2. AI-integrated communication: conceptualization and a critical review

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In 2004, Susan Herring wrote the seminal piece "Slouching Toward the Ordinary: Current Trends in Computer-mediated Communication (CMC)" (Herring, 2004). In this piece, she argued that a technology-driven agenda suffers from a "systematic bias" (p. 27) – which is a bias inherent and supported by the agenda itself and that fails to consider all involved parties. Herring (2004) noted that despite the technology, CMC remains "predominantly grounded in 'old' textual practices," which, for example, considers lack of electricity as the most significant effect of the mediation process, overlooking other profound effects on the communication process, such as narrative shaping and others. Herring (2004) claimed that the complexity of online communication tools prompted users to want a simpler approach, resulting in the development of more straightforward tools that do not require strong technical skills. She wrote, "After barely more than 30 years of existence, CMC has become more of a practical necessity than an object of fascination and fetish" (p. 33), pointing out that the overuse of CMC, disenchantment, and fatigue contributed to these phenomena.

Herring predicted that increasing technological integration over the next five years would make the internet a simpler, safer, yet less fascinating communication environment. However, there remains a lack of evidence supporting Herring's three-point prediction, which perhaps, is fortunate for researchers studying CMC almost 20 years after the publication of this pivotal piece.

In this chapter, we present the concept of artificial intelligence (AI) integrated communication, which views computers not as neutral mediators of communication but as active entities in communication processes and outcomes. Understanding computers as an integrated part of communication rather than a neutral mediator is essential for communication scholars, especially those examining media effects, as communication technologies become more complex by incorporating algorithms and artificial intelligence. Thus, as communication technology researchers, it is imperative to have a systematic understanding of technological properties to choose the most appropriate research methods and think about the system-level effects on communication processes. For instance, aspects of AI-integrated communication could be considered a 2.0 version of McLuhan's "medium is the message" (McLuhan, 1964). However, when algorithms come into play, the medium is no longer a single artifact but a socio-technical ecosystem. This online communication ecosystem is constantly evolving, posing challenges for communication researchers trying to keep up with the rapidly changing technologies.

In the past ten years, a growing number of "new" terms have generally tried to address communication processes in which computers play a more prominent role. Although these terms involve different aspects of communication processes, they share a similar primary focus on the function of the computer. For example, some terms specifically look at the role of AI compared to others that look at socio-technical complex systems. Therefore, this chapter aims to identify the different terms and concepts scholars have previously used to explain how computers affect communication processes by conducting a systematic review of research from diverse fields. Through this systematic review, we will provide scholars with a framework to help further understand the role of the computer in communication and expand theories of mediated communication into integrated communication.

The main contributions of this chapter are:

a) An overview of the different terms used to describe AI, algorithms, or other technical intermediaries in communication.
b) A classification framework of AI-integrated communication based on computers' role vs human role.

SYSTEMATIC REVIEW METHOD

We began the review process by seeking advice from two library consultants at a U.S. university. One of the librarians specialized in information systems, and both librarians were familiar with the topic and field of the research. During our meeting with the librarians, we first searched for systematic reviews in our field of interest – AI use, AI's role, and the AI effect in communication – to find gaps in the current reviews or extend their depth. However, we could not find any papers related to these areas. Next, we attempted to find a wide range of keywords that would define the boundaries of this research. We began the systematic literature review process by using a small set of keywords. We evaluated each article found for its relevance and importance in the field. After adding every article to the list of references, we updated the list of keywords. After identifying the keywords, we limited the focus of the study by excluding papers that mention relevant terms that are purely technical but do not address communication between humans and machines.

We report the keywords above for other researchers to further explore the proposed understanding of AI-integrated communication. The remainder of this section will discuss the resulting literature, including the databases used to conduct the analysis.

Resulting Literature

In our endeavor to answer the research questions, we used two main sources of data: Google Scholar and university-provided databases. The reason Google Scholar was a main search tool in this systematic review is because most new research supports its vitality for search in the academic field. In fact, Fagan (2017) found that "recent studies repeatedly find that Google Scholar's coverage meets or exceeds that of other search tools, no matter what is identified by target samples, including journals, articles, and citations." For the university-provided databases, we utilized databases such as the ACM digital library, IEEE Xplore, and Scopus.

