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# Impact and Use of Artificial Intelligence in Risk Communication: Challenges and New Opportunities

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**ABSTRACT**

Artificial Intelligence (AI) is having a growing impact on society, and its presence is increasing in many areas. At the same time, risk communication has been gaining prominence and importance in both society, especially in the wake of the recent COVID-19 pandemic, and academia. In view of the magnitude of both phenomena, this article aims to identify the different points and aspects where they converge, as well as the potential theoretical and practical implications of AI in risk communication. To this end, we carried out an exploratory, systematic review of the scientific literature from a holistic perspective, taking a mixed methods approach that considered both quantitative and qualitative aspects in order to analyse the state of academic research and its implications. The results show a marked increase in scientific production that addresses both concepts jointly, particularly from 2019 onward, coinciding with the COVID-19 pandemic, with this risk being the main subject of study. Moreover, social networks, especially X (formerly Twitter), emerge as the most interesting platforms for research, while other platforms receive a lower level of attention. Our findings suggest that AI has a dual impact on risk communication, presenting both challenges by generating new risk scenarios, and opportunities by providing new methods that allow new horizons to be explored. Finally, different theoretical and practical implications arise from this research, and it is necessary to address the challenges and take advantage of the opportunities provided by AI to improve risk communication.

**Keywords:** Artificial Intelligence, Risk Communication, Health, Social Networks, Review.

## INTRODUCTION

In an increasingly interconnected world exposed to a wide range of hazards, from natural disasters to health emergencies and socio-economic crises, the ability to communicate risks clearly, accurately, and in a timely manner has never been more important (Glik, 2007). We understand risk communication as a two-way exchange of information on risks between the different parties involved in and/or affected by them. This communication can take place in a wide variety of ways, coming from different sources—government institutions, media, stakeholders, social media, etc.—and in a broad range of situations, including crises, emergencies, disasters, and so on. In this context, it is necessary to work with different audiences, each with its own characteristics, needs, concerns, and idiosyncrasies (Covello, Slovic, & Von Winterfeldt, 1986; Covello, Von Winterfeldt, & Slovic, 1988). The main objective of risk communication is to inform the parties involved in risk management decisions in order to maximise welfare by reducing exposure to hazards or threats (National Research Council, 1989; Plough & Krimsky, 2013). Effective risk communication is essential to persuade people to adopt self-protective behaviours in order to minimise the potential adverse effects of such risks (DiClemente & Jackson, 2016; Vaughan & Tinker, 2009). This type of communication impacts the population in numerous ways, from influencing trust in public institutions and mitigating fear and uncertainty to improving risk perception and encouraging preventive behaviours, to name just a few (Heydari et al., 2021; Yoo, 2019).

We understand risk as the possibility of human actions or events harming some essential aspect of things that people value (Rasmussen & Ihlen, 2017). Risk is commonly described in terms of the probability of a loss occurring (Fineberg & Stern, 1996). However, to understand the concept of risk, we must go beyond the technical definition, which is limited to an event's probability and magnitude, to include the influence of psychological, social, institutional, and cultural factors; risk is therefore a social construct. Furthermore, the nature of risk is not merely probabilistic, but also communicative. It is not only a mathematical calculation that makes people perceive a phenomenon as dangerous, but also its background history, its cultural interpretation, and the ideological context of the region in question (García García, 2014).

From an academic perspective, risk communication focuses on analysing and trying to understand the different processes of risk-related information exchange, decisions and behaviours (Renn, 1991). The most recurrent approaches to trying to deepen our understanding of risk communication focus on different dimensions, such as the constant changes in the scope and impact of information dissemination, the nature of public perception and behaviour, or the variability of messages in different risk contexts (Milani, Weitkamp, & Webb, 2020). Therefore, one of the most important aspects is to gain a better understanding of individual differences and similarities in risk perception, as well as different information needs. This will enable more efficient and effective risk communication (Frewer, 2004).

Since the first steps in the field, efficient and effective risk communication has been a challenge that is constantly evolving (DiClemente & Jackson, 2016). For this reason, some studies have highlighted the need for the integration of new disciplines to enable new approaches to risk communication (Bouder et al., 2021; McComas, 2006). Currently, risk communication is facing new challenges, such as the consolidation of web searches on the Internet as one of the main sources of information, the rise of social media, the phenomenon known as infodemics, or the introduction of conversational models equipped with artificial intelligence (AI), such as ChatGPT (Ali et al., 2019; Ems & Gonzalez, 2016; Huang & Wang, 2022; Nguyen & Catalan-Matamoros, 2020; Pascual-Presa, Fernández-Pichel, Losada, & García-Orosa, 2024; Sixto-García, García-Orosa, González-Lois, & Pascual-Presa, 2024). This is why we need to focus on the potential impact of AI in this complex context. Its impact to date is so great that some authors refer to it as the driver of the Fifth Industrial Revolution (Sung, Stewart, & Freedman., 2020). This technology is driving significant and transformative change across a wide range of sectors, and its reach transcends geographical, political and legal boundaries (Cunneen, Mullins, & Murphy, 2019), presenting both risks and opportunities for society (Zerfass, Hagelstein, & Tench, 2020).

On the other hand, AI is a field of study that brings together a wide range of disciplines and encompasses, at both theoretical and practical levels, the development of systems based on simulating the reasoning and behaviour that we associate with human intelligence. This area of science is influenced by and connected to various disciplines, including computer science, mathematics, linguistics, psychology, neuroscience, mechanical engineering, statistics, and economics, among others (Tecuci, 2012). The field of AI encompasses a wide variety of methods and models, such as machine learning, Natural Language Processing (NLP), neural networks, supervised learning, deep learning, and so on. These technologies, on the whole, have managed to revolutionise and transform science and society (García-Orosa, 2021).

