

# How Generative AI Went From Innovation to Risk: Discussions in the Korean Public Sphere

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**Submitted:** 29 October 2024 **Accepted:** 6 January 2024 **Published:** 17 April 2025

**Issue:** This article is part of the issue “AI, Media, and People: The Changing Landscape of User Experiences and Behaviors” edited by Jeong-Nam Kim (University of Oklahoma) and Jaemin Jung (Korea Advanced Institute of Science and Technology), fully open access at <https://doi.org/10.17645/mac.i475>

## Abstract

Technological progress breeds both innovation and potential risks, a duality exemplified by the recent debate over generative artificial intelligence (GAI). This study examines how GAI has become a perceived risk in the Korean public sphere. To explore this, we analyzed news articles ( $N = 56,468$ ) and public comments ( $N = 68,393$ ) from early 2023 to mid-2024, a period marked by heightened interest in GAI. Our analysis focused on articles mentioning “generative artificial intelligence.” Using the social amplification of risk framework (Kasperson et al., 1988), we investigated how risks associated with GAI are amplified or attenuated. To identify key topics, we employed the bidirectional encoder representations from transformers model on news content and public comments, revealing distinct media and public agendas. The findings show a clear divergence in risk perception between news media and public discourse. While the media’s amplification of risk was evident, its influence remained largely confined to specific amplification stations. Moreover, the focus of public discussion is expected to shift from AI ethics and regulatory issues to the broader consequences of industrial change.

## Keywords

AI; amplification stations; ChatGPT; generative AI; public discourse; risk amplification; risk attenuation; risk communication

## 1. Introduction

Technological progress always has two sides, offering opportunities for innovation while posing significant risks. Beck (2012) predicted that 21st-century society would face threats not from traditional “dangers” but from “risks” shaped by human activity. In his concept of a global risk society, Beck (2012) highlighted risks

such as climate change, financial crises, and terrorism, emphasizing how these challenges are amplified in a knowledge-driven world.

Today, global risks are increasingly evident, exacerbated by advances in science and technology. One prominent example is the growing controversy surrounding generative artificial intelligence (GAI), which has recently captured public and market attention. GAI, a technology capable of generating content based on user input, is regarded as a game-changer in various industries, with profound social and cultural implications. Microsoft co-founder Bill Gates has described AI's development as the most significant technological advancement in decades, likening its impact to the advent of the iPhone (Gates, 2023; Nolan, 2023).

However, alongside its transformative potential, GAI has also sparked concerns and uncertainties. For instance, when OpenAI unveiled ChatGPT, media outlets speculated that the dominance of Google's search engine could be under threat. Reports from Google executives referred to this as a "code red," signalling a potential crisis (Cuthbertson, 2022; Grant & Metz, 2022). More broadly, the rapid proliferation of GAI has led to calls for caution, exemplified by the open letter titled *Pause Giant AI Experiments* and signed by AI researchers and tech leaders (Bengio et al., 2023). Such developments underscore the relevance of Beck's "global risk society" in contemporary contexts.

A review of existing literature has categorized the risks and controversies surrounding GAI into several key areas: (a) lack of market regulation and urgent regulatory needs; (b) poor content quality, disinformation, deepfakes, and algorithmic bias; (c) job losses due to automation; (d) breaches of privacy and data security; (e) social manipulation and erosion of ethics; (f) widening socioeconomic inequality; and (g) technology-related stress (Wach et al., 2023). Wach et al. (2023) argues that it is imperative to examine the social and ethical implications as GAI continues to develop.

This study investigates the risks associated with GAI, focusing on its amplification in the Korean public sphere. We analyze the period from the launch of ChatGPT in January 2023 through June 2024, during which public discourse on GAI surged. Using the social amplification of risk framework (SARF), a well-established theory in risk communication research, this study examines how GAI risks are amplified or attenuated in Korean society.

SARF posits that an individual's perception of risk is influenced by social and cultural factors, with amplification occurring through "social stations" such as media, experts, civil society, and personal networks. The framework emphasizes that risk perception varies across different social and cultural environments, making it particularly relevant to South Korea. As a global ICT leader with 97.4% internet penetration and advanced mobile connectivity (International Telecommunication Union, n.d.), South Korea represents a unique case for studying GAI. Korean companies like Naver and Kakao dominate local news and internet service platforms, and their entry into the GAI market, where they compete with global ICT companies such as Google, OpenAI, and Amazon, offers valuable insights into responses in an ICT-sensitive society (Internet Trend, n.d.).