Key Definitions

Computer-mediated Communication (CMC) is an "umbrella term which refers to human communication via computers" (Simpson, 2002). The definition itself could incorporate communication that involves AI. However, the terminology includes the word "mediated," which may imply that the technology is being perceived as a neutral medium that allows communication to take place and have a passive role in the entire process. In order to facilitate a better understanding of how other literature has defined the evolving role of technology in communication, we review several introduced definitions in prior literature that have emerged that challenge the main construct of CMC.

Artificial Intelligence-Mediated Communication (AI-MC)

Jakesch and colleagues (2019) introduced the term artificial intelligence-mediated communication (AI-MC) and stated that "interpersonal communication [is] not simply transmitted by technology but augmented – or even generated – by algorithms to achieve specific communicative or relational outcomes" (Jakesch, French, Ma, Hancock, & Naaman, 2019). The authors use the term AI-MC to discuss how technologies are taking on a heftier role in human-to-human communication. The authors in this paper emphasize the effect of algorithms on communication between humans by adding to, or generating, the communication content for users, which contrasts with the traditional CMC theory. The term differs from the traditional CMC theory in multiple ways. First, it carries a larger role than being a mere medium in the communication process. Second, it infers an ability to influence communication by either generating the content for users or complementing it through offering text suggestions, such as in the case of text auto-complete found in Gmail. The authors argue that they believe their work is the first of its kind that demonstrates a profound effect of computer mediation on communication outcomes. To the best of our knowledge, the term AI-MC was not mentioned in other publications as of the time of this literature search. However, although the specific term AI-MC seems novel, it does overlap with other ubiquitously used terms such as human–machine communication (HMC) and others. We list those terms below.

Human–Machine Communication (HMC)

Human–machine communication conceptualizes machines as a medium with which humans interact (Zhao, 2006). In a clarification of where HMC stands in the context of other similar terminologies, Guzman (2018) argues that HMC overlaps with human–computer interaction (HCI) and human–robot interaction (HRI) but only addresses the process of communication between hhumans and machines. However, in HMC, the computer is more than a medium: it also takes on the role of the communicator, which can lead to creation of meaning between humans and machines (Guzman, 2018).

Yet even among scholars who use this term, there are some nuanced differences in conceptualization. For example, in Porter, Muztoba, and Ogras (2016), the term HMC is used interchangeably with human–machine interaction. Because this is an earlier work, the authors claim the lack of intelligence in such systems, calling for design implications to improve the functionality of such systems to work as better assistants for the disabled population. Here, the authors say that the HMC systems are mostly concerned with control panels or mouse and keyboard, which is a similar understanding of the CMC theory in which the role of technology is to mediate. Therefore, the authors in this work use the term HMC to a similar extent as to what the CMC theory intends, which is only to mediate and not to have a more integrated role in the communication process. This indicates how the term has evolved even in the period of just a few years. More recently, the term HMC has been defined as "[the] adopt[ion of] a more flexible understanding of human–machine relations as designed to support collaborations within which both human and machine are regarded, in their own specific ways, as active participants" (Sandry, 2018).

Initially, this was distinct from CMC because the interaction was between the human and machine rather than the machine being the mediator between humans. Yet, others have used HMC with different nuances. In Hong and Curran (2019), HMC describes how AI in machines can produce artwork that is regarded as worthy as artwork produced by humans. The meaning inferred from this work is different from Sandry's (2018) paper in the sense that the authors do not mention collaboration between humans and machines. Rather, they investigate how people perceive the communicated work done by machines.

The Algorithmic Imaginary

Bucher (2017) describes the term algorithmic imaginary as how people understand and perceive algorithms and their roles. The term addresses the need for awareness of the presence of algorithms in our lives and how they affect our decisions and not just serve as simple mediators between human communication. Another work (Eslami et al., 2015) is concerned with the effect of algorithms' awareness on humans. Although the term algorithmic imaginary is not used in this work specifically, the authors exhibited a similar meaning to how it is described in the Bucher (2017) paper. The authors claim that most people are unaware of the algorithms' vast presence in their lives and that such knowledge would certainly influence how people perceive those algorithms. While these papers do not specify "communication" in their terminology, they still raise awareness about the role of algorithms in communication processes.