AI presents both challenges and opportunities in the field of risk communication. Various studies point to its potential applications, such as its academic use for the analysis of large-scale and complex environments or data, personalisation of risk messages, task automation, adaptive assessment for different environments, etc. (Seo, Tang, Roll, Fels, & Yoon, 2021; Ogie, Rho, & Clarke, 2018). At the same time, however, AI has the potential to generate negative impacts or ethical and liability issues that must be assessed and weighed for their potential implications (Hohma, Boch, Trauth, & Lütge, 2023; Topol, 2019).

This is the framework of our study, which aims to explore and understand the use and impact of AI in risk communication by analysing scientific research from a holistic perspective. For this purpose, we carried out an exploratory, systematic review of the scientific literature available in the Web of Science and Scopus databases, taking both a qualitative and a quantitative approach.

# METHODOLOGY

In order to analyse AI-related scientific production (in its different aspects and methods) and its convergence with the field of risk communication—including risk communication in crisis situations, emergencies, catastrophes, etc.—we carried out a systematic literature review. These types of studies are becoming increasingly important in the field of communications because they allow previous results to be systematised and new challenges and lines of research to be explored (Aguaded, Vizcaíno-Verdú, García-Prieto, & de-Casas-Moreno, 2023; García-Orosa, Canavilhas, & Vázquez-Herrero, 2023; Terren & Borge, 2021; Vizoso & Pérez-Seijo, 2024). They also make it possible to identify, assess, and interpret data from previous studies, in order to answer questions related to a specific field of study (Cherry, Boland, & Dickson, 2023; Ramírez & García-Peñalvo, 2018). Unlike a conventional literature review, this method provides an overview of all the studies in a specific area of research by using a search strategy and previously defined criteria for inclusion and exclusion (Moher, 2009). In this case, we decided to use a mixed methods approach. We therefore used quantitative analysis techniques that provide an exact, detailed description based on certain variables, as well as qualitative techniques that facilitate and allow a more inferential and in-depth approach to the data (Bedregal, Besoain, Reinoso, & Zubarew, 2017).

As mentioned above, the main objective of our research is to understand AI's potential impact on risk communication. Based on this aim, a series of questions was defined to guide the process:

Q1. What are the characteristics of the scientific research that relates AI to risk communication?

Q2. Which AI methods (machine learning, NLP, neural networks, etc.) have a greater presence or use in this field?

Q3. What are the predominant subjects, platforms, and ecosystems of study?

Q4. What are the theoretical and practical implications of the research relating to and involving AI in the study of risk communication?

The search phase was conducted using two of the main scientific databases: Web of Science (WoS) and Scopus. For our search equation, we used the English language and the term 'Artificial Intelligence' or 'AI', as well as related terms, such as 'Natural Language Processing', 'Machine Learning', and comparable words. We also used 'Risk Communication' and similar terms that could be related to it in the different studies, such as 'Crisis Communication', 'Disaster Communication', etc.

(('Artificial Intelligence' OR 'AI' OR 'Machine Learning' OR 'Deep Learning' OR 'Neural Networks' OR 'Genetic Algorithms' OR 'Fuzzy Logic' OR 'Natural Language Processing' OR 'NLP' OR 'Data Mining' OR 'Expert Systems' OR 'Computer Vision' OR 'Pattern Recognition' OR 'Classification Algorithms' OR 'Clustering Algorithms' OR 'Predictive Models' OR 'Robotics' OR 'Intelligent Agents' OR 'Chatbot' OR 'Language model' OR 'Conversational model') AND ('Risk Communication' OR 'Crisis Communication' OR 'Emergency Communication' OR 'Disaster Communication' OR 'Risk Messaging' OR 'Hazard Communication'))

Our initial search yielded 143 results in the WoS database and 273 in Scopus, for a total of 416. In order to select the research papers to make up the final analysis sample of this systematic literature review, the authors established a series of criteria for inclusion and exclusion.

As the main criteria for inclusion, only research papers that were 'articles' were chosen. Therefore, all research papers from the previous searches that were articles and that did not meet one or more criteria for exclusion were included in the final sample. As the criteria for exclusion, duplicate papers were eliminated, and a time limit was established based on the year of publication of the papers, which was delimited by [s.n-2023]. Articles whose full text was unavailable were also eliminated. Furthermore, considering the nature of the study, as well as its objectives, we excluded articles which:

1. Were not directly related to risk communication.

2. Were not focused on Artificial Intelligence or its potential relationship with risk communication. For instance, studies on other topics that were related to AI or risk communication, but did not address them together.

3. Did not contribute results or conclusions that were relevant to our study.

4. Cited specific information or new advances in a determined research area about a specific topic. For example, a study that used AI methods to predict the occurrence of disease in patients, would facilitate future communication about these risks.