This study contributes to the literature by employing topic modelling to analyze news coverage based on SARF and examining public comments to capture direct societal reactions. By empirically exploring the relationship between media and public discourse, which is traditionally viewed as a mechanism of risk amplification, this research sheds light on the dynamics of risk communication in the context of GAI.

## 2. Theoretical Framework

### 2.1. SARF

The definition of “risk” has evolved throughout history, reflecting shifts in societal and cultural contexts. Risk can be viewed objectively, as a quantifiable phenomenon assessed through technical expertise, or subjectively, as a construct shaped by societal values and perceptions (Kim, 2006).

SARF was first conceptualized by Kasperson et al. (1988) to explore how risk-related events, initially assessed as minor or technical by experts, can evolve into major societal concerns. The framework integrates psychological, organizational, social, and communicative processes to explain how risk signals are amplified or attenuated through “amplification stations,” such as media, government, and public discourse. These stations act as filters that shape the transmission and reception of risk signals, ultimately influencing public perception and societal responses (Kasperson et al., 1988; Song et al., 2012).

SARF’s utility lies in its ability to analyze the ripple effects of risk events, originally likened to waves in a pond. With the advent of the internet and social media, these ripple effects have become increasingly complex and interconnected, requiring a nuanced understanding of how digital platforms act as amplification stations (Chung, 2011; Kasperson et al., 2022). SARF has also been instrumental in understanding the cultural and societal dimensions of risk perception, highlighting how values, beliefs, and institutional responses interact to shape risk dynamics.

### 2.2. Works related to SARF

SARF has been extensively applied to diverse contexts, including natural disasters, technological risks, and health crises. From the perspective of communication studies, the concept of risk has been increasingly linked to the dynamics of public discourse and societal responses. This connection, especially in risk communication research, led to the emergence of SARF.

Early studies primarily analyzed traditional media’s role in risk amplification. For instance, Renn (1991) and Pidgeon et al. (2003) examined how media framing influences societal reactions to environmental hazards. Similarly, Crespi and Taibi (2020) highlighted how German news media amplified perceptions of earthquake risks in Italy by emphasizing uncertainty and dramatic outcomes. SARF offers risk communication scholars a useful conceptual tool for examining the social experience of risk by extending our understanding of news media as a component of the framework (Binder et al., 2014).

The rise of social media has significantly influenced SARF research, as platforms like X (formerly Twitter) and Facebook act as dynamic amplification stations. Fellenor et al. (2017, 2020) explored X’s role in amplifying public concern during the 2012 bubonic plague outbreak in the UK. They demonstrated how social media blurs boundaries between journalists and consumers, enabling the rapid dissemination and amplification of risk signals.

Schmid-Petri et al. (2023) collected and analysed tweets about Covid-19 vaccination among German, Russian, Turkish, and Polish groups to measure information gaps between specific demographic groups

about vaccination during the Covid-19 pandemic. Using SARF, E. W. J. Lee et al. (2023) identified 11 key themes based on tweets in public discourse on Covid-19, including health impacts, economic consequences, and public calls for action. Survey research building on SARF identified the importance of online discussion in influencing the spread of risk information during the early stages of Covid-19 outbreaks when publics rely primarily on social media for information (J. Lee et al., 2023; Zhang & Cozma, 2022).

In the context of emerging technologies, SARF has been employed to analyze public perceptions of AI and digital innovations. Recent studies on AI have begun to explore its societal and ethical implications. Neri and Cozman (2020) examined shifts in public sentiment toward AI by analyzing X data over a decade. Park et al. (2022) analyzed AI-related news articles from Korea and the United States, employing topic modelling to identify dominant narratives. Beltran et al. (2024) examined GAI usage guidelines across several countries, highlighting risks such as data privacy concerns, security threats, and public trust issues. By analyzing a sample of 501 of the most-viewed YouTube videos about AI, Schwarz (2024) found that frames with a higher emphasis on the societal threat of AI were more likely to be viewed and commented on by users. Furthermore, Leiter et al. (2023) and Taecharungroj (2023) utilized social media analysis to capture the rapid evolution of public discourse surrounding ChatGPT within short timeframes.

### 2.3. Research Questions

Despite growing interest in SARF applications in digital technologies, a limited number of studies have addressed its role in analyzing GAI discourse, particularly in Korea. This study applies SARF to examine the public discourse on GAI in Korea. By focusing on interactions within amplification stations such as news media and public commentary, the framework enables a systematic analysis of how risk perceptions surrounding GAI are amplified or attenuated in the Korean context. Using the bidirectional encoder representations from transformers (BERT) model, a machine learning algorithm, this study seeks to identify the thematic structures and dynamics influencing the public's risk perception of GAI. By leveraging SARF, this study seeks to address the following research question:

RQ1: Is there a difference between how the media and the public perceive risk in the Korean public sphere?