Machine Authorship

Machine authorship refers to news pieces written by algorithms. The content is usually based on facts; however, the original algorithm creator's bias might descend to the algorithm, providing possibly biased news pieces (Latar, 2015). In related work (Van Dalen, 2012), the author uses the term "Automated Content Creation" to refer to machine authorship, raising questions about ethics and its effect on human jobs. Many articles discuss the role and effect of machine authorship. However, authors usually use different terms to refer to similar concepts, such as automated storytelling, computer-written news, and robot journalism (Jung et al., 2017; Van der Kaa & Krahmer, 2014). Other works also use the term "automated computer-written news" to deliver the same meaning of machine authorship (Graefe, Haim, Haarmann, & Brosius, 2018). In other work, machine authorship bears the same definition of news curated by machines (Hofeditz et al., 2021; Lee et al., 2020; Waddell, 2018). Here, the role of the machine is profound in the sense that it is creating the content for other readers. In this category, we found that authors use a variety of terms to address the AI component that writes the news while communicating the same meaning. Compared to other terms, machine authorship seems clearest and has universal meaning despite having numerous terminologies. The other terms found and listed in the previous sections carried different and overlapping meanings that pose some issues for readers when trying to comprehend their precise meanings.

AI-Supported Messaging

This term usually refers to smart replies that complement text communications between users. The term AI-supported messaging is defined as an AI assistant in human-to-human communication, specifically in-app messaging, in which AI is thought to influence the overall outcomes of the conversation (Hohenstein & Jung, 2018). The term is often used interchangeably with "smart replies," which are automated text recommendations for humans when they attempt to communicate a message to another human. The earlier work by Google researchers (Kannan et al., 2016) delineates how smart replies utilize deep learning and provide suggestions that are frequently used in Google Gmail. Another scholarly work using the same term (Weng, Zheng, Bell, & Tur, 2019) provides an overview of a new smart reply system that Uber drivers use to ease their communication with their riders through intent detection and reply retrieval.

Machine Translation (MT) Supported/Mediated Communication

The work by Yamashita and Ishida (2006) claims to be the first work to research the concept of MT-mediated communication and to understand its effects on communication outcomes. The authors in the previous work were interested in identifying the problems and issues that arise from machine translation and pointed out that more research should focus on collaboration in non-English contexts using

Table 2.1 Comparison table for AIIC identified terms

Feature/AIIC definition	AI-MC	HMC	Algorithmic imaginary	Machine authorship	AI-supported messaging	Machine translation supported comm.
Augment Content?	✓	✓	✓	×	✓	✓
Generate Content?	✓	✓	N/A	✓	✓	✓
Require Human–Machine Collaboration?	×	✓	N/A	×	✓	Unclear
Support Human Face-to-Face Communication?	Unclear	Unclear	✓	×	×	✓

MT-mediated communication (Yamashita & Ishida, 2006). In work by Shigenobu (2007), the author uses the same understanding of MT-mediated communication in the sense of improving MT of foreign content through back translation, although the terminology is not explicitly used (Shigenobu, 2007). In recent work, those terms refer to using machines and algorithms to help improve the quality of translated content by finding errors in the translation and providing enhancements or additions to the translated content (Lim, Cosley, & Fussell, 2018). MT-mediated communication has also been used to refer to how machines support the translation of content in face-to-face situations (Pituxcoosuvarn, Ishida, Yamashita, Takasaki, & Mori, 2018). Here, the authors investigate the non-verbal cues added to content to enhance their meaning. Thus, MT-mediated communication, while applying itself to the limited context of the translation of content, is situated in the broader understanding that AI can have an assistive role in communication. Table 2.1 includes a summary of some of the main similarities and differences between the identified terms.

CLASSIFICATION OF AI IN COMMUNICATION

Based on the overview of the varied terms describing forms of AI in communication, in this section, we delineate a high-level classification framework for AI use in communication. We found two main roles in the communication process that affect AI use in communication, i.e., AI's role and the human role. These two roles, however, are different and do not always bear the same weight in terms of importance and effect. In the following sections, we discuss the differing roles of AI and humans.

AI Role

This section addresses the role of AI in communication. We identified two broad roles, namely, an assistive role and AI self-communication role. Below, we discuss these roles in more detail.

Assistive role

The first role we identified in our literature review was the assistive role of AI in communication. Here, the technology was designed to aid humans in their endeavors to communicate messages between humans in the form of providing support or giving suggestions that will ease task completion and make the process faster and more seamless. Under this category, we identified an assistive role in task completion and an assistive role in decision-making.

Assisted task completion

The traditional understanding of computers' role in communication is to mediate the flow of correspondence between humans. However, in this section, we address a more visible role of computers in communication. Here, computers augment and supplement the communication between humans. Broadly speaking, computers are built to make the lives of humans easier. One role of AI is to assist humans in completing their communication-related tasks. In this section, we overview a number of prominent works addressing this vital role.

