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Types, methods, and evaluations of artificial intelligence (AI) in public communication research in the early phases of adoption: a systematic review

Irina Lock [1,*], Lukas Benedikt Hoffmann [2], Christian Burgers [3] and Theo Araujo [3]

[1]Institute of Communication Science, Friedrich Schiller University Jena, Jena, Germany
[2]Institute for Media and Communication Science, Freie Universität Berlin, Berlin, Germany
[3]Amsterdam School of Communication Research (ASCoR), University of Amsterdam, Amsterdam, The Netherlands

*Corresponding author: Institute of Communication Science, Friedrich Schiller University Jena, Ernst-Abbe-Platz 8, 07743 Jena, Thuringia, Germany.
Email: irina.lock@uni-jena.de

Abstract

Artificial intelligence (AI) has become pervasive in everyday life, and with the publication of large language models such as ChatGPT especially relevant in the context of media and public communication. This paper synthesizes the conceptualizations, types, methods, and evaluations of AI in public communication in the early phases of innovation adoption, before the broad public discussion around generative AI set in. We conducted a systematic review of empirical research focusing on AI in six social and computing-science databases up until and including 2022 ($k = 198$). Results show a steep increase in the number of studies published on AI in public communication in just four years. To facilitate a common understanding of what AI is and how it is studied, AI applications are grouped into four AI types: (a) AI as method, (b) Generative AI, (c) AI as communicator, and (d) AI generally. People's interaction with and attitudes towards AI seem to be central in this research. In addition, AI has mostly been investigated with quantitative methods, often with human participants, as evidenced by the dominance of surveys and experiments. The reviewed research primarily comes from English-speaking countries and often fails to define what AI is or to formulate normative implications. Five blind spots of AI research in public communication and their implications for future empirical studies are discussed.

Keywords: artificial intelligence; public communication; systematic review

Artificial intelligence (AI) is featured daily in the media and AI-related research is burgeoning. AI applications often touch upon communication contexts (Guzman & Lewis, 2020): When social-media bots multiply actors' messages (Keller & Klinger, 2019), conversational agents communicate with users in a variety of settings (Følstad et al., 2023), news recommenders pre-select news items (Möller et al., 2020), or automated text generators aid in crafting messages (Illia et al., 2023), AI applications interfere with human communication processes (Natale, 2021).

The fact that AI comes in many forms and multiple contexts makes it hard to clearly conceptualize this phenomenon. Yet, given that many of its applications affect communication processes, the topic of AI provides fertile ground for an empirical inquiry from a communication-scientific perspective. This proliferation has materialized in communication research on AI. Similar to big data (Elish & boyd, 2018), AI is often used as a buzzword (Leufer, 2020), definitions of AI are inconsistent (e.g., Brennen et al. 2018; Gil de Zúñiga et al., 2024; Wang, 2019), and, therefore, AI's meaning remains unclear (Ekbia, 2010). That is why a synthesis of current knowledge is needed as it aids in clarifying what the phenomenon is about, and in which types it shows. Thus, this systematic review asks: *How has AI been studied in empirical research on public communication?*

Given the variety of AI applications, our focus on public communication contexts allows for comparability of researchers' AI conceptualizations. Public communication involves interactions that are "plain to see" (Pieczka, 2019, p. 228), or where the consequences of private interactions for others are discussed (Dewey, 1927). Thus, we zoom in on communication that relates to issues of public interest and takes place in the public sphere (Macnamara, 2017) as a space that *ideally* is open to all members of society to form an opinion about societal issues (Habermas, 1989).

Most applications that are publicly debated as AI are employed and encountered by citizens as conversational agents, social bots, recommender systems, or large language models. At the same time, public communication includes economic, political, and cultural subsystems (Fuchs, 2021), such as marketing, journalism, entertainment, or politics, some of which are not institutionalized communication science subfields (e.g., compared to the International Communication Association's divisional structure).

The impact of AI has foremost been studied and reviewed for marketing (Chintalapati & Pandey, 2022; Mariani et al., 2022; Peyravi et al., 2020), journalism (Calvo-Rubio & Ufarte-Ruiz, 2021; Kothari & Cruikshank, 2022; Parratt-Fernández et al., 2021), and, most recently, strategic communication (Weller & Lock, 2025). There is also a growing amount of research reviewing specific AI applications, such as conversational agents (van Pinxteren et al., 2020), social-opinion mining (Cortis & Davis, 2021), social and other bots (Blut et al., 2021), deepfakes (Vasist & Krishnan, 2022), or social-media analytics (Ghani et al., 2019). Yet, we lack a comprehensive review of empirical public communication research of AI. Such a comprehensive review becomes pressing considering the broad adoption of AI as a technology in the

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past years, with a clear popular uptake since the emergence of Generative AI, such as ChatGPT or Midjourney. To advance as a field, we need a solid understanding of the research that has led up to the broad adoption of AI. As such, following Diffusion of Innovations Theory (Rogers, 2003), we synthesize empirical research on AI in different public communication contexts in the first phases of adoption of disruptive innovations, before they are normalized in society (Rogers, 2003). The turning point between these early phases and widespread use marks the publication of ChatGPT in autumn 2022, and the ensuing public discourse around this "intelligent" agent (Hepp et al., 2023). We focus specifically on empirical research to ensure we can systematically analyze how studies have conceptualized AI in research practice, ie, during the research process.

As such, this systematic review sets out to gather and synthesize the conceptualizations, types, methods, and evaluations of AI in public communication. This research is not confined to the discipline of communication science, but nevertheless, or precisely for that reason, aims to understand how AI affects the (public) communication process in a broad manner. It relies on a comprehensive search of all empirical research in six social and computing-science databases up until and including 2022 coupled with a quantitative content analysis of the resulting 198 articles. Next to formal variables that capture the diversity of researchers and publishing outlets in the field, AI's applications and settings, empirical conditions, and normative evaluations were coded.

This article makes three core contributions. First, this overview aids in mapping the field of research in early phases of an innovation's public salience, which are predictive of its further adoption in society. Thereby, it identifies blind spots that bear important implications for future research on AI. Second, the article shows what kind of AI applications have been studied and groups them into types of AI to facilitate a common understanding of the broad field of AI applications and trends. Such a clustering may spur cross-fertilization across fields for theory development. Third, the article discusses geographic diversity in AI research (see also Demeter, 2019) and the degree to which researchers interpret AI from a normative standpoint (Bourne, 2019; Geise et al., 2021; Xu, 2024).

AI in public communication processes

AI is one of the most publicly debated technological innovations in recent years (Bareis & Katzenbach, 2022). Such public communication can generally be conceptualized along its spatial, procedural, and topical dimensions. Spatially, public communication happens in and constitutes the public sphere (Dewey, 1916; Habermas, 1989), the intersection of civil society and politics (Habermas, 1989) extended to economic and cultural subsystems (Fuchs, 2021). In today's digital communication environment, the public sphere is largely mediated, and, particularly on social media it is both semi-private and semi-public (Habermas, 2021), blurring the distinction between private and public that in pre-Internet times defined the public sphere (Habermas, 2021). In this environment, García (2024) argues that the public sphere can be considered a tragedy of the commons, because the excessive amount of communication is congesting meaningful civic discourse. Procedurally, communication in the public sphere is about information exchange and throughput between citizens and those in power, and negotiating consensus (Habermas, 1989). This happens interpersonally, inter- and intraorganizationally, as well as between organizations and individuals in the sense of organization-public relations (Heath, 2013). From a constructive perspective, we can define communication along Van Ruler and Vercic (2005) as a process of meaning-making. Topically, public communication can be about public issues but also includes semi-private topics that are publicized through, mostly, social media (Habermas, 2021). No matter the topic, communication is considered public when it is "commonly mediated to substantial numbers of people" (Macnamara, 2017, p. 8).

Thus, public communication here is defined as the mediated process of meaning-making in the public sphere between societal actors. For this study, this includes all mediated communication about AI that happens interpersonally in public, between organizations, within organizations if mediated and accessible to a significant amount of people, and in organization-public relations.

AI as a disruptive innovation

The digital age is a time of frequent innovation, with technology advancing rapidly while older technologies quickly become obsolete (Barbour et al., 2023; Mortimer, 2014). Some innovations, however, stand out. They exert enduring influence across various domains including markets, public communication and deliberative democratic processes, among others. Disruptive innovation theory offers a lens for comprehending such newly introduced technological innovations (Christensen, 2013). According to this theory, disruptive innovations are characterized by their ability to supplant existing technologies by supplying previously neglected attributes (Si & Chen, 2020). However, media innovations in the past, such as the advent of the mobile phone, show a more nuanced dynamic: rather than supplanting previous technologies, disruptive media innovations diversified media repertoires and the way specific media were used (Barbour et al., 2023). In line with Nagy et al.'s (2016) wider characterization of disruptive innovation as "chang[ing] the performance metrics, or consumer expectations, of a market by providing radically new functionality, discontinuous technical standards, or new forms of ownership" (p. 122), media innovations such as the mobile phone, television, and the internet nonetheless may be considered disruptive innovations given their transformative functionalities and their introduction of new technical paradigms.

AI is the most recent technology that is conceived as disruptive for public communication in the literature. First, because AI "has disrupted the nature and extent of audience access and uses of news, information and entertainment content" (Lin, 2019, p. 592) and second, because AI has vastly improved accessibility to information and disrupted language barriers (Păvăloaia & Necula, 2023). Thus, AI provides radically new technology and disruptive technical standards, thereby aligning with Nagy et al.'s (2016) definition of disruptive innovation.

The advent of AI parallels previous disruptive innovations in the media market, sparking both societal debates and subsequent processes of assessing their impacts through academic research. Some background on research patterns surrounding prior disruptive media innovations is therefore helpful to understand what to expect from public communication research on AI and to facilitate pointing out central research desiderates.

The internet and mobile phones arguably both represent disruptive innovations. In the early stages of their development, both technologies sparked significant societal debates and prompted early academic research (Kim & Weaver, 2002; Kim et al., 2017). Such initial research focused on their respective characteristics and technical aspects with early communication research on mobile phones mostly relying on large-scale quantitative studies (Kim et al., 2017). This was also the case for earlier instances of emerging media (Khang et al., 2012). However, as they were more widely adopted by citizens, research on both internet and mobile phones diversified into multiple strands simultaneously, encompassing improving the technologies themselves, users and their usage patterns, as well as their broader effects on society (Kim & Weaver, 2002; Kim et al., 2017). Thus, research developments on both the Internet and mobile communication show striking similarities and reflect the evolution of communication technologies and subsequent research patterns for disruptive innovations. These previous cases can serve as an orientation as to what to expect from public communication research on AI. With the large-scale introduction of AI applications like Siri, Alexa, and ChatGPT in recent years, we expect to observe an early generalist perspective on AI with mostly quantitative methods, followed by an increase and diversification of public communication research on AI over the years.

Similar to developments in mass communication technology over the decades (Kim & Weaver, 2002; Kim et al., 2017; Rice & Bucy, 2023), public attention to AI has been following the natural (computer) science research that brought them about. News media attention has increased from the 2010s onwards such that AI has continuously been climbing the issue life cycle (Cools et al., 2022; Fast & Horvitz, 2017). This was accompanied by the professional strategic communication of the innovating businesses who set their AI innovations on the agenda of different media (Bourne, 2019). As such, the diffusion of AI innovations in the media follows the classic diffusion of innovations curve (Rogers, 2003).