SARF posits that amplification stations, such as media, shape risk signals differently depending on societal and cultural contexts. By analyzing news articles and public comments, this question examines the disparities in risk perception between news media and the public. Understanding these differences can provide insights into how media narratives influence public discourse on GAI risks.

The second research question focuses on identifying whether risk perceptions of GAI technologies are heightened or diminished through interaction with amplification stations. By employing the BERT model, this study explores the thematic structures and dynamics underlying public discourse, assessing the areas where risks are most amplified or attenuated. These findings can reveal key factors driving societal responses to GAI risks in Korea. As such, we propose the following research question:

RQ2: Perceiving the risk of GAI, have the Korean public been amplified or attenuated through the amplification station?

Through these research questions, this study contributes to a deeper understanding of how SARF can be utilized to analyze the evolving dynamics of risk amplification in the context of emerging technologies.

### 3. Methods

#### 3.1. Dataset

To analyze the Korean public sphere, it is essential to understand the unique news consumption patterns in Korea. Koreans rely on internet portal services for news more than citizens of any other country. According to the Reuters Journalism Institute, 69% of Korean users access news through search engines and news aggregators, more than double the global average of 33% across 46 countries (Newman et al., 2022).

In this study, we collected news distributed via Naver (<http://www.naver.com>), which holds the largest market share among portal services in Korea. For data collection, we focused on in-linked news on Naver. The dataset includes news articles published between January 1, 2023, and June 30, 2024, a period during which issues related to GAI began to gain significant attention.

We extracted news articles containing the keywords “Generative AI” or “Generative Artificial Intelligence” (in Korean: 생성형AI or 생성형 인공지능). Python was used to facilitate data collection. As a result, we gathered 56,468 articles from 115 media outlets, including national and local dailies, business newspapers, broadcasting, online news platforms, magazines, and news agencies.

To examine public reactions, we also collected comments posted on the analyzed articles. From the various comment-sorting options available on Naver—such as sorting by empathy, newest, oldest, empathy ratio, and many nested replies—the top 10 comments with the highest empathy were selected for analysis. In this context, empathy is measured as the number of likes minus the number of dislikes. A total of 68,393 comments were collected through this process.

#### 3.2. Preprocessing Data

We collected data comprising news articles and their associated comments. Since the collected data is text-based and unstructured, it was necessary to preprocess it by removing unspecified words and breaking the text into morphological units. We focused on analyzing Korean lexical morphemes (e.g., nouns, adjectives, and verbs) with two or more syllables while filtering out words deemed unimportant or lacking meaningful content.

News articles can be analyzed at either the sentence level or the article level. For identifying distinct topics within an article and enabling more detailed topic analysis, sentence-level analysis offers a greater advantage. Following preprocessing, the articles were segmented into sentence units, generating a total of 1,781,121 documents.

In contrast, comments, which typically consist of short sentences or paragraphs and often include profanity, were analyzed as whole units rather than being divided into sentence-level components like the articles.

Comments with three words or fewer were excluded from the analysis because they were generally too ambiguous to be effectively interpreted. This resulted in 46,662 documents.

### **3.3. Analysis With BERT Model**

The objective of this study was to use text-mining techniques to investigate how the risks associated with GAI are amplified or attenuated in public discourse. Text mining methods are broadly categorized into two types: topic frequency analysis, which identifies frequently occurring words in a text; and association frequency analysis, which examines the frequency and correlation of co-occurring words. While topic frequency analysis is effective for identifying prevalent topics, it falls short in revealing relationships between them. Given the study's focus on interactions between amplification stations, association word frequency analysis was deemed more suitable.

Topic modelling enables the grouping of documents with similar meanings and the clustering of words with shared contexts into distinct topics. For instance, in a collection of documents on a specific topic, certain words are expected to appear more frequently than others. The most commonly used approach for this purpose is the latent Dirichlet allocation model. However, this model has a significant limitation in that it does not account for word order or sentence structure.

To address this limitation, we adopted the BERT topic modelling technique, which enhances the embedding performance of textual data (Grootendorst, 2022). BERT leverages robust contextual embeddings within the BERT framework, combined with a class-based term frequency-inverse document frequency algorithm. This approach facilitates the comparison of term importance within dense clusters and the development of refined term representations (Sánchez-Franco & Rey-Moreno, 2022).

## **4. Results**

### **4.1. Analysis of News Articles and Comments**

Analysis of the 56,468 news articles in this study reveals a steady increase in frequency over time, interspersed with sudden spikes during specific periods. These concentrated bursts of news coverage can be interpreted as the media's efforts to set an agenda and amplify certain topics. Major events related to GAI, highlighted by the media, act as risk signals.