Perhaps, the most prevalent example that comes to mind when discussing the role of computers in communication is smart replies, specifically, their assistive role in task completion. As defined earlier, it is the quick and short suggestions we encounter when drafting an email to improve and assist in the process of communicating with another person. In a recent work about smart replies (Hohenstein & Jung, 2018), through an experiment, the authors demonstrate the assistive role of smart replies in a messaging app called Allo. The app provided suggestions for participants to aid them in finishing their sentences. Although the suggestions were rated as being overly positive, some participants reported that the suggestions were similar to what they wanted to say. Another example (Weng et al., 2019) is smart replies embedded in an Uber app for drivers to help them streamline their communication with their passengers to ease the communication process.

The term MT-mediated communication usually refers to the assisting role of machines in foreign communications. The work by Lim et al. (2018) addresses the problem of translation and interpreting humans' communication in a different language. However, translating word for word might not be the optimum way to fully comprehend the other person. Therefore, the work by Lim (2018) addresses this issue and uses AI to add "cues" and hints to improve the expression and increase the validity of the translated content. Such additions would cause a favorable change in the meaning of the translated content, therefore, demonstrating a more elaborate assistive role of AI in communication.

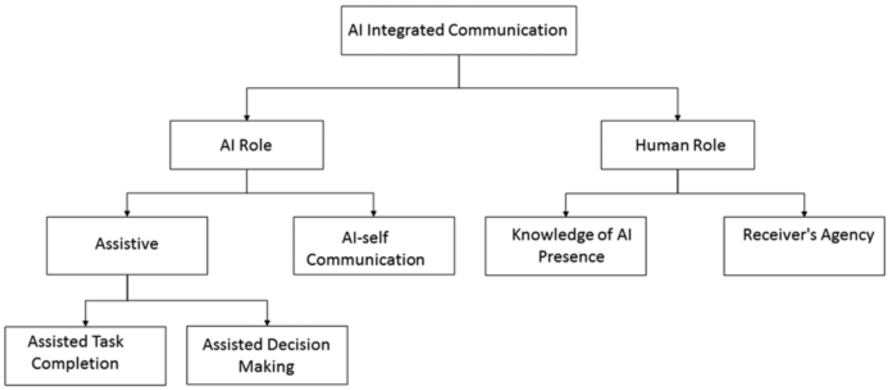

Figure 2.1 The proposed AI-integrated communication classification framework

Assisted decision-making

Another role of AI is to provide assistance for human decision-makers in sometimes critical areas such as in medicine. The main role of computers here is to reduce the thought process for humans, allowing them to allocate their cognitive load to other more demanding tasks. Here, we review examples that demonstrate this role. Rajpurkar et al. (2022) discuss the use of AI in medicine in terms of assisting in image reading and decision-making. The authors also discuss some ethical dilemmas such as the inherent racial profiling that is a possible consequence of limited learning algorithms. Price and Nicholson (2017) address the role of algorithms in the medical field and how they have a substantial role in the decision-making process. The author used the term black box to express the complexity of algorithms. More specifically, although algorithms might be working well, understanding how they work exactly is not easy to disentangle (Poon & Sung, 2021). In their work (Price & Nicholson, 2017), the algorithms they studied are used to help doctors make a medicine-dosing decision for their patients. Additionally, they call for regulating the use of algorithms but in a way that allows technological innovation in the medical field. Apart from private practices, algorithms are also very prevalent online in the form of recommendation systems. In web 2.0, there is more emphasis on recommendations based on similar people not just similar products. The authors in the latter work also found that the relationship between liking the system and perceiving the recommendations as “smart” is not straightforward and that many dimensions affect how people perceive those recommendations (Ochi, Rao, Takayama, & Nass, 2010). Nevertheless, people are developing more trust in recommendation systems, which depicts the effect of algorithms on people’s decisions.

AI self-communication

Many internet applications rely on self-reporting bots to help streamline basic tasks and free human labor for more laborious activities that require more sophisticated comprehension and cognitive load. In this section, we discuss how computers (in the form of bots) make decisions in communications with humans, as opposed to aiding two or more humans in communication amongst themselves. It is also important to point out that although it seems that bots communicate purely on behalf of themselves, humans program those machines, and the algorithms follow the built-in sequence of instructions placed by human programmers. However, once bots are placed in action, they may be subject to deep learning, which means that the bots can evolve in a way that humans will be unable to understand how they are programmed.