Diffusion is the process in which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 2003, p. 5), and moves along the stages of *knowledge, persuasion, decision*, *implementation*, and *confirmation*. Initially, people acquire *knowledge* about an innovation and try it out for the first time, they then build an attitude toward it (*persuasion*), which partially predicts the *decision* to adopt it, or not. What follows is the active *implementation* of the innovation and last, seeking information that *confirms* this decision. This study covers the knowledge and persuasion phases of diffusion of AI innovations preceding the ChatGPT hype (Hepp et al., 2023). These phases are particularly relevant because they mark the steps in which disruptive innovations are born, information about them is new and sought after, and first experiences are made, which influence the attitudes that people form about the technology and eventually their adoption. With the launch of ChatGPT3.5 in November 2022, the societal and media debate around AI started focusing on the utility of the innovation for everyday life, which, we argue, marks a shift from the persuasion to the decision phase that society entered after this event. An open question is whether public communication research on AI can be seen as a reflection of the knowledge of AI among societal members (Rice & Bucy, 2023). If research in these early phases is growing, this is a sign of increased knowledge generation on this innovation. Thus, we inquire:

RQ1: How has AI research in public communication developed during the first phases of adoption?

The academic AI agenda in communication science

Definitions of AI

AI may be defined either as a *field of study* with a specific aim or as a *qualifier* for a technological artifact. When considered a field of study, AI has been defined as an “activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.” (Nilsson, 2009, p. 13) or “the study of agents that receive percepts from the environment and perform actions.” (Russell & Norvig, 2016, p. viii). These definitions often relate back to the Dartmouth Summer Research Project on Artificial Intelligence in 1956—one of the founding events for the field—which proposed to make an attempt to “find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves” (McCarthy et al., 2006, p. 12).

Definitions for AI as a *qualifier* for a technological artifact may be considered more challenging than definitions of the field, not because of the notion of “artificial”, but rather because of the question of what might be considered to count as “intelligence” (Wang, 2019). In this sense, these definitions often refer to challenges that the artifact must pass for it to be considered intelligent. Turing’s (1950) imitation game is an often-used example, and reflective of a broader tendency of the field—and technology companies—of resorting to the performance of technological artifacts in games, including *Jeopardy*, chess or *Go*, as a way to create narratives about AI’s potential and what AI may be (Elish & boyd, 2018). Another definitional approach is to determine a minimum set of characteristics that a system may have for it to be considered an AI. The European Union’s AI Act defines an AI system as “a machine-based system designed to operate with varying levels of autonomy, that may exhibit adaptiveness after deployment and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments” (Artificial Intelligence Act, 2024, p. 167). Another twist in definitions of AI as a qualifier is to describe what AI *does*: “to perform, task solve, communicate, interact, and act logically as it occurs with biological humans” (Gil de Zúñiga et al., 2024, p. 320). This focus on performance, autonomy, and human likeness recurs in many application types of AI discussed in the following section.

Given the challenges in defining AI (Wang, 2019)—especially of what may *be* “an AI”—and the emergence of narratives, myths, and hypes regarding technology (Elish & boyd, 2018), it becomes important to understand what underlying assumptions public communication research has made when investigating AI. As such, we ask:

RQ2: How is AI defined in public communication research?

Applications of AI: *what* we discuss and *how* we discuss it

While most definitions about AI have been relatively general, another approach can be to zoom in on specific types of AI. Given the myriad of AI applications, it is important to have an overarching typology of uses and applications of AI. Schwartz (1989) observed the importance of context when considering AI and argued that—in some cases—people had different conceptualizations of what the word *intelligence* means when referring to artificial intelligence. On the one hand, people anthropomorphize AI applications in that they map their knowledge of human intelligence onto AI, implying that computational intelligence is akin to human intelligence (e.g., Troshani et al., 2021). On the other hand, human intelligence has also been described in computational terms, indicating that the way human intelligence works is comparable to the ways that computers and machines are intelligent (e.g., Cobb, 2020).

Given these framing connections between artificial and human intelligence, we approach the myriad of AI applications by considering the degree to which the AI application resembles a human communicator. On one end, we find AI applications using AI as a method (e.g., for data analysis in relation to public communication), which approach AI mostly as a machine. On the other end, we find AI applications that act as a communicator in public communication (e.g., chatbots), thus indicating that—like humans—AI applications can be communicative actors. There are also AI applications that combine machine-like and humanlike elements, such as generative AI (e.g., large-language models) which act both as a tool and generate (seemingly) creative new communicative content. Finally, some general AI applications combine two or more elements from these categories. This heterogeneity and multitude of AI applications studied in relation to public communication begs the question of how these applications can be grouped into AI types that share specific characteristics. This leads to:

RQ3: What types of AI research have been studied in public communication research?

While AI can be seen as a disruptive innovation and the policy recommendations may be biased toward an overly positive normative view (Bareis & Katzenbach, 2022; Cools et al., 2022), an important question is whether a similar pattern can also be perceived in research on AI in public communication. Recent research has revealed that communication-scientific research often has normative implications, yet these are not always visible or made explicit (e.g., Geise et al., 2022; Rothenberger et al., 2017). This might be linked to a general trend observed in computational communication science where only a minority of published studies include ethical considerations (Knöpfle et al., 2024; Xu, 2024). Therefore, various scholars have advocated for more research revealing whether and how communication-scientific research is built around normative assumptions (Geise et al., 2022; Knöpfle et al., 2024; Rothenberger et al., 2017). We take up this challenge for research on AI in public communication, and ask:

RQ4: To which extent is AI research in public communication normative?

Studying AI with different empirical approaches

Communication science, along with the broader social sciences, has witnessed a vivid discussion about the adequacy, validity, and reliability of qualitative versus quantitative empirical approaches to study communication phenomena and processes (Bryman, 2008; Lang, 2013). The social-scientific paradigm that relies on quantitative methods to test hypotheses of models and theories, mostly of mass communication, has been dominant within the field for decades (Lock et al., 2020). But within this paradigm, the focus on media-effects research and its consistently small effect sizes has evoked criticism resulting in an alternative line of research that refers to qualitative and humanistic methods and critical discussions of culture and communication (Lang, 2013). Since AI research encompasses STEM, social sciences, and the humanities, this quantitative versus qualitative divide might be present as well. When assuming that research on AI follows a similar development as research on previous technological innovations, AI research is likely to start off from more quantitative perspectives early-on and move toward more diverse perspectives in the long run (Kim et al. 2017; Walter et al. 2018).

Another distinction in AI research is that of AI applications as objects of study against AI systems employed to study communication phenomena, hence, AI as a method. Public communication research contains both approaches, as evident, for instance, by the widespread use of machine learning algorithms for content analysis (AI as method; Kroon et al., 2024; Peng et al., 2024) and the burgeoning research on AI applications such as conversational agents (e.g., Følstad et al., 2023). What perspective of AI research is dominant is a question yet to be explored:

RQ5: How has AI been studied methodologically in public communication research?

Method

Search Strategy

To gather an exhaustive set of research articles on AI and public communication, five social (PsycINFO, Communication & Mass Media Complete, Business Source Premier, SocINDEX, Worldwide Political Science Abstracts) and one computer (ACM Digital Library) science databases were accessed. The use of databases from different fields ensured that a diverse set of articles from different communication-science subfields was sampled and that articles on AI in public communication published in journals of other disciplines were captured as well. The search string was composed of two components, according to the overarching research question: (a) artificial intelligence and (b) public communication. For the former, "artificial intelligence" and its common abbreviations "AI" and "A.I." were used, for the latter, a combination of 16 different search terms that capture public communication (e.g., "coverage", "political communication" and "public opinion") was established by trial searching and consulting *PsychINFO*'s thesaurus until the search string was sufficiently refined to extract relevant articles. The search was conducted in the title, abstract, and keywords. The full search strings, adapted per database, are available in the Supplementary Material (OSF link), Chapter 2. In response to an anonymous reviewer comment, we additionally included a highly relevant article from the journal Human-Machine Communication, which was not listed in the six databases.

Sample

Data collection was carried out in two rounds on 24 June 2022 and 31 December 2022. After the removal of non-peer-reviewed publications and duplicates, the final sample consisted of 3,438 publications that were subjected to a two-step screening process to include only articles relevant to the research questions. Two authors narrowed down the sample by abstract screening of all articles, followed by a full-text screening of the remaining articles in the systematic review tool rayyan.ai (see Figure 1 for the PRISMA flow chart of the review; see also Page et al., 2021). For both steps, a list of include and exclude criteria on three dimensions was created: studies were included when they were (a) about AI or an application form of AI, (b) about public communication and (c) empirical. Empirical research referred to research that employed qualitative, quantitative or mixed-method designs (the complete list of include and exclude criteria can be found in Supplementary Material, Chapter 3). Systematic reviews, meta-analyses, theoretical papers, essays, and conceptual papers were excluded to facilitate a specific focus on how AI has been conceptualized in empirical research practice. To give an example, articles that were on an AI's interactive communication features and used an experimental design to test it empirically were included, while a contribution with a similar focus without an empirical test would have been excluded. Unclear cases were discussed between these two authors and then decided. The remaining 258 articles were subject to a full-text screening of one of the authors and a

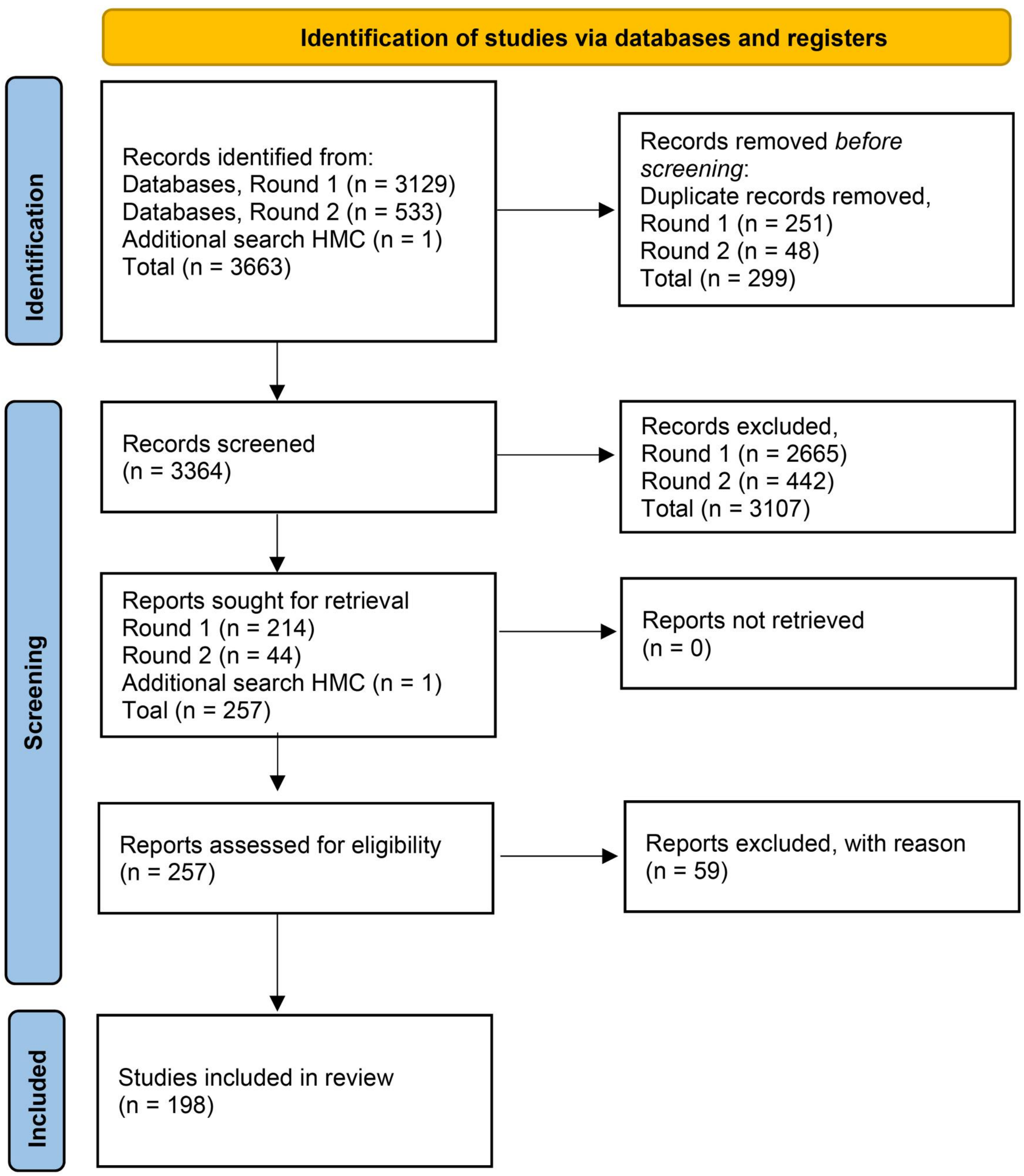

Figure 1. PRISMA flow chart.

coder. The final sample for the manual content analysis consisted of 198 articles (see Supplementary Materials, Chapter 7, for a reference list).