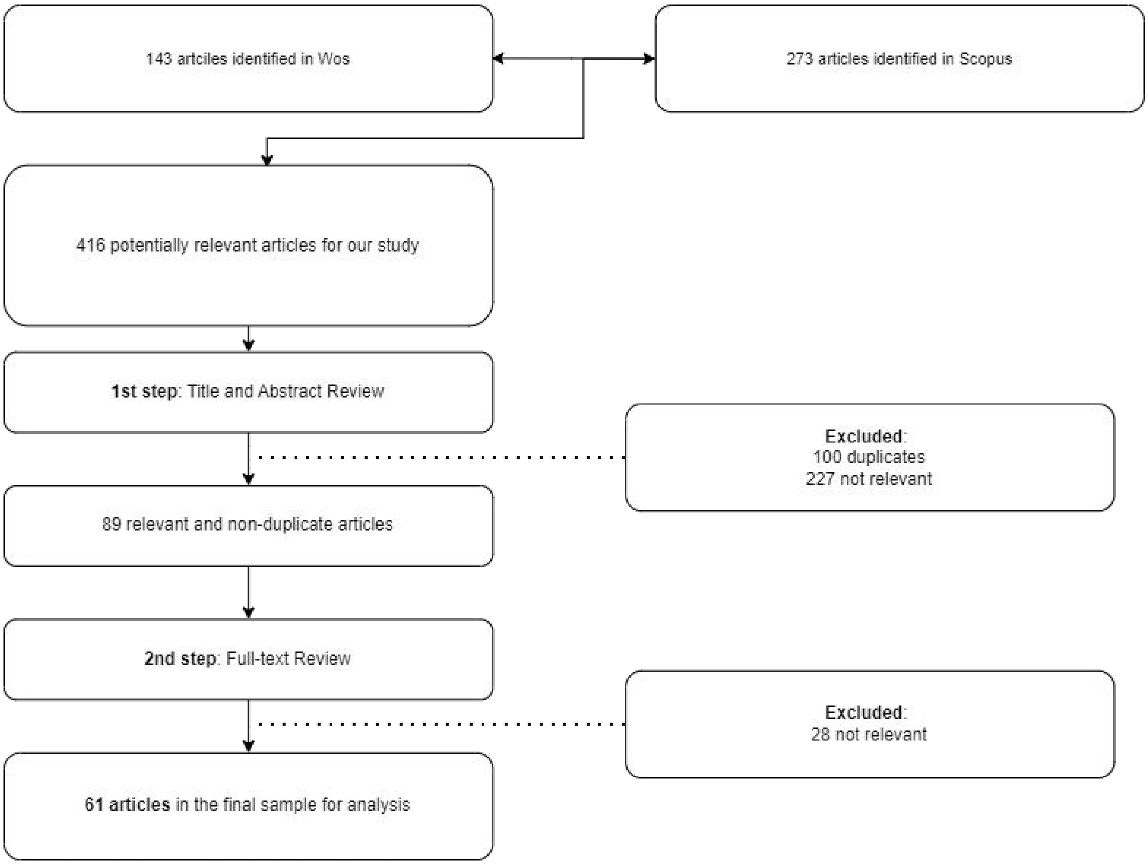


**Figure 1.** Workflow for the Sample Selection Process

Ultimately, following the process shown in **Figure 1** and applying these criteria, our final sample consisted of a total of 61 research papers.

Based on our study plan, using a quantitative and qualitative method and taking a holistic approach, our analysis was structured as follows: First, we carried out a quantitative bibliometric analysis of the scientific production that made up our sample, based on the model proposed by Codina (2018) (**Table 1**). Also, we used VOSviewer software to visualise the relationship between the keywords of the articles in the sample, which makes this type of bibliometric analysis easier to understand (van Eck & Waltman, 2010). Then, during the second phase, we conducted a qualitative analysis of the studies in the sample, focusing mainly on: (i) methodological approach; (ii) theoretical implications; and (iii) practical implications. We completed this process through coding and the application of Atlas.ti analysis software (Sabariego Puig, Vilà Baños, & Sandín Esteban, 2014). This made it easier to make inferences about the subject of study and our proposed research questions.

**Table 1.** Biometric Analysis Variables for the Documents in our Study Sample

| **Document information** | **Database** |
|---|---|
| | DOI |
| | Authorship |
| | Number of authors |
| | Authors' affiliation |
| | Title |
| | Journal |
| | Volume, number, and pages |
| | Year of publication |
| | Language of publication |
| | Research area |
| **Content** | Abstract |
| | Keywords |
| | Language |
| | Subject |
| | Ecosystem or platforms |

| Document information | Database |
|---|---|
| **Methodology** | Methods used |
| | Use of AI, or AI technologies, for the study |
| **Impact** | Citations |

## RESULTS

### Bibliometric Analysis

First of all, in relation to Q1, we observe that all the articles published on artificial intelligence and risk communication are dated between 2005 and 2023. We also noticed a significant increase in scientific production on this subject in 2020, which grew markedly in the subsequent years (**Figure 2**).

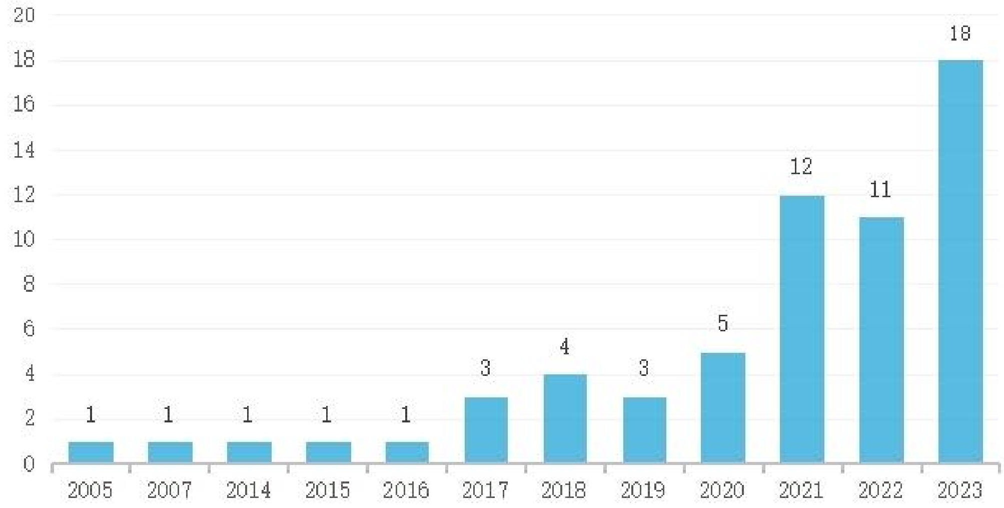


**Figure 2.** Scientific Articles by Year of Publication

The journals that published the largest number of works in the sample include: *Journal of Medical Internet Research* (4); *International Journal of Disaster Risk Reduction* (4); *Jmir Public Health and Surveillance* (2); *PLOS One* (2); *International Journal of Information Management* (2); *Risk Analysis* (2), and *Transportation Research Record* (2).

