016).

4.1. Trust and Relationships

The ability of conversational agents like chatbots to form meaningful connections and relationships with humans remains limited, which means without capacities for emotional intelligence, empathy, and shared experiences, it is difficult to establish trust. (Haugeland et al., 2022). Some research also indicates skepticism and caution around over-reliance on uncanny AI personas (Zhou et al., 2019). Therefore, fostering appropriate trust calibrated to chatbots’ constraints poses an ongoing challenge.

4.2. Identity and Self-Disclosure

As AI conversational agents appear increasingly human-like, questions arise about machines potentially deceiving or exploiting people unable to distinguish them from humans (Stahl, 2021). While guidelines prohibit chatbots from impersonating real individuals, realistic personas could manufacture fake intimacy by disclosing personal details, eliciting reciprocal self-disclosure from users based on false premises (Shukla & Mishra, 2020). This risk requires ongoing analysis as personas grow more elaborate, and protecting vulnerable populations necessitates indicating their identity clearly.

4.3. Language Biases and Representational Harms

Like other machine learning systems, conversational AI can perpetuate and amplify societal biases manifested in language datasets used to train models (Sheng et al., 2021). For instance, translation engines have exhibited racist, misogynistic output (Bolukbasi et al., 2016). Similar issues with generative chatbots directly impact human interactions. Mitigating harm will require increased model scrutiny and framework development, considering fairness and inclusiveness in communication.

4.4. Multimodal Content Analysis and Generation

While most conversational AIs focus on text and speech, effectively handling other modes like images, videos, and sensors in dialogue remains challenging (Mostafa & Kasamani, 2021). This limits contexts from remote troubleshooting to eyewitness interviews. Advances in multimodal representation learning, cross-modal retrieval, and style transfer offer promising directions to enhance versatility (Baltrusaitis et al., 2018). However, assessing security, privacy, and authenticity around synthetic media generated in communication poses open questions.

Overall, while AI promises great utility in enhancing communication, its limitations, and social impacts necessitate diligent governance. Protecting vulnerable populations and fostering informed public understanding of risks should remain top priorities amidst the rapid change. Scientific caution and ethics must guide development alongside technological excitement in this critical domain.

5. Concluding Remarks

In conclusion, this review has provided a comprehensive overview of the rapid emergence of AI capabilities for facilitating and participating across diverse communication contexts. Voice assistants, chatbots, smart replies, sentiment analysis tools, and machine translation mechanisms are transforming practices across interpersonal, organizational, and societal communication. However, critical challenges around privacy, manipulation, transparency, bias, and trust necessitate ongoing governance and cross-disciplinary collaboration.

Further research is still needed in several key areas:

- Longitudinal impacts of AI mediation on language production, emotional expression, and relational dynamics over time as these technologies become more deeply integrated into daily communication
- Customized conversational agent design for vulnerable populations, such as children, the elderly, and disabled users, to facilitate positive, accessible experiences catered to their needs
- Multimodal conversational systems and effectively incorporating images, videos, and other modes alongside language to enhance versatility across situational contexts
- Explainable AI techniques to decode model reasoning for accountability and identifying potential harms in generative text or dialogue
- Guidelines and standards development for quality, safety, and ethics assessments tailored to different conversational AI applications and use cases before widespread deployment
- User studies on public understanding, attitudes, and intended adoption rates around emerging conversation technologies to guide responsible innovation and value alignment

As this review has shown, AI promises great potential for augmenting human communication while posing risks that necessitate diligent governance. By pursuing priorities like those above through cross-disciplinary collaboration, scientific progress in this domain can align with the public good.

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