Coding procedure

The manual content analysis was carried out by one of the authors and an external coder. The complete codebook with examples and detailed coder instructions can be found in the Supplementary Material, Chapter 4. After an initial coder instructions meeting, four pretest rounds with respective additional meetings followed, and resulted in acceptable intercoder-reliability (ICR): Cohen's kappa scores were mostly perfect ($\kappa = 0.81$–1.00, eight variables), while three variables showed substantial agreement ($\kappa = 0.61$–0.80) and one variable was unsatisfactory ($\kappa = 0$, normativity; see Table A1, Appendix A; Cohen, 1960). Given the binary, nominal nature of the normativity measure and the low number of occurrences of the answer options, we additionally calculated percent agreement between the coders to assess ICR. This measure showed agreements ranging from 60% (one variable, normativity) and 80% (four variables) to 100% (eight variables). Because of these satisfactory reliability scores, the coding was then further carried out between December 2022 and May 2023.

Measures

The dimensions analyzed relate to our research interests outlined above. They were developed based on the research questions described, in order to map how the field of public communication research developed over time, and globally, in different disciplines and sub-fields. Moreover, they capture the studied types of AI and the respective methods.

Formal variables related to who is doing AI public communication research, with variables measuring (a) the journal (open answer), (b) the year of publication (open answer), (c) whether it was part of a special issue (yes/no), (d) the university (open answer) and (e) department (single-choice) affiliation of the first author (Freelon et al., 2023), and (f) the country of the first author's affiliation (open answer). Further, (g) the sub-field of communication research (single-choice) was included in order to map the field also from an (inter-)disciplinary perspective. These seven variables allowed for measuring potential global divides in AI research, and how the foci of disciplines and fields in the matter developed over time. They were measured based on the publications' meta-data and abstracts as units of analysis.

Content variables about the conceptualization of AI focused on the introduction section and theoretical framework of the publications as units of analysis. These variables measure the conceptualization of AI (inspired by the approach of Jensen, 2013), specifically (a) which type of AI has been studied (open answer), (b) whether (yes/no) and (c) how the type of AI has been defined (open answer), and (d) whether (yes/no) and (e) how AI as such has been defined by the respective authors (open answer). These five variables allow for analyzing what exactly is being studied in AI public communication research while also respecting differences in the level of precision when it comes to defining the broad terminology used.

Additionally, we measured the empirical conditions (Lock, 2019), with method sections as unit of analysis, and included questions to measure both the qualitative-quantitative differentiation and the respective methods. Specifically, we included variables on (a) whether a quantitative, qualitative or mixed-method design was chosen (single-choice), and on (b) which qualitative (e.g., interviews, qualitative content analysis) (multiple-choice) and (c) quantitative (e.g., automated content analysis, experiment) (multiple-choice) methods where used.

To gather more detailed insights into what exactly has been studied empirically, a variable on the unit of analysis was included that contained two items, (a) whether the unit of analysis was text, visual, audio or human subjects (multiple-choice), and when applicable (b) for the respective media content options (audio, video, text), whether the unit of analysis relates to literature, corporate communication, advertisements, news, social media or other (multiple choice). This thorough setup for measuring the empirical conditions of the publications allows for a fine-grained analysis of how the field developed methodologically over time.

The final block of variables about evaluations, with discussion and conclusion as units of analysis, included variables to measure whether the article's outlook perspective is normative (Rothenberger et al., 2017), that is, whether a normative statement has been made or not (yes/no).[1] Further, the coders copy-pasted the respective normative statements into an open field where applicable. This facilitates analyzing the evaluative stances taken in the publications (Geise et al., 2021).

Data analysis

The data were cleaned and structured with Python. This step included recoding the open-field answers of AI type, field and department into coherent categories. Whereas field and department led to very clear labels, the process for types of AI was more complex and required an inductive approach to identify unknown patterns in the data and to detect new lines of research, potentially unobserved in previous systematic reviews.

In two meetings, the authors discussed the groupings of the 198 different types of AI that emerged from the data (Appendix B). We finally agreed on a fourfold categorization that is informed by the literature review and covers AI as a communicator, AI as method, generative AI, and general AI as described earlier. The detailed process is outlined in the results section.

For data analysis, the cases over time and further descriptive outputs for relevant variables (including countries, departments, AI definitions, normativity and method), were computed as a basis for visualizations and inferential statistics. We mapped the frequency of cases, the frequency of cases across the globe visually, created an output of the AI definitions (see Appendix A, Table A2), visualized and measured the distribution of the different AI types and methods used and finally computed distributions of normative and prescriptive statements also in relations to other variables, centrally the different AI types.

Results

The sample consists of $N = 198$ articles from 2008 to 2022 with marginal numbers in the earlier years and a strong increase in publications especially since 2018 (Figure 2).

[1] We also coded whether the outlook perspective of the article is prescriptive, i.e., statements about how the future could or will be (yes/no). Yet, intercoder reliability for this variable resulted in Cohen's kappa of 0.62, which was considered too low for inclusion in this study.

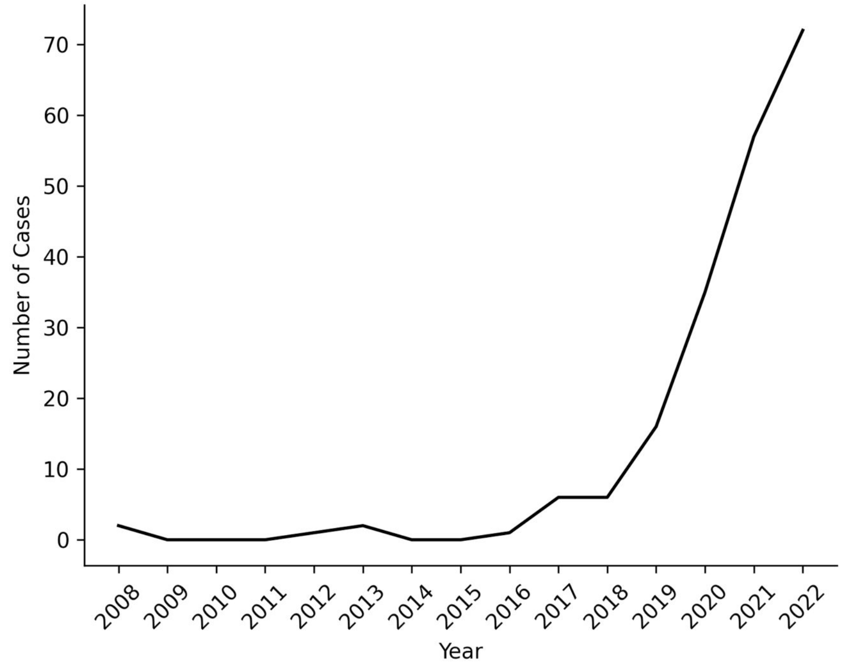

Figure 2. Cases over time.

RQ1: over-time development

Most articles ($n = 55$, 27.92%) came from communication departments, followed by informatics ($n = 40$, 20.30%) and business/management ($n = 24$, 12.18%). The journals show a similar pattern with seven studies each from *Communication Studies* and *Computers in Human Behavior* and five from *Journal of Computer-Mediated Communication*. The fields of research show that most publications were about entertainment communication ($n = 63$, 31.82%), journalism ($n = 47$, 23.74%), and corporate communication ($n = 33$, 16.67%). As Figure 3 shows, many studies were from the US ($n = 67$, 33.84%) and the EU28 ($n = 59$, 29.78%), less from Asia (China ($n = 20$, 10.10%), South Korea ($n = 8$, 4.04%), Singapore ($n = 5$, 2.53%), United Arab Emirates ($n = 4$, 2.02%), or India ($n = 3$, 1.52%)). Two stemmed from Latin America (Brazil, Colombia) and one from Africa (Eswatini). This indicates a Western-centric field, although with relevant contributions especially from East Asia.

RQ2: definitions

Only eleven studies (5.56%) explicitly defined AI. A central perspective employed in many of them regarded computers mimicking human behavior (e.g., Liu, 2021), as exemplified in the definition of Vu and Lim (2022): "the use of algorithms to make a computer perform complex functions that require human intelligence" (p. 1516). Furthermore, several authors do not provide explicit definitions of AI, but rather only list examples of what AI may be (Brennen et al., 2022; Lui et al., 2022). Others list different AI definitions, some of which are from different scientific fields, including linguistics, psychology and computer science, without choosing one, due to the complexity of the phenomenon and its diverse types (e.g., Noain-Sánchez, 2022). Finally, two studies differentiate between weak AI, capable of performing specific tasks, and strong AI that is able to perform complex tasks with intelligence that can be described as human-like (Natale & Ballatore, 2020; Vergeer, 2020). Table A2 in Appendix A lists all AI definitions of the analyzed sample.

RQ3: types

The applications of AI were grouped into types of AI. The creation of these types resulted from an inductive approach relating closely to Mayring's (2014) inductive category formation: The final categorization of types is the result of a process of reducing the coded applications of AI to overarching types of AI that were then discussed and finally decided between the authors during two meetings (for a detailed list of decisions see Appendix 2: Categorization of AI-Types).

The following typology resulted: AI types that relate to AI occupying a social role in communicative interaction, including human-AI communication, are part of the category "AI as communicator;" for example, "chatbots" and "digital assistants" such as Siri. Types of AI that are used to generate content as text, video or in another form, were coded into the category "Generative AI." Examples for this are "robotic reporter" and instances of ChatGPT, when it was used for generating content. The third category, "AI as method" incorporates all cases in which AI was used as a method for data analysis, or when a study tested an AI method empirically. Examples for such cases are "a holistic system for troll detection" and "machine learning." Finally, all rather unspecific conceptualizations of AI including those cases in which AI as such was analyzed, are part of the category "AI Generally".

We would like to emphasize that several different ways of grouping the openly coded AI applications would have been possible. Nonetheless, while not being the only solution, we think that this fourfold typology is apt for an initial mapping of the field and to showcase the major trends in AI research in public communication, especially in the light of the mentioned research patterns on previous digital innovation.

Turning to the distribution between the four types, the largest share of studies ($n = 73$, 36.87%) was about AI Generally, that is, naming "Artificial Intelligence," "AI Systems," "AI Generally." In 54 studies (27.27%), "AI as

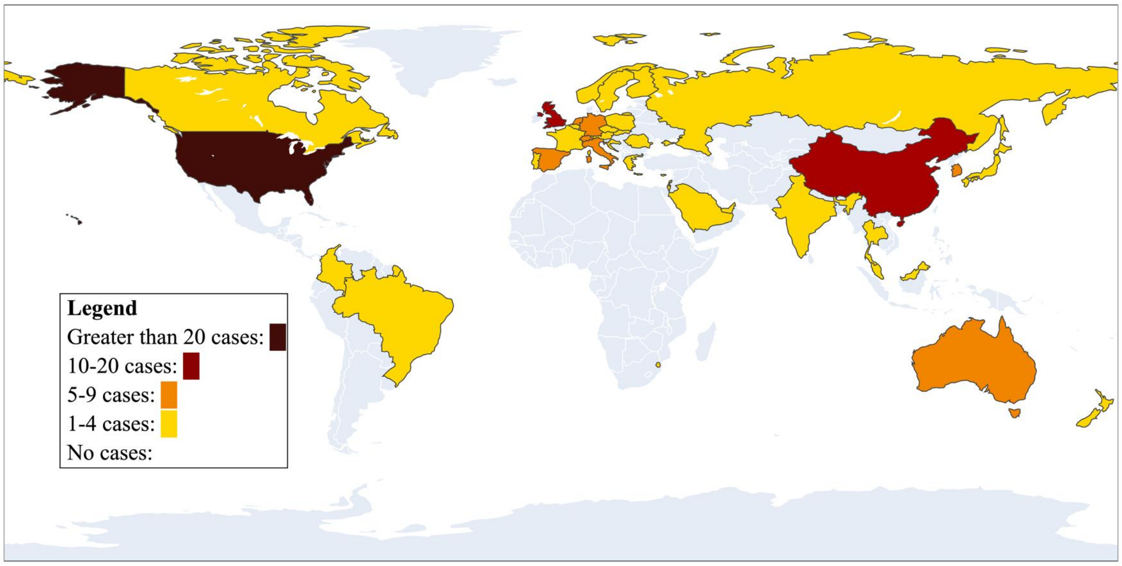

Figure 3. Frequency of public communication research publications on AI per country.