**Table 2.** Articles Published by Journal[1], Language and Number of Authors

| Journal | No. articles published | |
|---|---|---|
| Journal of Medical Internet Research | 4 | |
| International Journal of Disaster Risk Reduction | 4 | |
| PLOS One | 2 | |
| Transportation Research Record | 2 | |
| Risk Analysis | 2 | |
| Jmir Public Health and Surveillance | 2 | |
| International Journal of Information Management | 2 | |
| **Language** | **Articles** | **%** |
| English | 58 | 95.1% |
| Spanish | 2 | 3.3% |
| Turkish | 1 | 1.6% |
| **Authors** | **Articles** | **%** |
| 1 | 2 | 3.3% |
| 2 | 10 | 16.4% |
| 3 | 15 | 24.6% |
| 4 | 11 | 18.0% |

[1] Only the leading journals with the largest number of articles published.

| Authors | Articles | % |
|---|---|---|
| 5 | 8 | 13.1% |
| 6 | 8 | 13.1% |
| 7 | 1 | 1.6% |
| 8 | 1 | 1.6% |
| 9 | 2 | 3.3% |
| 12 | 1 | 1.6% |
| 13 | 1 | 1.6% |
| 16 | 1 | 1.6% |

As shown in **Table 2**, almost all of the articles were originally written in English, while Spanish was chosen in only 3.3% of cases, and Turkish in 1.6%. There were also articles published in Portuguese and French, although the documents were not originally written in those languages. Articles with only one author make up 3.3% of the total. The most frequent number of authors is 3, accounting for 24.6% of the total. The average number of authors per article is 4.47. The articles in the sample have 2,975 citations in the aggregate, with an average of 48.77 citations per article. The articles with the largest number of citations include Ragini, Anand, and Bhaskar (2018), with 254, Lazard, Scheinfeld, Bernhardt, Wilcox, and Suran (2015), with 132, Wirz et al. (2018), with 115, Bukar et al. (2022), with 105, Yan, Mai, Wu, Chen, and Li (2023), with 103, and Michela et al. (2022), with 100 citations. It should be noted that the year of publication of each article affects this variable.

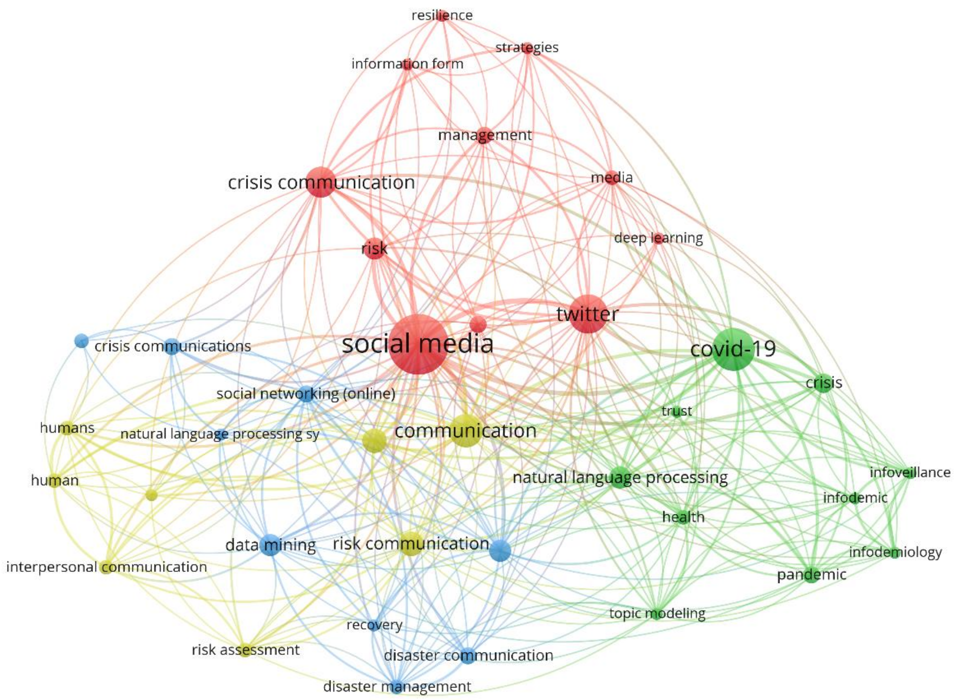


**Figure 3.** Concurrence of 'Keywords Attributed by the Authors'

This correlation of article keywords shown in **Figure 3** provides an initial approach to the subject of study, identifying the most relevant topics in the articles in the sample. Five clusters are identified in the group, highlighting the keywords 'social media', 'Twitter', and 'covid-19'. In the centre of this correlation are the keywords 'machine learning' and 'communication'. These five terms are the keywords with the greatest relevance, presence, and correlation in the group.

As for the research method design, two approaches stand out in particular: the mixed methods approach, used in 45.9% of articles, and the quantitative one, used in 37.7%. In relation to research question Q2, as shown in **Table 3**, Artificial Intelligence is used as a main analysis or research support tool in 91.8% of articles. Only 8.2% of articles focus on other aspects of AI in risk communication and do not use AI as a research support tool.