Recent research investigates the role of machines in communication to improve the user experience design (Sandry, 2018). Vyo, a robot that communicates on behalf of itself, was the subject of a recent work to understand the effects of communication with bots (Sandry, 2018). The authors conclude that machines and bots are active agents in the communication process with humans. Therefore, design choices need to be developed to address this evolving role. A similar and older study (Van Oost & Reed, 2010) concerned with robots as emotional companions, discussed how traditionally the role of technology was to mediate communication and emotional transactions between two humans, in which the role evolved to consider bots as independent agents possessing emotional agency.

Human Role

In this section, we discuss humans' role in the communication process when AI is included in the communication. Two interesting perspectives on humans' role are humans' agency and knowledge of AI's presence in the communication process – particularly the information receiver.

Agency vs. knowledge of AI presence

We split human agency into information sender and receiver agency. We define agency as the ability of an agent to act freely and mindfully to make decisions in different circumstances in relation to communication. Banks (2019) defines agency in psychology as "one's ability to exercise self-regulation, intentionality, and embodied action, or in relation to a sense of agency by which people experience self-efficacy, autotelic needs satisfaction, or beliefs about one's own freedom." Knowledge of AI's presence refers to whether humans understand that AI is involved in the communication process.

In most traditional CMC theories, in which the technology is used only as a medium, both receivers and senders of information have high agency. This could be explained in the sense that the information sender has high abilities to manipulate the technology and influence the communication content being transmitted. The same applies to the receiver in that they are able to receive the message as it was sent and are fully able to receive the message as is, free to respond without any influence from the used technology.

By attempting to classify the terms identified previously, we use a two-axis sphere and, based on agency and knowledge of AI presence, we plot our terms. In Figure 2.2, we see that the majority of identified terms cluster in the top left corner, which shows high sender agency but low receiver agency. This means that the sender is able to relatively freely manipulate the message to be sent. However, the receiver is not able to decide the extent of the AI role in the communication process. The sender can change the scale of AI involvement in the communication process, but the receiver only receives what was sent to them with little to no control over the technology part of the communication and without knowing the extent of AI augmentation in the received content. This partly contrasts with the CMC theory in which the receiver has high agency regarding the technology medium.

Another dimension in the graph is the receivers' knowledge of AI presence. This is particularly important in the context of trustworthiness and ethical consequences (Van Dalen, 2012). In the traditional CMC, the receiver is fully aware of the used technology. However, due to the fast learning and intelligence of algorithms and AI, it is possible to be involved in a communication task and receive content that was generated, whether partially or fully, by an algorithm. Most of the newly coined terms that explain AI's involvement in communication can conceal their presence from the receiver. For example, in terms of machine authorship, most news content is now generated by algorithms that tie facts into readable sentences, while leaving the sender at odds with whether the news piece was generated by a human writer or an algorithm (Haim & Graefe, 2017; Wölker & Powell, 2018). Issues of trustworthiness surrounding the transmitted content arise given that these algorithms are written by humans who are not considered the most objective agents (Graefe et al., 2018).

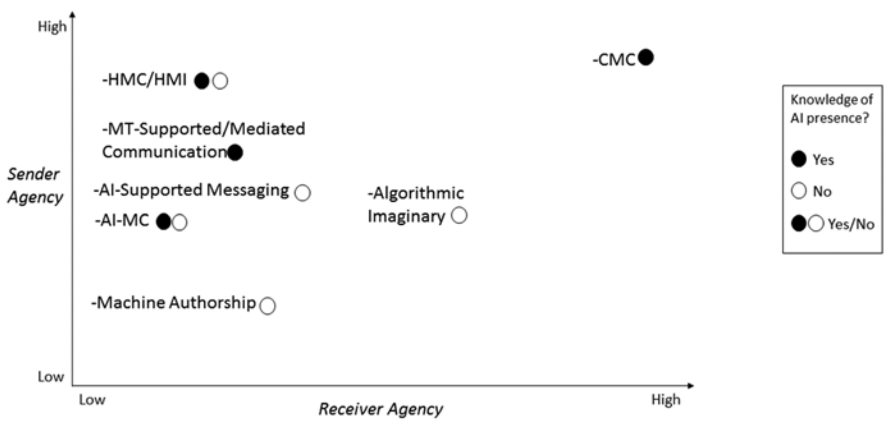

Figure 2.2 Agency vs. knowledge of algorithm presence and AI in communication terms