Communicator" was studied, thus AI types occupying a social role in communicative interaction (e.g., "chatbot," "smart speakers," "recommender systems"). Further, 42 publications (21.21%) were on types of AI to generate content including text, video, and images ("Generative AI"). Examples include "deepfakes," "automated journalism," and "AI-generated music." Finally, 29 studies (14.65%) were about types used as a method for data analysis and thus part of "AI as method" (e.g., "deep learning model," "face detection," "news analytic systems").

As for the over-time perspective, all four AI types gained more attention since 2018 and 2019 and grew in relevance for communication research ever since (Figure 4). In detail, however, the share of the different types relative to one another changed (Figure 4): Whereas the share of AI Generally and AI as Communicator rather remained constant relative to the absolute numbers, research on Generative AI increased relative to other types since 2019. Finally, absolute numbers of studies on AI as method were rather stable and therefore slightly decreased relative to the other types since 2019. Despite these differences between the types, over time, communication research about AI diversified. The frequencies per year per type are also shown Table A3 in Appendix A.

RQ4: normativity

Moreover, the articles were analyzed in terms of their evaluation of AI. 72 studies (36.36%) contained normative statements in the discussion or conclusion section. Studies on AI Generally tended to be normative (46.58%), whereas studies on AI as a method were least normative (24.14%; Table 1). The association between type and normativity was found to be non-significant, χ^2 (3, 198) = 6.29, p = .098).

RQ5: methods

Turning toward methods used, a focus on quantitative studies (n = 138, 69.7%) in contrast to qualitative (n = 48, 24.24%) and mixed method studies (n = 12, 6.06%) is apparent. All methods gained in importance over the years, with the field diversifying at least in absolute numbers, with, however, a dominance of quantitative approaches. This gap is constant over time (Figure 5). A closer look at the different forms of quantitative studies shows that surveys and experiments were most frequently employed, whereas content analyses, especially manual ones, decreased in importance since 2020 (Figure 6). The trend towards surveys and experiments over time is reflected in the patterns of the units of analysis: there was a strong increase in the focus on subjects, who were the unit of analysis in 113 studies (57.07%). Other units of analysis remained constant or increased only marginally: Communication content (text, image/video, audio) was present 79 times (39.89%), whereas subjects and communication content were analyzed together in the same study in six occasions (3.03%).

A closer look at the different qualitative and quantitative methods further reveals a focus on research with human subjects, as is apparent in the frequency and strong increase of studies using experiments, surveys and interviews (Figure 6a and b). This is supported by the findings on the units of analysis. Qualitative studies were mostly interviews, followed by content analyses, with discourse analyses remaining constant in absolute numbers over time (Figure 6a).

Discussion

As a disruptive technological innovation, AI has entered the public and media debates (Cools et al., 2022; Fast & Horvitz, 2017). Our results demonstrate that, since 2018, AI has increasingly been researched in relation to public communication. Given the steep increase in the number of studies published on AI in public communication in just four years (from 6 in 2018 to 72 in 2022), AI can indeed be labelled as a disruptive innovation spreading across the phases of early adoption (Barbour et al., 2023; Rogers, 2003).

Innovations such as mobile communication and the Internet showed a pattern where research moves from more general inquiries to become more detailed on specific phenomena over time (Kim & Weaver, 2002; Kim et al., 2017). In the early phases of adoption reviewed here, most studies addressed AI in an unspecified, general sense. Research reflects technological AI developments, as generative AI is being increasingly investigated, leading up to the publication of ChatGPT that marks a turning point (Hepp et al., 2023).

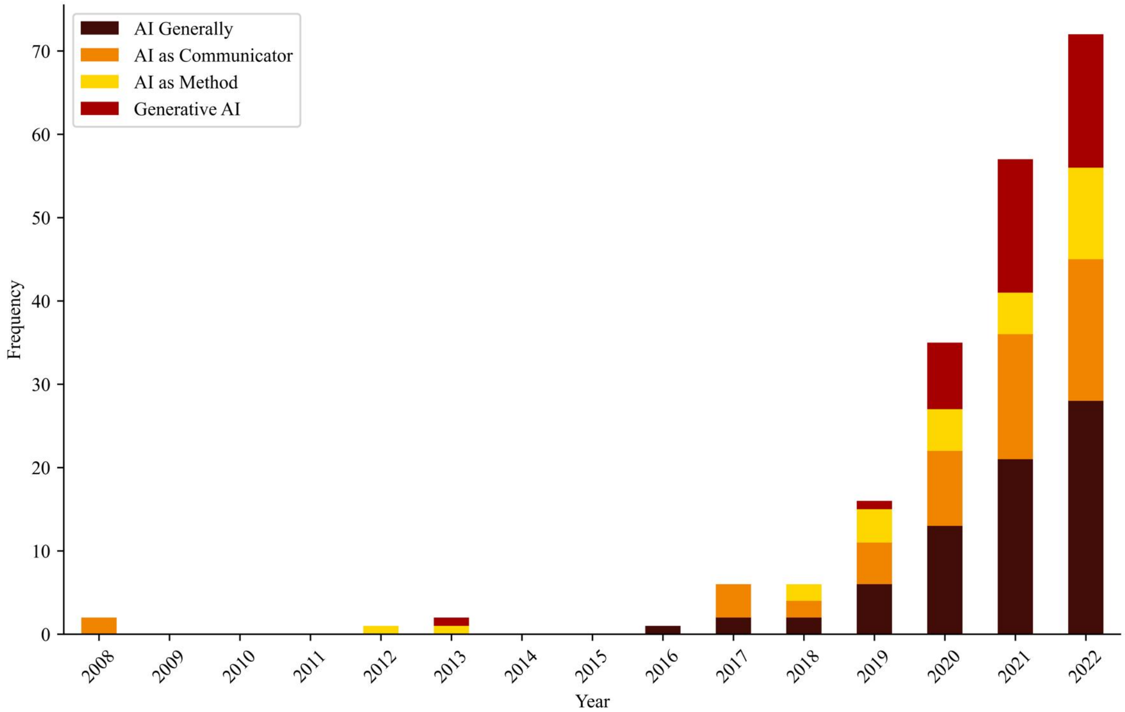

Figure 4. Frequency of AI types over time.

Table 1. Normativity per Type of AI.

Type	Not normative		Normative		Total
	n	%	n	%	*n*
AI Generally	39	53.42	34	46.58	73
AI as Communicator	35	64.81	19	35.19	54
Data Analysis/Method	22	75.86	7	24.14	29
Generative AI	30	71.43	12	28.57	42
Total	126	63.64	72	36.36	198

However, the application of AI as a method is slightly decreasing. Yet, the latter should be interpreted with caution. While studies on generative AI will name AI explicitly, researchers who apply AI as a method or review such studies might, with increasing experience, start (demanding) naming the method explicitly, and drop the AI-label (e.g., natural-language processing instead of AI in article keywords).

With the broad and interdisciplinary approach of this review that aimed to capture empirical AI research on public communication also from outside communication science, similar patterns emerge as these studies are comparatively uniform in terms of methods, geographic origin, and subfields (Walter et al., 2018). AI is mostly investigated through quantitative methods, with a dominance of research with recipients. This is evident by the dominance of surveys and experiments, over content analyses, given the decrease in manual and automated content analyses over time. Qualitative studies show a balanced analysis of communication contents (qualitative content and discourse analyses) and subjects (interviews). Thus, people's interaction with, and attitudes toward AI seem to be central in public communication research on AI rather than content about it. This is especially interesting given the many publications about journalism in the sample that mostly seem to concentrate on news audiences. Most of the sampled studies have been conducted in institutions from English-speaking countries, with the US in the lead, even though China is among the follow-up countries. Underrepresented are South America and Africa, along with the Middle East and Central Asia. This reflects the Western focus of the communication science discipline and the rise of Chinese scholarship (Demeter, 2019).

But unlike communication science that is much concerned with explicating phenomena (Chaffee, 1991), research on AI in public communication often fails to define what AI is, given that only a fraction of the studies provided an explicit definition. It might be that authors consider the overarching term of AI as being less relevant to define than the specific AI type being studied, just as communication researchers oftentimes do not define central concepts such as "the public", even though there are myriad understandings of what they mean (Pieczka, 2019). Particularly when innovations such as AI are novel and in the early phases of adoption (Rogers, 2003), the concept is being interpreted, negotiated, and reconstructed both in public discourse and research. Thus, on the one hand, AI appears to continue being used as a buzzword (Ekbia, 2010; Leufer, 2020). On the other hand, researchers start making sense of AI by referring to the specific AI types they are studying, such as bots or news recommenders, and place them all under the AI label. For instance, whether smart speakers (Poushneh, 2021) or web-based homework (Palocsay & Stevens, 2008) will be considered and labelled as a type of AI in a few years, is open to debate.

It is clear that defining AI is challenging (Wang, 2019), but not explicating AI opens the door for even more AI myths and hypes (Elish & boyd, 2018; Weller & Lock, 2025). Proposals have been made more recently (after the sampling period) that have foremost described AI in terms of what it does and how autonomous it is (Gil de Zúñiga et al., 2024). A point of discussion is whether AI needs to be "tangible," as this definition proposes. The applications from this sample of AI studies in public communication also show intangible applications, across all four AI types: for example, machine

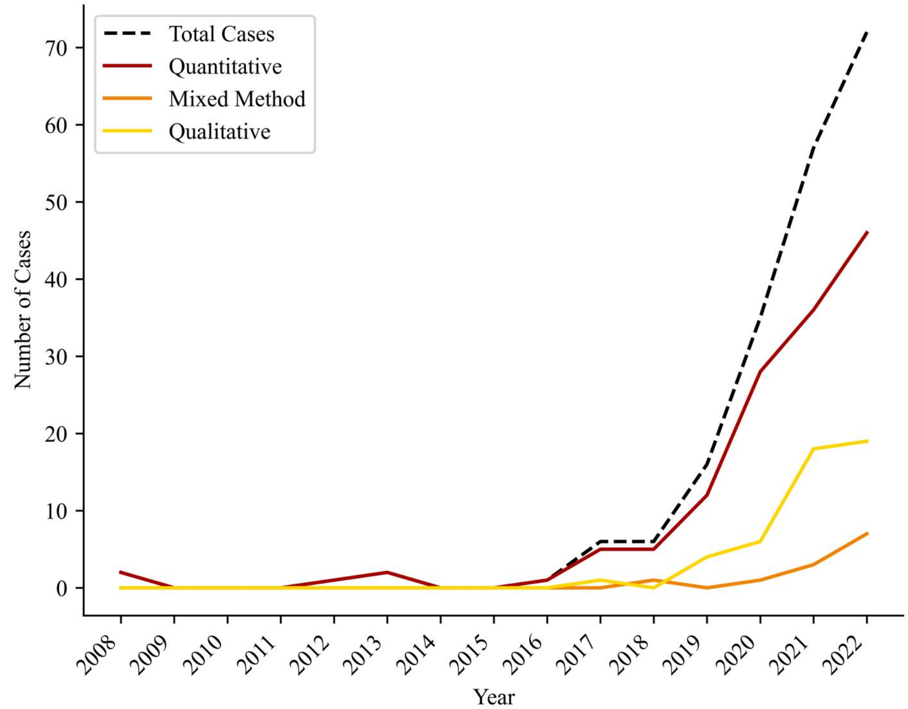

Figure 5. Frequency of methods over time.

learning (AI as method), generative pretrained language models (Generative AI), recommender systems (AI as communicator), and AI generally. The empirical utility of AI definitions, thus, is subject to constant discussion and testing, and may also depend on the type of AI being studied in different settings (e.g., contrast research on AI-mediated communication between an individual and an AI agent with research on societal-level effects of AI adoption across specific industry sectors). More important is that researchers put forward a definition of what they study to enable such conceptual explication and comparison (Chaffee, 1991). In this communication process, the goal posts that demarcate what counts as AI and what not, are continuously shifted. One way to further understand this shift may be through the in-depth analysis of critical and conceptual papers on the topic of AI within public communication, which should be addressed by future research.