As far as outstanding AI methods, there are two clear leaders: Natural Language Processing (NLP) and Machine Learning, in their different versions (mainly supervised and deep learning). NLP is used as an analysis tool in 42.9% of research studies that use some form of AI as a study method. Meanwhile, Machine Learning is present in 26.8% of studies, and both methods are used simultaneously in 12.5%.

**Table 3.** Articles by Research Method and Use of AI

| Research method design | No. of articles | % |
|---|---|---|
| Mixed | 28 | 45.9% |
| Quantitative | 23 | 37.7% |
| Experimental | 5 | 8.2% |
| Qualitative | 4 | 6.6% |
| Theoretical | 1 | 1.6% |
| **Use of AI as a research method** | **No. of articles** | **%** |
| Articles that use it | 56 | 91.8% |
| Articles that do not use it | 5 | 8.2% |
| **AI methods used for research** | **No. of articles** | **%** |
| Natural Language Processing (NLP) | 24 | 42.9% |
| Machine learning | 15 | 26.8% |
| Other | 7 | 12.5% |
| Machine learning, Natural Language Processing (NLP) | 7 | 12.5% |
| Unspecified | 3 | 5.4% |

Meanwhile, in relation to Q3, we analysed the platforms or ecosystems in which the different research studies were carried out and delimited. These platforms or ecosystems refer to, for example, studying a certain phenomenon or issue in a specific environment, such as a social network (X, Facebook, Instagram), online media, people, etc.

More than half of the studies in the sample use social media as a scenario or platform, specifically 52.5%. Among these studies, X (formerly Twitter) stands out in particular, as it is present in 52.5% of studies carried out on social media. Facebook (15.3%), Weibo (12.5%), Reddit (3.1%), YouTube (3.1%), and TikTok (3.1%) are also present.

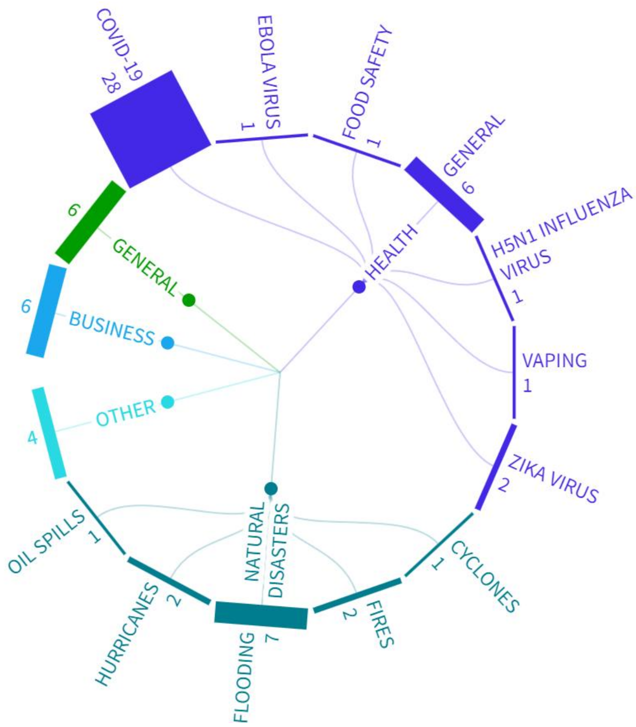


**Figure 4.** Articles by Topics

Meanwhile, in relation to Q3, the topics in the sample articles were analysed. As shown in **Figure 4**, the health field stands out above all, with 51.1% of articles addressing this topic. Almost all of these articles focus specifically on COVID-19 (84.8%), although topics such as the Zika virus (6.1%), Ebola virus (3.0%), vaping (3.0%), food safety (3.0%), and H5N1 influenza virus (3.0%) are also covered.

In second place, the field of natural disasters stands out, comprising 19.7% of the sample articles, focusing mainly on floods (63.3%), hurricanes (18.2%), fires (18.2%), cyclones (9.1%), and even oil spills (9.1%). General topics on risk communication are also mentioned (9.8%), as well as business (9.8%).

### New Challenges for Risk Communication in the Age of AI

Artificial Intelligence has emerged as an agent that generates new challenges in this field, creating unprecedented scenarios and introducing previously non-existent variables. Specifically, this is reflected in studies that analyse risk communication associated with failures in the implementation of AI in business contexts with relevant social impacts, such as the perpetuation of human biases or the violation of personal dignity. This type of failure is a new challenge that poses new challenges to communication studies and requires new approaches, not only from a communication point of view, but also from a legislative point of view (Mannes, 2020). In this sense, one of the strategies that has been used to try to mitigate the possible effects of this type of failure is the "mirror" strategy. This strategy is based on trying to deflect liability from these AI systems, based on the lack of knowledge and uncertainty surrounding them. However, such strategies are likely to become less effective as the public becomes more knowledgeable about these technologies (Prahl & Goh, 2021).

Although, as we will see later in the manuscript, AI facilitates the personalisation of content, it should also be noted that the data used for this purpose raises issues of ethics, privacy, manipulation and transparency. While this personalisation can be useful and effective, it can also have counterproductive effects, such as violating users' privacy or delivering messages that reinforce moral biases. Transparency in AI algorithms is essential to balance personalisation with ethical standards (Mannes, 2020). For example, using AI to predict an individual's health risk without clear disclosure could lead to privacy violations and undermine public trust. To maintain ethical integrity and public trust, it is important that AI-driven risk communications clearly disclose data use practices (Dehghani, Ghomian, Rakhshanderou, Khankeh, & Kavousi, 2022).

Meanwhile, the advancement and new uses of AI are also severely impacting online risk information contexts due to the automated production of fake news. It is becoming increasingly difficult to distinguish between this type of information and legitimate news, posing new challenges for the detection of fake news and requiring new detection methods. This represents a major challenge, especially in the health field (Karinshak & Jin, 2023).