AI EFFECT ON THE COMMUNICATION PROCESS

After presenting the high-level classification framework, we delve into an equally significant matter: the AI effect. In the introduction, we state the reasons for this scholarly work, which is to highlight that technology is no longer a simple medium of communication. We also accentuate that the AI effect is important and that it is profound in the communication process. This idea is not novel, as research on the topic is available and presented in this chapter which describes the extending effect of AI on communication. Therefore, in this section, we acknowledge that the AI effect matters and that we need to look at it as a separate entity to help us anatomize AI in the context of the evolving communication system.

Following our classification, we present the AI effect in communication first in the context of assistance. In Nitto, Taniyama, and Inagaki (2017), the authors surveyed participants from Japan, Germany, and the United States to understand the prevalence and perception of bot use. The study found that the Japanese population showed positive perceptions of robot use, Germans were skeptical, and the U.S. population was excited about the future of bots. The findings are important and should be considered locally when designing bots and using AI in commercial products. Another study (Hohenstein & Jung, 2018) looked at the transitive effect of those recommendations humans regularly receive from certain applications. The authors used the messaging app Allo, developed by Google, to conduct an experiment followed by interviews to understand the effect of such technology. The authors found that only 6.24% of the time the suggestions were used. However, google Gmail suggestions are used around 10% of the time (Kannan et al., 2016). Participants also reported a more integrated effect of the technology. For example, participants reported that they were possibly guided toward a certain response and that suggested emojis were very tempting to select (Hohenstein & Jung, 2018). Another work (Jakesch et al., 2019) also discusses the advanced role of technology as a mediating element. The authors conducted studies to understand the perceived trustworthiness of bot-written Airbnb profiles. The authors found that online self-presentation could be affected by AI and that it indeed negatively affects the perceived trustworthiness of those online profiles if written by a bot. An earlier research study (Yamashita & Ishida, 2006) claims that "we still lack a complete understanding of how machine translation affects communication" (p. 1) and attempts to address those questions.

Turning to the effect of AI in AI self-communication, we see a similar range of effects. In the context of automatic content generation, we see that bots have larger effects on the communication process, such as affecting consumers' perception of news (Graefe et al., 2018). However, people perceive news written by journalists as more readable (Graefe et al., 2018), affecting how the news piece is communicated to the audience. Waddell (2018) also found that participants reported that news generated by algorithms is viewed as less credible (Waddell, 2018). Automatic news generation presents obvious predicaments in relation to its questioned authenticity and favoritism because it was curated by algorithms that convey the ideologies of the human who created them. Therefore, the effect of such news pieces is rather substantial (Latar, 2015).

DISCUSSION

What exactly is the computer in CMC? Essentially, CMC is the exchange of signals that are transferred through a device, and AI has the means to influence this exchange beyond a mediating role. We must ask, again, the question posed by scholars (Rice & Love, 1987) in the early days of CMC research: "A general question raised by the diffusion of CMC systems is the extent to which human communication is altered by such media" (p. 86). Traditional communication research places high importance on internal validity, as seen in the structured laboratory experiments that mirror early social psychology research. While internal validity should not be sacrificed for the sake of external validity, in studies that involve mediated communication, it is imperative to understand the features or affordances of AI when studying communication systems that use AI. Yet as seen in our review, the use of AI also means that there are situations, especially when the algorithms involve deep learning, in which even the sender may not have a complete understanding or control over the algorithm.

In this chapter, we discussed some available work related to the AI effect. However, most of these studies pinpoint a problem related to identifying the underlying reason for the AI effect and could not clearly define its causes. Indeed, the black-box nature of algorithms is deemed the culprit of the unintentional consequences of AI. However, we still do not know everything that contributes to this problem. Is it the nature of technology to *think* in unorthodox ways to the human mind or is it a human-embedded problem through the biased algorithm design? (Latar, 2015).