The typology of AI types proposed here is oriented toward the human versus machine resemblance of AI (Cobb, 2020), next to instances where AI is studied in general. Thus, we find AI applications that resemble a human communicator, such as a robot journalist (e.g., Vergeer, 2020) or a chatbot (Cheng & Jiang, 2020). But there are also applications where AI is considered a method for data analysis such as face-detection algorithms (Kou et al., 2022). Other systems inherit both the generative and communicative functions of AI. Examples include generative communication applications such as large language models that interact with humans in the communication process (e.g., Yuan et al., 2022).

Note that this is but one attempt to find a way through the different AI trees in the dark forest. Our approach describes rather broad types that mimic the communication process (who sends and who creates content) and proposes an anthropomorphic view of AI (Troshani et al., 2021). Another approach would be to aggregate types of AI more narrowly according to the field of application, i.e., social-media bots, news recommenders, or art generation. Yet, the disadvantage is that many AI types can be employed in multiple application contexts: an image generator, for instance, can generate artistic, financial, and stock images. Of course, the labels employed for typologies should also be scrutinized (see Beukeboom & Burgers, 2019). For the AI as communicator category, we also considered Human-AI communication, communicative interaction, or AI occupying a social role in communicative interaction. Yet, all these terms are related to other concepts existing in the field: human-AI communication comes very close to human-computer interaction and is a neighboring field of study. When referring to AI generally, we also discussed unspecified AI or generalist AI as alternatives, but refrained from these as they do not always capture what the studies in this category were about: namely, testing perceptions of AI generally (e.g., Gregor & Gotwald, 2021), different labels (Langer et al., 2022), or its acceptance (Shin, 2021; Vu & Lim, 2022). Thus, the typology of AI types is but one proposal of how to categorize the many applications of the technology we observe now and might encounter in the future.

The public sentiment around AI regarding media coverage but also policy positions has been described as rather positive (Bareis & Katzenbach, 2022; Cools et al., 2022; Fast & Horvitz, 2017). Communication science, too, is oftentimes normative and researchers have called to address such assumptions explicitly (Geise et al., 2022; Rothenberger et al., 2017). Particularly in value-laden fields such as AI (Bourne, 2019; Elish & boyd, 2018), the normative conclusions drawn from research are important to uncover as they might affect public discussions of the technology. Yet, it has also been noted that communication research that applies computational methods (some of which might be labelled as AI) hardly refers to ethical considerations (Knöpfle et al.,

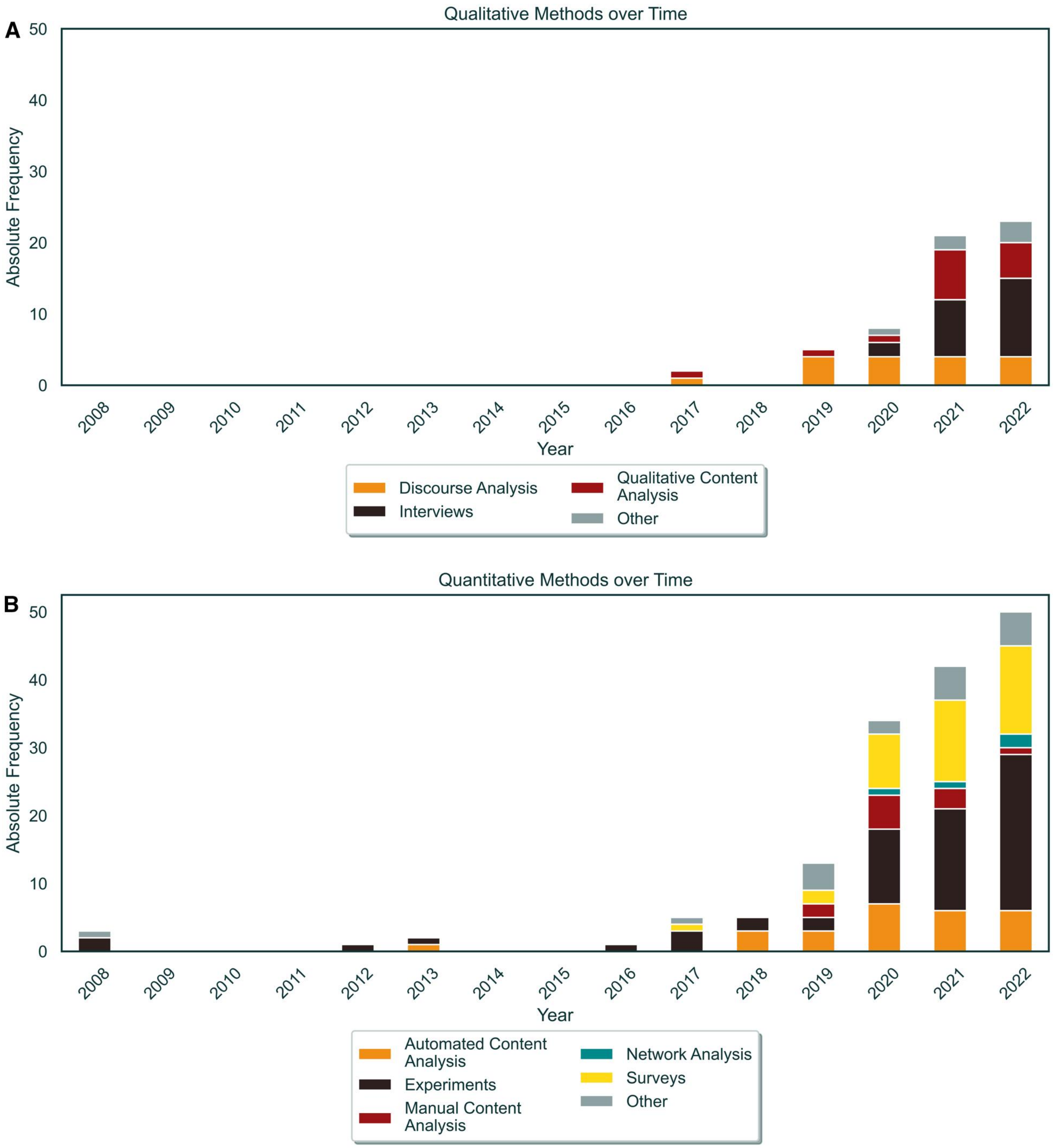

Figure 6. Frequency of quantitative and qualitative methods over time, stacked.

2024). And we found a similar pattern: Most of the studies on AI in public communication did not formulate normative implications, which is lower compared to communication science articles in general (Geise et al., 2021). Yet, this comparison needs to be interpreted with caution as Geise and colleagues looked at the entire article for normativity and employed a much more sophisticated measure, while our unit of analysis concerned the discussion and conclusion sections only and is based on one variable. A more complex measure with multiple indicators might be better suited to uncover details about normativity in public communication research on AI.

Further, our results on normativity do not show a significant association between the presence of normativity statements in the discussion and the type of AI being researched. Nonetheless, we do note a general trend in which articles in the category AI Generally seem to have the most normative statements (47%) when compared to the other categories, which might be related to the broader scope of this category—focused on AI in general, at times with a societal scope. Some authors focused on implications of artificial intelligence for communication professionals and their awareness of the risks of AI and their competences for using AI (Zerfass et al., 2020). Others addressed how news outlets frame AI with an emphasis on risks and benefits (Chuan et al., 2019) and possible implications of AI for the elderly among others (Nagano, 2022). Studies on AI as a method, in contrast, were less concerned with societal implications but often focused on functionality. Those studies, for instance, emphasized the technical challenges of how to detect rumors automatically online (Osho et al., 2020), or of how to improve automated subtitling (Soe et al., 2021). Given their narrower, methodological scope, these studies may thus be more focused on explaining a method than reflecting on its normative implications. We thus tentatively observe that rather technical AI studies in public communication research contain comparatively little normativity, next to those that are concerned with (normative) societal implications. This may be related to the tendency of computational communication science research to lack explicit mentions of ethical considerations (Knöpfle et al., 2024). That said, these differences should be interpreted with caution given the lack of significant associations.

Blind spots and future research

Our study revealed several blind spots in the study of AI in the communication field (Table 2) that call for future research.

First, we observe a geographic discrepancy in the countries in which research on AI in public communication has been conducted. Particularly research from countries in the Global South (e.g., parts of Africa and Latin America) hardly finds its way into the English-language communication literature. It could be that such research has been conducted and published in non-English-language journals. Nevertheless, we call for more research on the topic of AI in public communication across the globe, especially in countries from the Global South and studies that take a cross-cultural perspective. Such studies could reveal which public communication dynamics are universal across various geographic areas and which are unique to a specific national and/or cultural context to identify patterns of AI research across the globe. Practically, such research can be facilitated by international research collaborations with scholars from underrepresented world regions. Alternatively, studies that inquire public perceptions of AI could strategically sample (online) participants from these countries. Steadily improving automated translation algorithms will allow for including media contents from different languages and facilitate comparative research.

Second, we find a discrepancy in AI definitions used within the literature and compared to lay definitions of AI in public discourse. Future research can explore this dynamic further by investigating and contrasting expert and layperson perspectives on what can be seen as AI across stakeholder groups and application areas. Such research can provide important insights in how a crucial term as AI travels through academic and societal fields and may thus attract different meanings in different contexts for different groups. With the public salience and widespread use of large language models, it might be that lay people in the future will associate AI predominantly with these applications.

Third, we also detect some blind spots in the study of different AI types with a relatively large number of studies focusing on general applications of AI. Given that it can be expected that AI will develop exponentially over the coming years (in light of the increase of studies observed by us and similar research patterns for previous disruptive media innovations; Barbour et al., 2023), and many new applications of AI may be developed and identified in the future, we recommend that scholars are specific about the AI types that they investigate. We noticed that, currently, many communication studies discuss the concept of AI, yet—on closer inspection—focus on a wide variety of applications and uses of AI. It will help future research to build on these findings to be more specific about the type of AI and the application of AI studied in a specific context. This can help other scholars to easily see the opportunities and limitations of their projects and allow studying state-of-the-art trends in the field.

Fourth, we did not focus on the theoretical depth with which AI was discussed and integrated into communication-scientific theory. Nevertheless, we recommend that future research on this topic actively connects AI research to important communication theories and paradigms. This challenge can be approached from three distinct ways. First, scholars can use or update classic theories of computer-mediated communication such as the MAIN model (Sundar & Flanagin, 2008) and further developments specifically focused on AI interaction such as the HAAI-TIME (Sundar, 2020) or the Computers Are Social Actors (CASA) paradigm (Nass et al., 1994; Reeves & Nass, 1996) which has received calls for updates and further conceptualization in the current environment (Gambino et al., 2020; Lombard & Xu, 2021; see also Dehnert & Mongeau, 2022, for an example of this approach). Second, scholars can take classic models that were developed outside of a computer-mediated communication context to explore communication through and with AI. Theories on anthropomorphism (Epley et al., 2007), figurative framing (Burgers et al., 2016), and conceptual

Table 2. Five blind spots of AI research in public communication and their implications for future empirical studies.