### Opportunities for Risk Communication Research Using AI-based Methods

As stated in the introduction, risk communication encompasses various aspects of the communication process: not only the message, but also the information available about risks, changes in people's behaviour after receiving such information, and the public's perception of risk, among others. In this regard, some AI-based methods are excellent tools for conducting innovative studies and analysis, allowing the exploration of new dimensions and variables that were previously out of reach.

Firstly, Natural Language Processing (NLP), machine learning, and deep learning techniques make it possible to analyse large volumes of data (Mir, Rathinam, & Gul, 2022; Park et al., 2021). The effort that would be required for the manual analysis of such vast amounts of information would be inconceivable in many cases. By analysing large bodies of information, these methods can identify communication patterns (Sadri, Hasan, Ukkusuri, & Cebrian, 2018); provide a deeper understanding of the media response during the COVID-19 pandemic by determining the amount of news disseminated and its content (Beliga, Martincic-Ipsic, Matesic, Vuksanovic, & Mestrovic, 2021; Chang, Schulz, Tu, & Liu, 2020); detail how users of a given platform, such as X, share and interact with information about the risks associated with natural disasters (Beedasy, Zúñiga, Chandler, & Slack, 2020); identify patterns and themes of users' concern around a risk (Lazard et al., 2015; Ragini et al., 2018; Rusho, Ahmed, & Sadri, 2021); provide data on how certain information may complement or differ from official or government risk messages (Liu, Kar, Zhang, & Cochran, 2019); assess the politicisation and polarisation of risk communication (Hu & Zhong, 2023); record how different political or government discourses on COVID-19 risks changed and evolved over the various phases of the pandemic (Y. Wang, 2022); or reveal discrepancies or similarities between the interests of the general public and what public health authorities communicate regarding a risk (Gui et al., 2017).

Secondly, these methods also make it possible to analyse sentiment based on the information provided or available. This is particularly useful for identifying the public's perception of a risk or the changes that may occur at any moment (Babic, Petrovic, Beliga, Martincic-Ipsic, Matesic, & Mestrovic, 2021; Zhang et al., 2023). Generally, sentiments are classified as positive, neutral, or negative, and have been applied in different scenarios;

for example, in food safety to analyse public perception of an incident that may affect public health (Goh & Fung, 2005); in natural disasters such as floods to provide valuable information on people's responses before, during, and after the disaster (Zander, Nguyen, Mirbabaie, & Garnett, 2023); and to analyse the public's emotional tendencies in response to public health agencies' communication strategies during the COVID-19 pandemic (Che & Kim, 2023), among others.

### Practical Implications of AI in Risk Communication

Regarding Q4, Artificial Intelligence also improves risk communication in the most practical sense, providing new tools to enhance the quality, scope, and personalisation of tasks. For example, fuzzy logic-based AI systems, considering epidemiological indicators, not only improve decision-making, as they consider a wide range of data and variables associated with risk, but also allow for more transparent and objective risk communication. This transparency, backed by epidemiological indicators, strengthens the public's trust and encourages self-protective behaviours (Sánchez, Méndez, Brun, Traub-Muñoz, & Barros, 2023).

On top of that, AI can significantly improve the quality and effectiveness of risk messaging by contributing to more sophisticated personalisation. This is an important factor, as the same risk does not affect all people in the same way. For the correct personalisation of messages, it is important to segment the audience as accurately as possible. In this sense, this type of tool allows for more detailed and diverse segmentation of the audience, based on demographic, cultural or psychological variables, among others (Brown-Devlin, Lim, & Tao, 2022; Dehghani, Ghomian, Rakhshanderou, Khankeh, & Kavousi, 2022). During the COVID-19 pandemic, two of the aspects that had the greatest impact on risk perception were local cultural beliefs and social trust (Park et al., 2021). AI can consider the possible regional nuances of a particular area and tailor messages to address specific area-specific concerns or fears. In general, people's responses to risk may vary depending on culturally embedded values, social structures, and information processing habits. For example, AI-based linguistic models could adapt message framing to local beliefs about community authority or responsibility, thereby increasing the effectiveness of health or environmental risk messages in different cultural settings (Wirz et al., 2018).

Systems such as pre-trained convolutional neural networks provide more accurate data about the visual elements—whether in image or video format—that attract people's attention. For example, by using these systems to analyse various Covid-19 prevention campaigns, it was found that the use of the word 'virus' attracted more attention when it was placed in a more central position in the communication material. As a result, it has also been shown that to increase the credibility and trust of users in health information, the logos of the responsible institutions must be sufficiently visible to be one of the first elements that users see. Posters and videos with simple iconography and images of people capture the public's attention best and are easier to understand (Silva-Torres, Martínez-Martínez, & Cuesta-Cambra, 2020).

Another relevant case is using machine learning models to predict the political distrust of users in social networks (Unlu, Truong, Tammi, & Lohiniva, 2023), as well as to identify changing priorities and information needs of these users in situations such as natural disasters (Purnat et al., 2021). It is also important to highlight that the development of chatbots based on natural language technologies allows non-expert users to interact in a simple way that simulates a human conversation. This interaction can help them obtain accurate and contrasting information that motivates positive changes in their decision making. An example of this is in the context of COVID-19, where a chatbot can help users resolve their questions or concerns about vaccines, and thus motivate them in the process (Weeks et al., 2023). Such tools are not only of great help to the public in these contexts but are also valuable allies to the responsible authorities and institutions, reducing their workload and allowing them to prioritise other aspects (Stieglitz et al., 2022).