In a work by Burrell (2016), the author discusses algorithmic opacity and states that there are three kinds of opacity: an opacity induced by a corporate or regulatory authority, opacity due to technical and specialist skills required for coding, and an opacity due to the different ways humans and algorithms learn and make decisions. The author focused their work on the latter type of opacity, trying to decipher how algorithms are constructed and operate (Burrell, 2016). The issue of opacity could be explored through progressive initiatives and collaborations with industry partners to expose how certain algorithms are designed and the possible ways that could influence communication. Perhaps, a top-to-bottom approach to delineate how algorithms are planned, designed, constructed, and deployed would unravel some of the opacity. Second, we can develop our own systems to classify the extent of the AI effect. For example, the simple classification framework introduced in this work regarding agency and knowledge can serve as the basis for future in-depth classifications. Third, through replication and repeated studies in different contexts and platforms to tease out whether the effect of AI is specific or universal. In the work by Hayes and colleagues (2016), the authors describe how different social media platforms have distinct affordances and that people use them to reach different results. On the other hand, AI, especially more advanced AI, is difficult to understand how it operates, even by the person who designed it. Thus, the black-box nature of algorithms will persist. Moreover, when it comes to more complex socio-technical systems, algorithms will also be influenced by other people. Thus, in an ecologically valid environment, it is almost impossible to pick apart the social effects from the technological effects. Future studies may focus less on "pure" media effects and instead attempt to assess how much variance is being explained by the particular technology effect they are trying to measure.

CONCLUSION

In this systematic literature review, we overview a sample of the available literature that discusses the role and effect of AI in communication and how research papers use different terms to refer to that effect. We propose a classification framework for AI-integrated communication based on AI's role vs. humans' role. AI's role was either an assistive one, helping humans complete a task through communication, or AI would communicate on behalf of itself. We investigated the human role in terms of the receivers' knowledge of AI presence in the communication process and based on the receivers' agency. This provides a framework for how AI is integrated into communication processes and outlines several points to consider for future research.

REFERENCES

Banks, J. (2019). A perceived moral agency scale: Development and validation of a metric for humans and social machines. *Computers in Human Behavior*, *90*, 363–371.

Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society*, *20* (1), 30–44.

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, *3* (1), 2053951715622512.

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., … Sandvig, C. (2015). I always assumed that I wasn't really that close to [her]: Reasoning about invisible algorithms in news feeds. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems* (pp. 153–162). ACM.

Fagan, J. C. (2017). An evidence-based review of academic web search engines, 2014–2016: Implications for librarians' practice and research agenda. *Information Technology and Libraries*, *36*(2), 7–47.

Graefe, A., Haim, M., Haarmann, B., & Brosius, H.-B. (2018). Readers' perception of computer-generated news: Credibility, expertise, and readability. *Journalism*, *19*(5), 595–610.

Guzman, A. L. (2018). What is human-machine communication anyway? In A. L. Guzman (Ed.) *Human-machine communication: Rethinking communication, technology, and ourselves* (pp. 1–28). Peter Lang.

Haim, M., & Graefe, A. (2017). Automated news: Better than expected? *Digital Journalism*, *5*(8), 1044–1059.

Hayes, R. A., Carr, C. T., & Wohn, D. Y. (2016). It's the audience: Differences in social support across social media. *Social Media+ Society*, *2* (4), 2056305116678894.

Herring, S. C. (2004). Slouching toward the ordinary: Current trends in computer-mediated communication. *New Media & Society*, *6* (1), 26–36.

Hohenstein, J., & Jung, M. (2018). Ai-supported messaging: An investigation of human-human text conversation with AI support. In *Extended abstracts of the 2018 chi conference on human factors in computing systems* (LBW089). ACM.

Hofeditz, L., Mirbabaie, M., Holstein, J., & Stieglitz, S. (2021). Do you trust an AI-journalist? A credibility analysis of news content with AI-authorship. In *ECIS 2021 Research Papers*, *50*.

Hong, J. W., & Curran, N. M. (2019). Artificial intelligence, artists, and art: Attitudes toward artwork produced by humans vs. artificial intelligence. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, *15* (2s), 58.

Jakesch, M., French, M., Ma, X., Hancock, J. T., & Naaman, M. (2019). Ai-mediated communication: How the perception that profile text was written by ai affects trustworthiness. In *Proceedings of the 2019 chi conference on human factors in computing systems* (p. 239). ACM.

Jung, J., Song, H., Kim, Y., Im, H., & Oh, S. (2017). Intrusion of software robots into journalism: The public's and journalists' perceptions of news written by algorithms and human journalists. *Computers in Human Behavior*, *71*, 291–298.

Kannan, A., Kurach, K., Ravi, S., Kaufmann, T., Tomkins, A., Miklos, B., … Young, P. et al. (2016). Smart reply: Automated response suggestion for email. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 955–964). ACM.