#	Issue	Blind spot	Future research implications
1	Global scope	Large majority of current studies in the field conducted in the Global North	Foster research focusing on understudied cultural contexts (e.g., Global South)
2	Definition of AI	Inconsistency and discrepancies of AI definitions in lay and academic terms	Research perceptions of what AI is and entails across different groups of people (also combined with #1, across different cultural contexts), and outline definitions in future studies about AI
3	Types of AI	Large number of studies concerned with AI in general, few are specific about what type of AI they study and why it is considered AI	Study upcoming trends of AI and critically reflect if and why a specific communication setting and application is AI
4	Theoretical depth	Lack of AI theory for public communication research	Explicitly relate empirical studies to current communication theory or developed new theory to explain types of AI and their role in the communication process
5	Normativity and ethics	Ethical considerations and normative implications of empirical AI research are under-reflected	Learn from AI ethics and adapt existing guidelines for the empirical study of AI phenomena in public communication

metaphors (Lakoff & Johnson, 1980) each provide valuable insights to determine when speakers do or do not assign specific human qualities to AI applications they interact with. Actor-network theory (Latour, 2005), or, at a macro-level, complex systems approaches (Lock, 2023), are non-anthropomorphic theories that help describe and explain AI-related communication processes in public communication (Weller & Lock, 2025). Third, scholars can strive towards developing new theories that place human-AI interaction center stage. Theoretical perspectives that emphasize AI-mediated communication (e.g., Hancock et al., 2020) provide a fruitful avenue here. In that way, our community can clearly identify in which ways AI aligns with and deviates from other communication media in usage and effects.

Fifth, the discussion of ethical implications of AI types and their role in public communication is rather shallow in empirical studies. There is a tendency to sideline discussions on ethics and normativity for studies that focus on methods and use AI for data analysis. Yet, there is a burgeoning debate in the field of applied ethics that is concerned with AI specifically, including specialized journals (e.g., *AI & Society;* Xu, 2024). It is eminent to include their guidelines and considerations for empirical research in public communication, if not to develop our own adapted ethical principles to demarcate goalposts of what is right and wrong in AI research in public communication. One potential place to start is in translating and operationalizing principles found in AI ethics guidelines—such as transparency, justice and fairness, non-maleficence, responsibility, and privacy (Jobin et al., 2019) – specifically for the field of public communication. To end with a normative claim, the stakes of the technology are on the one hand too promising and on the other hand too high to ignore the ethical implications that AI has for research and society.

Supplementary material

Supplementary material is available at *Annals of the International Communication Association* online.

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Conflicts of interest

None declared.

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[2] Publications that are part of the sample of our systematic review are marked with an asterisk*. The full list of included articles is available in the supplementary material, Chapter 7.

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Appendix

Appendix A

Table A1. Intercoder-reliability.

Variable	Variable Name	%-Agreement	Cohen's Kappa
FV_04	University Affiliation of 1st Author	100	1
FV_05	Institutional Affiliation of 1st Author	80	0,736
FV_06	Country Affiliation of 1st Author	80	0,884
FV_07	Field of Communication Research	80	0,773
CO_01	Type of AI	60	0,5
CO_02	Definition of the Type of AI	100	1
CO_03	Definition of AI	100	1
EC_01	Method	100	1
EC_02	Qualitative Analysis/Study	100	1
EC_03	Quantitative Analysis/Study	100	1
EC_04	Unit of Analysis	100	1
EC_05	Unit of Analysis Specific: Text	100	1
EV_01	Prescriptive	80	0,615
EV_02	Normative	60	0

Table A2. AI definitions.

Definition	Reference
Taking these different definitional approaches into account, AI can, in our understanding, be described as flexible decision-making processes and actions of software-driven agents. They adapt to changing goals and unpredictable situations, learn from experience, aim for rationality, but also carry on in spite of perceptual and computational limitations. AI is based on technologies like natural language processing, data retrieval and knowledge representation, semantic reasoning, and machine learning.	Zerfass et al. (2020)
Strong AI', in Searle's view, purports to devise general, human-like intelligence. 'Weak AI', on the other hand, aims at creating highly specialized tools that mimic specific cases of intelligent human behavior (Searle, 1980; Haugeland, 1985) labelled the Strong AI approach 'Good Old-Fashioned Artificial Intelligence', which dominated the field until the 1970s. While weak AI applications are ubiquitous and go largely unnoticed, the AI myth emerged around the possibility of strong AI. In the magazines considered in our case study, the emergence of AI was discussed as an innovation that promised not only exciting applications but also drastic changes in the relationship between humans and machines.	Natale and Ballatore (2020)
AI, however, is a fairly broad concept that refers to the use of algorithms to make a computer perform complex functions that require human intelligence (Kurzweil, 1990; Russell and Norvig, 2010). According to Nilsson (2009, p. 13), AI is an 'activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment'	Vu and Lim (2022)
As a general term, AI refers to computer systems that perform tasks that usually require human intelligence; (Mueller and Massaron, 2021). AI is specifically referred but not limited to different types of technologies, such as expert systems, natural language processing, virtual/intelligent agents, robotic process automation, speech recognition and machine vision, artificial natural networks, etc. Moreover, AI is commonly regarded a disruptive technology since it can disrupt operations in different industries, including agriculture (Bannerje et al., 2018), manufacturing (Benotsmane et al., 2019), banking (Fethi and Pasiouras, 2010), and healthcare (Fan et al., 2020; Jiang et al., 2017).	Lui et al. (2022)
Social bots, i.e. code functions which operate as human accounts, proceed with *automated actions that resemble those that people would do* [1],	Kouvela et al. (2020)
Nilsson states "artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment" (as cited in Stone et al., 2022). Russell and Norvig (2019) organized the concept into four categories: thinking humanly, acting humanly, thinking rationally, and acting rationally, again, focusing on human-like thinking and rationality as the essence of AI. Scherer (2016) defined AI as machines that are "capable of performing tasks that, if performed by a human, would be said to require intelligence." Rich (as cited in Dirican, 2015) defined the field as "scientific studies that computers can think, do, interact and act in many fields as a human that people are good at." Dilek, Cakır, and Aydın (2015) described AI in two ways: (a) as a science that aims to discover the essence of intelligence and develop intelligent machines; or (b) as a science of finding methods for solving complex problems that cannot be solved without applying some intelligence (e.g., making right decisions based on large amounts of data). Various definitions essentially emphasize the main characteristics of AI as making computers do the sorts of things that minds can do (Boden, 2018).	Ahn and Chen (2022)

(continued)

Table A2. (continued)

Definition	Reference
AI was defined as the science of making a machine behave "in ways that would be called intelligent if a human were so behaving" (Russell and Norvig, 2019). According to Beckett, AI encompasses a collection of ideas, technologies, and techniques related to the ability of computer systems or software to perform tasks that normally require human intelligence (2019). To fulfil those tasks, these cognitive technologies make use of two basic attributes: (a) autonomy, and (b) the capacity to learn from experience. Since it appears to mimic human "intelligence," the adoption of AI provokes distrust and hostility. And as a consequence of the openness and ambiguity of the term, its introduction gives rise to more doubts than certainties. Furthermore, the umbrella of AI covers such subfields as machine learning, supervised learning, unsupervised learning, natural language generation (NLG) or natural language processing (NLP). All of them, though referred to as "AI," draw on different attributes and show different capacities	Noain-Sánchez (2022)
Most classifications of AI at least distinguish between narrow AI (weak) and general (strong) AI. Narrow AI can perform delineated specialized tasks very well and acts like it thinks, while strong AI can think (Searle, 1980). Although some people raise concerns about general AI (Baidu Forum, 2015), it is still not well developed.	Vergeer (2020)
Rather than a single technology, AI is a loosely defined set of algorithms, techniques, and technologies that offer a powerful 'mathematical method for prediction' (Broussard, 2018: p. 32).	Brennen et al. (2022)
Artificial intelligence (AI), defined as machines that can perform tasks that require human intelligence (Turing, 1950), has been widely deployed to make decisions for humans.	Liu (2021)
Generally, artificial intelligence refers to "the study of agents that receive percepts from the environment and perform actions" (Russell and Norvig, 2010, p. viii).	Johanssen and Wang (2021)

Table A3. Types of AI over time.

Year	AI generally	AI as communicator	Data analysis/method	Generative AI
2008	0	2	0	0
2009	0	0	0	0
2010	0	0	0	0
2011	0	0	0	0
2012	0	0	1	0
2013	0	0	1	1
2014	0	0	0	0
2015	0	0	0	0
2016	1	0	0	0
2017	2	4	0	0
2018	2	2	2	0
2019	6	5	4	1
2020	13	9	5	8
2021	21	15	5	16
2022	28	17	11	16

Appendix B. Categorization of AI applications into four types

Category 1: AI as method applications (Use of AI as a method for data analysis OR Testing an AI method)

Clear cases:

"machine learning", "a machine learning approach", "ml models", "machine learning algorithms like lda model", "deep learning model", "a multi-layer neural network model through integrating lstm and cnn to improve the performance of sentiment recognition", "news analytic systems", "natural language processing (nlp) techniques", "computational linguistics (cl) associated with the internet of multimedia things (iomt)", "decision support applications of ai", "credibility indicators, possibly generated by an ai model, is one way to help people combat misinformation", "face detection, face recognition", "a holistic system for troll detection", "big data analytics, ai", "Artificial intuition"

Less clear cases:

1. "semantic technology"

Title: "Applying semantic technology to business news analysis."

Reason: testing an AI method

Text-passagee: "An interdisciplinary method combining financial textual data mining and ontology-based reasoning is proposed and evaluated. The experiments are performed using a well-known Cyc ontology and textual material from the financial domain. Our experiments show that using semantic technologies for business news analysis helps to provide the user with more relevant answers to his/her queries."

2. "a plugin for detecting and reducing the spread of fake news and misinformation on the web"

Title: Check-It: A Plugin for Detecting and Reducing the Spread of Fake News and Misinformation on the Web

Reason: testing an AI method

Text-passage: "In this work, we present Check-It, a system that combines a variety of signals into a pipeline for fake news identification. Check-It is developed as a web browser plugin with the objective of efficient and timely fake news detection, while respecting user privacy. In this paper, we present the design, implementation and performance evaluation of Check-It. Experimental results show that it outperforms state-of-the-art methods on commonly-used datasets."

3. "algorithmic programme for suicide prevention"

Title: The Googlization of Health: Invasiveness and corporate responsibility in media discourses on Facebook's algorithmic programme for suicide prevention.

Reason: the AI is a form of data analysis

Text-passage: in this paper I report on a case study of Facebook employing AI for suicide prevention, moving beyond Facebook's justifications only to study the ways in which media commentators and their audiences discussed Facebook's programme and the values they saw as being at stake. In the results, I show how invasiveness was, in different ways and forms, a main theme in thinking about Facebook using AI to do suicide prevention.

4. "ai creativity system"

Title: Using an AI creativity system to explore how aesthetic experiences are processed along the brain's perceptual neural pathways

Reason: Testing an AI method

Text-passage: "Our lab has developed one such AI creativity deep learning system that can be used to create artworks in the form of images and videos. In this paper, we describe this system and its use in studying the human visual system and the formation of aesthetic experiences. Specifically, we show how time-based AI created media can be used to explore the nature of the dual-pathway neuro-architecture of the human visual system and how this relates to higher cognitive judgments such as aesthetic experiences that rely on these divergent information streams"

5. fake news using artificial intelligence

Title: Investigating the emotional appeal of fake news using artificial intelligence and human contributions.

Reason: AI as a method to analyse data (presence of fake news)

Text-passage: "automated tools, such as artificial intelligence (AI) algorithms, to support managers in identifying fake news. The study in this paper demonstrates how AI with its ability to analyze vast amounts of unstructured data, can help us tell apart fake and real news content. Using an AI application, this study examines if and how the emotional appeal, ie, sentiment valence and strength of specific emotions, in fake news content differs from that in real news content."