Finally, it should be noted that the ability of AI to create artificial voices can be a great ally in the field of risk communication. These AI-generated voices have been shown to be as useful as human voices in contributing to correct risk perception and motivating informed decision-making (Ni, Wu, & Huang, 2023). At the same time, convolutional neural networks offer the possibility of creating realistic and dynamic visualisations of potential natural disasters. Such visualisations allow authorities to communicate the severity of such events in a more practical and clear way, thus alerting people to take the necessary preventive and safety measures (Siegel & Kulp, 2021). Also, artificial neural networks allow complex data to be converted into understandable visual formats for many people, which can significantly lower the barriers that prevent scientific information from being conveyed in many cases (Moura, Beer, Patelli, & Lewis, 2017).

### Theoretical Implications of AI in Risk Communication

In this final section, and to continue answering Q4, we'll highlight the more theoretical implications of the articles in the sample that have impacted the field of risk communication. One key finding is social media's important role in risk communication, and the need to adapt communication strategies to the characteristics of each platform as well as user preferences (Abadía, Manfredi, & Sayago, 2023; Che, Zhou, Zhang, Nan, & Kim, 2023).

In this regard, several important considerations are mentioned, such as how the perception (positive, neutral, or negative) of the same message varies depending on the social network where it is shared (Che et al., 2023) and even the country where it is received. For example, information about risks associated with the Zika virus did not generate the same impact among Facebook users as it did among X users, and across the same platform, there were differences between geographic areas (Wirz et al., 2018). In this respect, the different topics discussed around the same risk can also lead to different levels of trust among users. For example, during COVID-19, on social media platforms such as Facebook or X, topics such as the severity of the disease or health measures generated more patterns of mistrust and vulnerability compared to other topics (Unlu et al., 2023). It is also important to understand the public's concerns and sentiment toward risk in order to improve both the response and the message (Zander, Garnett, Ogie, Alazab, & Nguyen, 2023). This understanding is especially important, because when the information provided is not aligned with the public's concerns, risk communication can be much less effective (Gui et al., 2017). Misinformation and conspiracy theories circulating on social media can also have a significant impact on the effectiveness of messages distributed on these platforms (Wirz et al., 2018). Furthermore, information overload on these platforms during a risk or crisis may lead many users to abandon them as sources of information, requiring new strategies and efforts to retain users and ensure effective communication (H. Wang, Xiong, Guo, Lu, & Meng, 2023).

Also, several studies highlight the importance of engagement on these platforms for various reasons. Above all, it improves the public's risk perception and trust, resulting in an informed population that can play a more active role in risk management. This engagement can be achieved on social media through active exchanges with the public (answering questions, reducing uncertainties, etc.). These engagement metrics, such as the frequency of comments, changes in sentiment and the number of likes, are also important indicators of how the public is responding. Monitoring these metrics supports the objectives of communications research by providing immediate insights into how well messages are resonating and how audiences are feeling. For instance, a favourable sentiment analysis during a health crisis might suggest increased trust in and adherence to health recommendations. This interaction is critical to not only strengthen the public's trust and risk perception, but also improve its resilience and ensure that social media is perceived as useful. In particular, transparent communication and constant updates are helpful for strengthening trust (Al Momin, Kays, & Sadri, 2023; Bukar et al., 2022; Wirz et al., 2018).

Direct, interactive, and conversational communication and the provision of relevant, high-quality information are essential as well. This helps to prevent users from experiencing social media fatigue and abandoning these platforms (Abadía et al., 2023; H. Wang et al., 2023). Interacting with users about risk messages broadens the dissemination of this information on the platform; it is also essential for content to be verifiable and objective, as this information is likelier to reach a wider audience (Lee & Yu, 2020). One key factor in the impact of messages on social media is account verification (Mir et al., 2022). Also, users who participate actively in discussions on social media are more likely to echo these messages and feel committed to them (Xu, Wei, & Wu, 2022). More rational messages seem to encourage behaviours such as comments and likes. It is also helpful to encourage more participation in risk communication on social media by the different stakeholders, especially local media and institutions that have a close relationship with local residents (Al Momin et al., 2023; Michela et al., 2022).

When designing messages about risks, overly politicised content can undermine their legitimacy and effectiveness. In fact, increased levels of politicisation in risk-specific communication may discourage online public engagement and adherence to risk protection and mitigation measures (Hu & Zhong, 2023). Conversely, when political leaders use a positive, optimistic tone in their messages, they can help to reduce panic and promote public welfare (Kaur, Verma, & Otoo, 2021). It is also crucial for governmental organisations to dynamically adapt their risk communication strategies to people's changing demands and manage the infodemic phenomenon carefully. This phenomenon significantly undermines public trust and erodes public confidence in public sources (Zhu & Hu, 2023). It has also been suggested that choosing the right people to communicate risk can significantly influence the public's emotional responses (Shanahan et al., 2019). For example, messages from celebrities can significantly increase positive public sentiment and therefore public engagement (Che & Kim, 2023).

The studies highlight a number of key aspects to consider when designing risk communication strategies to improve their effectiveness: (i) contextualisation of risk (providing additional context); (ii) clear and detailed descriptions (avoiding the use of complex technical terminology in risk messages, in addition, clearly explaining the actions or behaviours to adopt); (iii) visualisation of risk (using charts and images to illustrate the level of risk); (iv) transparency and trust (sharing accurate data, acknowledging uncertainty, regularly updating information, using evidence); (v) consistency in multi-platform information (using different channels for communication); (vi) frequency of publication (more frequent messaging encourages compliance with recommended actions); (vii) tone of messages (messages in a supportive, empathetic tone encourage public cooperation and reduce panic); (viii) visual content (the use of visual content, such as videos and charts, enables messages to be delivered effectively and catches the public's attention); (ix) adaptation and localisation (adapting messages to the local culture and context improves the target audience's receptivity and understanding); (x) avoiding probabilistic language (the use of probabilistic language generates negative emotional responses in the audience) (Gates et al., 2014; Ng, Chow, & Yang, 2021; Park et al., 2021; Shanahan et al., 2019; Solmaz, Urhan, Tarakci, & Gazaz., 2022; Unlu et al., 2023; Yin et al., 2023). In addition, it has been identified how public discourse can affect the vaccination process of the population. For example, the public debate about AstraZeneca's vaccines revolved around terms such as 'blood clots' or 'death' that reduced public support for vaccination. In contrast, public discourse about the Omicron variant focused on tracking infections and the number of deaths, encouraging the public to adopt more preventative behaviours (Catalan-Matamoros, Prieto-Sanchez, & Langbecker, 2023). Furthermore, it has been observed that the use of stigmatising language on digital media can increase hostility and blame towards certain groups or individuals, diverting public attention away from the risk itself and the necessary preventive measures, as observed in the context of COVID-19 (Chang et al., 2020).