Latar, N. L. (2015). The robot journalist in the age of social physics: The end of human journalism? In G. Einav (Ed.) *The new world of transitioned media* (pp. 65–80). Springer.

Lee, S., Nah, S., Chung, D. S., & Kim, J. (2020). Predicting ai news credibility: Communicative or social capital or both? *Communication Studies*, *71*(3), 428–447.

Lim, H., Cosley, D., & Fussell, S. R. (2018). Beyond translation: Design and evaluation of an emotional and contextual knowledge interface for foreign language social media posts. In *Proceedings of the 2018 chi conference on human factors in computing systems* (p. 217). ACM.

McLuhan, M. (1964). *The medium is the message in: Understanding media*. Signet.

Nitto, H., Taniyama, D., & Inagaki, H. (2017). Social acceptance and impact of robots and artificial intelligence: Findings of survey in Japan, the us and Germany. *NRI Papers (Japan)*, *213* (1).

Ochi, P., Rao, S., Takayama, L., & Nass, C. (2010). Predictors of user perceptions of web recommender systems: How the basis for generating experience and search product recommendations affects user responses. *International Journal of Human-Computer Studies*, *68* (8), 472–482.

Pituxcoosuvarn, M., Ishida, T., Yamashita, N., Takasaki, T., & Mori, Y. (2018). Supporting a children's workshop with machine translation. In *Proceedings of the 23rd international conference on intelligent user interfaces companion* (p. 32). ACM.

Poon, A. I., & Sung, J. J. (2021). Opening the black box of AI-Medicine. *Journal of Gastroenterology and Hepatology*, *36*(3), 581–584.

Porter, A., Muztoba, M., & Ogras, U. Y. (2016). Human-machine communication for assistive iot technologies. In *2016 international conference on hardware/software codesign and system synthesis (codes+ isss)* (pp. 1–2). IEEE.

Price, W., & Nicholson, I. (2017). Regulating black-box medicine. *Michigan Law Review*, *116*, 421.

Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. *Nature Medicine*, *28*(1), 31–38.

Rice, R. E., & Love, G. (1987). Electronic emotion: Socioemotional content in a computer-mediated network. *Communication Research*, *14*, 85–108. http:\\doi.org\10.1177/009365087014001005

Sandry, E. (2018). Encounter, story and dance: Human-machine communication and the design of human-technology interactions. In *Proceedings of the 30th australian conference on computer-human interaction* (pp. 364–367). ACM.

Shigenobu, T. (2007). Evaluation and usability of back translation for intercultural communication. In *International conference on usability and internationalization* (pp. 259–265). Springer.

Simpson, J. (2002). Computer-mediated communication. *ELT Journal*, *56* (4), 414–415.

Söderlund, M. (2022). When service robots look at themselves in the mirror: An examination of the effects of perceptions of robotic self-recognition. *Journal of Retailing and Consumer Services*, *64*, 102820.

Van Dalen, A. (2012). The algorithms behind the headlines: How machine-written news redefines the core skills of human journalists. *Journalism Practice*, *6* (5–6), 648–658.

Van der Kaa, H., & Krahmer, E. (2014). Journalist versus news consumer: The perceived credibility of machine written news. In *Proceedings of the computation+ journalism conference, Columbia University, New York* (Vol. 24, p. 25).

Van Oost, E., & Reed, D. (2010). Towards a sociological understanding of robots as companions. In *International conference on human-robot personal relationship* (pp. 11–18). Springer.

Waddell, T. F. (2018). A robot wrote this? How perceived machine authorship affects news credibility. *Digital Journalism*, *6* (2), 236–255.

Weng, Y., Zheng, H., Bell, F., & Tur, G. (2019). Occ: A smart reply system for efficient in-app communications. In *Proceedings of the 25th acm sigkdd international conference on knowledge discovery & data mining* (pp. 2596–2603). ACM.

Wölker, A., & Powell, T. E. (2018). Algorithms in the newsroom? News readers' perceived credibility and selection of automated journalism. *Journalism*, *22*(1), 1464884918757072.

Yamashita, N., & Ishida, T. (2006). Effects of machine translation on collaborative work. In *Proceedings of the 2006 20th anniversary conference on computer supported cooperative work* (pp. 515–524). ACM.

Zhao, S. (2006). Humanoid social robots as a medium of communication. *New Media & Society*, *8*(3), 401–419.