6. 'modelling online debate'

Title: Modelling online debates with argumentation theory

Reason: AI for data analysis

Text-passage: After summarising the relevant ideas of argumentation theory, we overview three recent contributions from the authors and their collaborators: (1) on how to automatically identify reply polarity (agreement or disagreement) between arguments submitted in online debates, (2) on locating where the justified arguments are likely to be and how that depends on the"degree of antagonism" of the debate, and (3) on how to present the arguments made in debates such that a reader would get as many of the justified arguments as possible without having to read the entire debate. We hope that this will lead to further work that applies argumentation theory to model and analyse online debates.

7. socialbots

Title: Socialbots on Fire: Modeling Adversarial Behaviors of Socialbots via Multi-Agent Hierarchical Reinforcement Learning

Reason: testing an AI method empirically

Text-passage: the adversarial nature of these socialbots has not yet been studied. This begs a question "can adversaries, controlling socialbots, exploit AI techniques to their advantage?" To this question, we successfully demonstrate that indeed it is possible for adversaries to exploit computational learning mechanism such as reinforcement learning (RL) to maximize the influence of socialbots while avoiding being detected.

8. social bots

Title: Social bots and the spread of disinformation in social media: The challenges of artificial intelligence.

Reason: testing a tool

Text-passage: Drawing from the actor-network theory (ANT), this study investigates human and non-human actors' roles in social media, particularly Twitter. We use text mining and machine learning techniques, and after applying different pre-processing techniques, we applied the bag of words model to a dataset of 30,000 English-language tweets. The present research is among the few studies to use a theory-based focus to look, through experimental research, at the role of social bots and the spread of disinformation in social media. Firms can use our tool for the early detection of harmful social bots before they can spread misinformation on social media about their organizations.

9. 'platforms' artificial intelligence'

Title: Can Social Media Listening Platforms' Artificial Intelligence Be Trusted? Examining the Accuracy of Crimson Hexagon's (Now Brandwatch Consumer Research's) AI-Driven Analyses.

Reason: testing the performance of an AI method against human coders

Text-passage: "this study seeks to provide greater understanding of the strengths and weaknesses of SMLPs by assessing the AI-based results of leading SMLP Crimson Hexagon (now Brandwatch Consumer Research) against those of a standard human content analysis and an analysis conducted using Linguistic Inquiry and Word Count (LIWC). Analyzing a random 10,000-post sample of the conversation around the Nike "Dream Crazy" ad featuring Colin Kaepernick, findings reveal Crimson Hexagon's AI tools to be woefully unreliable in terms of brand identification as well as detection of post and brand sentiment polarity, specific emotions, and brand outcomes, demonstrating the hazards of blindly relying upon conclusions drawn from black-box social media listening platforms."

10. news recommendations

Title: Top-N news recommendations in digital newspapers.

Reason: they test their model

Text-passage: We present two probabilistic models based on latent variables that recommend relevant news to users according to profiles of their visits to the newspaper website. As input, the models consider news content and categories, according to a predefined classification, of those news previously accessed. The experimental results show good performance with respect to baseline models in a data set of news extracted from a digital journal edition.

11. automatic emotion recognition (er)-enabled wellbeing interventions

Title: Data Subjects' Conceptualizations of and Attitudes Toward Automatic Emotion Recognition-Enabled Wellbeing Interventions on Social Media

Reason: testing the performance of automatic ER-enabled wellbeing interventions

Text-passage: Automatic emotion recognition (ER)-enabled wellbeing interventions use ER algorithms to infer the emotions of a data subject (ie, a person about whom data is collected or processed to enable ER) based on data generated from their online interactions, such as social media activity, and intervene accordingly. The potential commercial applications of this technology are widely acknowledged, particularly in the context of social media. Yet, little is known about data subjects' conceptualizations of and attitudes toward automatic ER-enabled wellbeing interventions. To address this gap, we interviewed 13 US adult social media data subjects regarding social media-based automatic ER-enabled wellbeing interventions. We found that participants' attitudes toward automatic ER-enabled wellbeing interventions were predominantly negative.

12. news recommender systems

Title: Being Diverse is Not Enough: Rethinking Diversity Evaluation to Meet Challenges of News Recommender Systems

Text-passage: Recommender Systems (RS) in particular, on the emergence of these extreme behaviors. Diversity in News Recommender Systems (NRS) was quickly perceived as a major issue for the preservation of a healthy democratic debate. However, after more than 15 years of research in Artificial Intelligence on the subject, the understanding of the real impact of diversity in recommendations remains limited. Through a case analysis on the well-known MIND dataset, we propose a critique of the diversity-aware recommendation and evaluation approaches, and provide some take-home messages related to the need of adapted datasets, diversity metrics and analytical methodologies.

13. hidden ai-driven algorithms

Title: Helping Users Tackle Algorithmic Threats on Social Media: A Multimedia Research Agenda

Reason: testing AI-methods

Text: We investigate how multimedia researchers can help tackle these problems to level the playing field for social media users. We perform a comprehensive survey of algorithmic threats on social media and use it as a lens to set a challenging but important research agenda for effective and real-time user nudging

Category 2: Generative AI applications (**Use of AI to generate content (text/video etc)**

Clear cases:

"ai-enabled deepfake news", "political deepfakes", "deepfake", "deepfakes", "deepfakes", "deepfake videos", "facial manipulated videos", "fake videos", "natural language processing model, the generative pre-trained transformer 3 (gpt-3)","generative artificial intelligence", "artificial intelligence in programmatic advertising", "ai journalists", "generative models for writing text","ai-generated text", "using artificial intelligence for generating claimreview automatically", "algorithmically generated profile text", "alternative (alt) text", "ai writers", "using artificial intelligence (ai) algorithms to automatically generate content", "automated journalism", "robotic reporter", "ai supported story co-creation via unsupervised multitask learning", "natural language generation (nlg) algorithms", "generative pretrained language models", "news headlines generated by ai", "artificial intelligence in news photographs", "ai news", "ai-generated music", "machine-generated artworks", "computer-assisted animation production"

Less clear cases:

1. "large neural language models","

Title: "Wordcraft: Story Writing With Large Language Models"

Reason: Using AI to generate stories

Text-passage: "We built Wordcraft, a text editor in which users collaborate with a generative language model to write a story. We evaluated Wordcraft with a user study in which participants wrote short stories with and without the tool. Our results show that large language models enable novel co-writing experiences. For example, the language model is able to engage in open-ended conversation about the story, respond to writers' custom requests expressed in natural language (such as" rewrite this text to be more Dickensian"), and generate suggestions that serve to unblock writers in the creative process."

2. "large language models"

Title: "Sparks: Inspiration for Science Writing using Language Models"

Reason: science writing with AI

Text-passage: "In this work we investigate how language models can support science writing, a challenging writing task that is both open-ended and highly constrained. We present a system for generating "sparks", sentences related to a scientific concept intended to inspire writers. We find that our sparks are more coherent and diverse than a competitive language model baseline, and approach a human-written gold standard."

3. "bot"

Title: Shelley: A Crowd-Sourced Collaborative Horror Writer

Reason: Writing horror-stories with AI

Text: In this work, we propose a deep-learning based collaborative horror writer that collaboratively writes scary stories with people on Twitter. We deploy our system as a bot on Twitter that regularly generates and posts new stories on Twitter, and invites users to participate.

4. "ai influences narrative transportation"

Title: Creative artificial intelligence and narrative transportation.

Reason: story-writing with AI

Text-passage: Artificial intelligence (AI) is increasingly used to accomplish complex tasks, including the creation of artworks and entertainment products. Our focus here is on user responses to AI systems as authors of fictional stories. Across two experiments, we examined how the information that a story was written by AI influences narrative transportation and related experiences.

Category 3: AI as communicator applications (Human-AI communication OR Communicative interaction OR AI occupying a social role in communicative interaction)

Clear cases:

"chatbots", "smart speakers", "conversational agents", "communicating bot", "chatterbot", "ai-enabled chatbots", "ai speaker", "microsoft ai chatbot", "voice-based ai conversational systems", "conversational bots", "chatbot", "chatbot", "chatbot", "chatbot", "chatbot", "smart speakers", "chatbot", "virtual influencers", "virtual influencers", "autonomous robots", "autonomous robot", "science fiction robots", "voice application", "voice-activated artificial intelligence (vai)", "digital assistants", "virtual assistants, personal robots, menacing movie ais", "digital home assistants", "ai voice assistants", "voice assistants", "humanizing voice assistant", "intelligent personal assistants", "voice bots", "ai agents", "robo-advisors", "voice application", "voice-activated artificial intelligence (vai)", "voice assistant recommendations", "artificial intelligence (ai) driven interactive recommendation agents"

Less clear cases:

1. "ai broadcast host expression technology based on neural network algorithm"

Title: "AI Broadcast Host Expression Technology Based on Neural Network Algorithm"

Reason: they are studying AI taking the role of a broadcast role

Text-passage: "based on neural network algorithm, this paper studies AI broadcasting host expression technology. Firstly, this paper expounds the concept of AI broadcasting, and then expounds the impact of AI on future broadcasting hosts and the problems of existing AI broadcasting. Finally, according to the optimization of neural network algorithm, this paper tests all aspects of AI broadcast host expression technology. The test results show that after the optimization of neural network algorithm, the average value of emotional expression of AI broadcast host is relatively stable in expression technology, and the audio output is also stable. At the same time, there is a sense of law in speech speed and speech rhythm, but it will still be unstable."

2. 'interactive ai design'

Title: "The Effects of Interactive AI Design on User Behavior: An Eye-Tracking Study of Fact-Checking COVID-19 Claims"

Reason: not a test of a specific tool, focus is on the interactive, thus communicative part of AI

Text-passage: We conducted a lab-based eye-tracking study to investigate how interactivity of an AI-powered fact-checking system affects user interactions, such as dwell time, attention, and mental resources involved in using the system. A within-subject experiment was conducted, where participants used an interactive and a non-interactive version of a mock AI fact-checking system, and rated their perceived correctness of COVID-19 related claims.

3. "chatbot journalism"

Title: Cross-cultural differences in information processing of chatbot journalism: Chatbot news service as a cultural artifact.

Reason: not focusing on testing a specific AI tool, but rather on interaction with AI bots broadly

Text-passage: Purpose: How does algorithmic information processing affect the thoughts and behavior of artificial intelligence (AI) users? In this study, the authors address this question by focusing on algorithm-based chatbots and examine the influence of culture on algorithms as a form of digital intermediation. Design/methodology/approach: The authors conducted a study comparing the United States (US) and Japan to examine how users in the two countries perceive the *features of chatbot services and how the perceived features affect user trust and emotion.*

4. "pro-government bots"

Title: "Why Botter: How Pro-Government Bots Fight Opposition in Russia"

Reason: focus is on the interactive AI (pro-regime bots taking a social role)

Text-passage: few previous attempts have been made to systematically analyze the use of bots that are aimed at a domestic audience in autocratic regimes. We develop two alternative theoretical frameworks for predicting the use of pro-regime bots: one which focuses on bot deployment in response to offline protest and the other in response to online protest. We then test the empirical implications of these frameworks with an original collection of Twitter data generated by Russian pro-government bots. We find that the online opposition activities produce stronger reactions from bots than offline protests.

5. media bots"

Title: Making up Audience: Media Bots and the Falsification of the Public Sphere.

Reason: not focusing on testing a specific AI tool, but rather on interaction with AI bots broadly

Text-passage: We examine how media bots can manipulate online ratings, change social perception of what is relevant and increase engagement with both on- and offline media entities. We extracted three types of data: (i) 530,942 tweets containing at least one URL from Globo Group or Folha Group collected via Twitter API; (ii) URL metadata from 158,690 articles by Globo Group and Folha Group; (iii) Twitter trending topics in Brazil. Profiles that posted links were later sampled and classified using the Botomete

5. "socialbot"

Title: "Introducing the socialbot: a novel touchpoint along the young adult customer journey."