## DISCUSSION AND CONCLUSIONS

This exploratory study, based on a systematic literature review, offers a complete overview of the use and impact of risk communication and Artificial Intelligence. Regarding the main objective of this study, the research confirms that AI has a dual impact on risk communication: (i) by generating new risk scenarios and new challenges in the field, and (ii) by introducing new methods and tools that broaden the scope of research and offer new opportunities. This is in line with previous research studies that have concluded that AI presents both challenges and opportunities (Cunneen et al., 2019; Zerfass et al, 2020).

The results of our bibliometric analysis of the intersection of AI and risk communication indicate a significant increase in scientific production from 2019 onwards, suggesting that COVID-19 was a clear driver of this increase. This has in turn fuelled other types of research related to the health field. Topics related to natural disasters, such as floods, hurricanes, earthquakes, and fires, also stand out as important. The risks addressed are all natural and beyond human control, which means that anthropogenic risks are not usually considered.

In terms of areas of study, social networks are the most researched platforms, starting with X. This is striking, since X ranks 13th in terms of the number of users, while Facebook, the world's most popular social network, is addressed by a very limited number of studies (Oladipo, 2024). However, the results underline the importance of these platforms in the dissemination of risk information while revealing academia's limited attention to other areas or platforms. This may also highlight the difficulty of analysing other platforms and therefore the need for new efforts to address this issue. New challenges for risk communication associated with AI use include the generation of unprecedented scenarios due to implementation failures, especially in the financial and corporate sectors, as well as in other spheres due to the addition of complex variables, such as human biases and the production of fake news.

Risk communication is a complex process that encompasses not only the message itself, but also the information available about risks, people's behavioural response to that information, and public perception of risk (Heydari et al., 2021; Yoo, 2019). In this context, AI methods play a critical role, allowing researchers to conduct advanced studies and analyses that were not possible before. These methods allow the identification of communication patterns and the monitoring of content dissemination flows and how users share and interact with the information, thus providing a better understanding of the response to a given risk. At the same time, they are a valuable resource for identifying different user concerns or fears, or for measuring the emotional impact of information. This makes AI a technology that can have a major impact on conceptual frameworks such as the SARF (Social Amplification of Risk Framework) (Kasperson et al., 1988).

In terms of practical implications for risk communication, AI offers a wide range of unprecedented opportunities, including improved quality, reach, automation and personalisation. Overall, these tools enable more objective communication that can more accurately build public trust to motivate positive changes in attitudes and behaviours. It is true that they require constant attention because of the risks associated with the complexity of the algorithms that govern them.

Finally, some of the main theoretical implications of the studies cited here should be mentioned. Firstly, they have demonstrated the importance of social networks in risk communication and the need to adapt strategies and messages to platforms and users. Communication strategies must adapt dynamically to changing demands and manage infodemics carefully. It is also crucial to understand the public's concerns and information needs to ensure more effective communication. From the perspective of the Elaboration Likelihood Model, AI's capacity to tailor messages allows communicators to effectively reach audiences with diverse levels of interest and expertise. By using NLP, it's possible to determine whether individuals are engaging with information in a central (high involvement) or peripheral (low involvement) manner, enabling risk communicators to modify the complexity and structure of their messages to suit the audience's processing style (Petty & Briñol, 2011). At the same time, engagement with these platforms helps to improve the public's perception and trust while encouraging users to be more proactive when risks arise. Active engagement, especially by governments and key protection agencies, is critical, as it strengthens trust and the perceived usefulness of the information.

It has also been determined that overly politicised and polarised messages may negatively impact risk communication strategies, as they reduce their legitimacy and effectiveness. The choice of spokespersons, such as celebrities, may influence the public's emotional response and increase participation. Meanwhile, information conveyed by leaders in a positive and optimistic tone tends to have a positive impact, promoting public well-being more effectively. Moreover, public discourse around risks, especially health risks, should avoid stigmatisation and promote preventive behaviours.

Finally, for the improvement of risk communication, this study reveals important insights, such as the need to consider the context of risks, clear and detailed descriptions, risk visualisation, transparency and trust, consistency across multiple platforms, frequency of publication, use of an empathetic tone, visual content, adaptation to the local context, and avoidance of probabilistic language.

In conclusion, our research provides a complete overview of how AI converges and interacts with risk communication, and this study illustrates how AI-driven risk communication not only facilitates the flow of information, but also aligns with theoretical frameworks that emphasise strategic message dissemination and audience engagement.

## LIMITATIONS

Conducting a systematic literature review entails several limitations, including the epistemic and methodological biases of the studies in the sample. Designing our search equation, by its very formulation, introduces limitations to the search results. In this case, the field had to be limited to certain terms, such as 'risk communication', etc., omitting words like 'risk' or 'communication' from the equation because these terms are noise words. The criteria for inclusion and exclusion and author bias could also affect the completeness and objectivity of the review.

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## CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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