Reason: not focusing on testing a specific AI tool, but rather on interaction with AI bots broadly

Text-passage: The purpose of this paper is to contribute to the special issue theme by exploring customer response to automated relationship management tactics on social media channels. Design/methodology/approach: A total of 17 in-depth interviews of young adults, ranging from the age of 19 to 26, were conducted. From this, customer journey maps were compiled incorporating socialbots as a valuable touch point along the service delivery cycle. Findings: The research frames the socialbot as a valued customer service agent to young adults with some favouring this over telephone and email communication methods. Younger consumers respond positively to the quick resolution offered by the socialbot mechanism with most acknowledging that the bot is only able to manage simplified requests. Human-to-human customer relationship management is preferential when the query reaches critical mass.

6. "twitter bot"

Title: "Bot-Detective: An Explainable Twitter Bot Detection Service with Crowdsourcing Functionalities"

Reason: focusing on interaction with AI bot

Text-passage: In this work we propose Bot-Detective, a web service that takes into account both the efficient detection of bot users and the interpretability of the results as well. Our main contributions are summarized as follows: i) we propose a novel explainable bot-detection approach, which, to the best of authors' knowledge, is the first one to offer interpretable, responsible, and AI driven bot identification in Twitter, ii) we deploy a publicly available bot detection Web service which integrates an explainable ML framework along with users feedback functionality under an effective crowdsourcing mechanism; iii) we build the proposed service under a newly created annotated dataset by exploiting Twitter's rules and existing tools.

7. "bots"

Title: "Bots are less central than verified accounts during contentious political events"

Reason: studying interactive bots more broadly rather than a specific tool

Text-passage: we assess the impact that bots had on the dissemination of content during two contentious political events that evolved in real time on social media. We focus on events of heightened political tension because they are particularly susceptible to information campaigns designed to mislead or exacerbate conflict. We compare the visibility of bots with human accounts, verified accounts, and mainstream news outlets.

8. " bots"

Title: "Even good bots fight: The case of Wikipedia"

Reason: focusing on two different bots and their interaction

Text-passage: In this article, we analyze the interactions between bots that edit articles on Wikipedia. We track the extent to which bots undid each other's edits over the period 2001–2010, model how pairs of bots interact over time, and identify different types of interaction trajectories.

9. "asynchronous video interviews (avis) and artificial intelligence (ai)-based decision agents"

Title: "Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes?"

Reason: inclusion of interactive AI interviews

Text-passage: this study employed a novel experimental design to compare human ratings and job applicants' response behaviours between the SVI (synchronous human) and AVI (asynchronous and AI) settings and compare job applicants' fairness perception between the AVI setting and the AVI setting using an AI decision agent (AVI-AI).

10. "intelligent travel assistant (ita)"

Title: "Understanding the Adoption Factors Influence on the Use of Intelligent Travel Assistant (ITA) for Eco-Tourists: An Extension of the UTAUT."

Reason: specifically studying factors for the acceptance of AI in a social role

Text-passage: "The objective of this research is to investigate the antecedent factors involving eight variables, ie ease of use, trust, enjoyment, design, usefulness, quality, safety and empathy, which influence user acceptance of the intelligent travel assistant (ITA), thus they are formulated into a research model and hypothesis according to wide and deep *exploration about the theories of travel and tourism. The technologies used were the VPA, IPA, AI, IoT, technology acceptance theories and related literature. The data collection used online questionnaires for the survey through social media promotion online, ie Facebook and Line."*

11. "ai devices in the home"

Title: "Hey Google: A thematic analysis of Twitter users' comments on the privacy of AI devices in the home."

Reason: studying the adoption of AI in a social role

Text: The advancement of technology has been accompanied by the rise of data breaches and privacy concerns. The integration of artificial intelligence (AI)-based virtual assistants into society has led to smart homes that enable users to complete commands instantly. This project uses the diffusion of innovation theory to explain why consumers adopt the technology. A thematic analysis was conducted on Twitter news stories, and open coding showed a strong negative reaction to the stories, with users concluding that privacy was too essential to purchase a virtual assistant for their home.

12. "ai teaching assistants"

Title:"My teacher is a machine: Understanding students' perceptions of AI teaching assistants in online education."

Reason: about perception of interactive AI teachers

Text: the present study investigated students' perceptions about AI teaching assistants in higher education by use of an online survey. Primary findings indicate that perceived usefulness of an AI teaching assistant and perceived ease of communication with an AI teaching assistant are key to understanding an eventual adoption of AI teaching assistant-based education.

13. "web-based homework"

Title: "A study of the effectiveness of web-based homework in teaching undergraduate business statistics."

Reason: Focus also on interactive web based homework bots

Text: Web-based homework (WBH) Technology can simplify the creation and grading of assignments as well as provide a feasible platform for assessment testing, but its effect on student learning in business statistics is unknown. This is particularly true of the latest software development of Web-based tutoring agents that dynamically evaluate individual students' skill level and purport to respond with appropriate, targeted teaching to improve learning efficiency.

14. "artificial intelligence (ai) contactless services"

Title: "Examining the effects of AI contactless services on customer psychological safety, perceived value, and hospitality service quality during the COVID-19 pandemic."

Reason: includes responsiveness, thus it is communicative ai

Text-passage: Based on media equation theory and means-end chain theory, this study proposed a model explaining the effect of AI contactless services on customers' psychological safety, perceived control, hedonic value, and service quality. Data were collected from hotel customers with an online panel survey and a site survey in Wuhan, China.

15. "ai-driven services"

Title: "AI-driven public services and the privacy paradox: do citizens really care about their privacy?"

Reason: focus on the interactive AI features in a mobile app

Text-passage: Based on privacy calculus theory, we derive hypotheses on the role of perceived usefulness and privacy risks of artificial intelligence (AI) in public services. In a representative vignette experiment ($n = 1{,}048$), we asked citizens whether they would download a mobile app to interact in an AI-driven public service. Despite general concerns about privacy, we find that citizens are not susceptible to the amount of personal information they must share, nor to a more anthropomorphic interface.

16. "preprogrammed bots"

Title: "Do You Care Who Flagged This Post? Effects of Moderator Visibility on Bystander Behavior"

Reason: the bot is used for flagging, which is a form a communcating (to recipients/consumers)

Text-passage: This study evaluates whether increasing information visibility around the identity of a moderator influences bystanders' likelihood to flag subsequent unmoderated harassing comments. In a 2-day preregistered experiment conducted in a realistic social media simulation, participants encountered ambiguous or unambiguous harassment comments, which were ostensibly flagged by either other users, an automated system (AI), or an unidentified moderation source. The results reveal that visibility of a content moderation source inhibited participants' flagging of a subsequent unmoderated harassment comment, presumably because their efforts were seen as dispensable, compared to when the moderation source was unknown.

17. "recommender systems"

Title: "Exploring Users' Experiences of "Suggested Posts" in Social Media Through the Lens of Social Networking and Interactions"

Reason: recommendation in this case represents a communicative act

Text:"We conducted semi-structured interviews with 12 Instagram users to investigate how they perceive the "Suggested Posts" feature in relation to their in-app social interaction practices. Our findings reveal that suggested posts acted as a double-edged sword for communication with their actual friends, acted as an obstacle for digital self-presentation, and acted as an unwanted force that compel users to increase social groups."

Category 4: AI generally instances (unspecified or generalist instantiations)

Clear cases:

"artificial intelligence", "ai agency", "ai generally", "ai generally", "ai generlly", "algorithms and artificial intelligence (ai)", "ai systems", "techniques based on artificial intelligence", "artificial intelligence (ai) system", 'explainable ai tools', 'ai crises', 'leveraging ai in influencer marketing', "ai in influencer marketing", "artificial intelligence on journalism"

Less clear cases:

1. "artificial intelligence driven disaster management"

Study Name: "Public perceptions on artificial intelligence driven disaster management: Evidence from Sydney, Melbourne and Brisbane."

Reason: public perception of AI performance

Text-passage: "public is engaged with AI in various ways in these activities. For instance, crowdsourcing applications developed for disaster management to handle the tasks of collecting data through social media platforms, and increasing disaster awareness through serious gaming applications. Nonetheless, there are limited empirical investigations and understanding on public perceptions concerning AI for disaster management. Bridging this knowledge gap is the justification for this paper. The methodological approach adopted involved: Initially, collecting data through an online survey from residents (n = 605) of three major Australian cities; Then, analysis of the data using statistical modelling"

2. "t adm systems"

Title: "Look! It's a Computer Program! It's an Algorithm! It's AI!": Does Terminology Affect Human Perceptions and Evaluations of Algorithmic Decision-Making Systems?

Reason: Focus on perception of AI as such

Text-passage: "In the media, in policy-making, but also in research articles, algorithmic decision-making (ADM) systems are referred to as algorithms, artificial intelligence, and computer programs, amongst other terms. We hypothesize that such terminological differences can affect people's perceptions of properties of ADM systems, people's evaluations of systems in application contexts, and the replicability of research as findings may be influenced by terminological differences. In two studies (N = 397, N = 622), we show that terminology does indeed affect laypeople's perceptions of system properties (e.g., perceived complexity) and evaluations of systems (e.g., trust)."

3. "artificial intelligence and robots"

Title: "Visions of artificial intelligence and robots in science fiction: A computational analysis."

Reason: Focus on perception of AI as such

Text-passage: "In this study, we analyzed depictions of artificial intelligence in SF together with expert critics and writers. First, 115 AI systems described in SF were selected based on three criteria, including diversity of intelligence, social aspects, and extension of human intelligence."

4. "artificial intelligence and robotics technologies"

Title: "Effects of country and individual factors on public acceptance of artificial intelligence and robotics technologies: a multilevel SEM analysis of 28-country survey data."

Reason: Focus on perception of AI as such

Text-passage: "this study examines factors influencing public attitude towards the use of AI/Robot. Its multilevel SEM analysis finds that several factors at the individual level including Perceived threat of job loss and Digital technology efficacy predict public Acceptance of AI/Robot."

5. "robots and ai"

Title: "Fear of autonomous robots and artificial intelligence: Evidence from national representative data with probability sampling."

Reason: Focus on perception of AI as such

Text-passage: "This research examines a specific form of sociological fear, which we name as fear of autonomous robots and artificial intelligence (FARAI). This fear may serve to affect how people will respond to and interact with robots. Applying data from a nationally representative dataset with probability sampling (N = 1541), research questions examine (1) the extent and frequency of FARAI, (2) demographic and media exposure predictors, and (3) correlates with other types of fear (ie, loneliness, drones, and unemployment). A latent class analysis reveals that approximately 26% of participants reported experiencing a heightened level of FARAI."

6. "robotics"

Title: "Robotics at workplace: An integrated Twitter analytics—SEM based approach for behavioral intention to accept."

Reason: Focus in the setup is on acceptance of different AIs at workplace generally

Text-passage: "This study explores the antecedents of employees' intention to accept robotics at workplace using two-step analyses: Twitter Analysis and Survey-based analysis."

7. "robots"

Title: "The inexorable rise of the robots: Trade journals' framing of machinery in the workplace."

Reason: Focus on reporting about AI

Text-passage: "As artificial intelligence and industrial automation continue to impact on the workplace, the manner in which they are reported by news media becomes increasingly of interest. Combining quantitative and qualitative analysis of trade journals, this paper investigates how machinery in the workplace is framed, in order to indicate the way in which such framing may shape thought and influence management decisions."

8. "service robots, ai devices or automated vehicles"

Title: "Digitised caring intimacies: More-than-human intergenerational care in Japan"

Reason: Focus on different forms of AI, inferences made on AI generally

Text: "In this article, we draw on our ethnographic research with Japanese families engaging in digitised self-care and intergenerational care to show how more mundane and well-established digital media and devices—such as the LINE message app, digital games and self-tracking apps—are contributing to digital kinship, mediated co-presences and care relations"

Removed cases:

'featuring armed artificial intelligence (ai)'

Reason: not on public communication

ilooklikeanengineer (illae)

Reason: not on AI

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