To understand the overall themes within the dataset, we applied the BERT model to both news articles and comments. To ensure meaningful clustering and avoid the creation of numerous small clusters, we merged similar topics and capped the maximum number of topics at 60.

#### **4.1.1. Topic Analysis of News Article**

First, we conducted BERT model testing on the news articles, extracting the six topics with the highest document frequencies (see Table 1 and Figure 1). Among the analyzed documents, Topic 0 had the largest representation, encompassing 59,835 documents. We labelled this topic "enterprise business," as it focused on how organizations respond to GAI adoption. Articles discussed activities by Kakao, a leading Korean ICT

company, as well as developments in advertising and cloud utilization. Key terms included: cloud, advertising, big, engine, forum, Kakao, open, office, startup, and technology. Examples of related headlines include: “ChatGPT Writes Advertise Copy: Get the Point vs not Creative” and “Kakao Opens Beta for Korean ChatGPT Da-Daum: Developed as a Prototype.”

Topic 1 centred on “GAI and robots,” exploring the integration of GAI technologies into robotics and deep learning services. Key terms included: artificial intelligence, robot, intelligent, language, learning, image, English, interpreter, and Siri. This topic included headlines such as: “Indigenous Cloud Companies Laugh at Last Year’s Results: Public-AI Demand Is Bigger This Year” and “MS Combines Generative AI Co-Pilots in Office: Changing the Way We Work.”

Topic 2 was labelled “game changer of the GAI era” and showcased innovative business models such as Microsoft’s co-pilot. Prominent terms included: cloud, game, centre, Copilot, processing, ultra, data, chain, and core. Examples of related headlines are: “The Keyword of the Year is Speed: The Era of 6G, Robot, and AI is Upon us” and “Talk to It, Play It Music, and It Will Draw a Picture for You.”

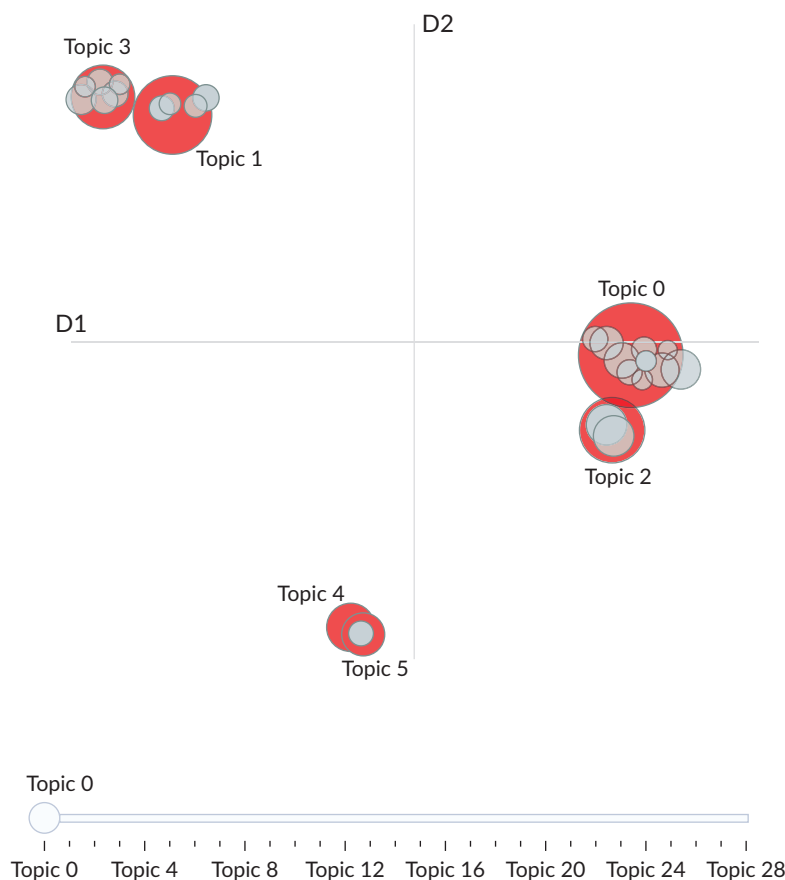
Topic 3 focused on “Samsung and Hynix,” emphasizing the role of Korean semiconductor companies in the GAI landscape. Key terms included: electronics, chairman, generation, Samsung, academic, Hynix, certification, group, and session. Relevant headlines are: “AI-Driven Semiconductor Big Bang: K-Semiconductor, Opportunities and Risks” and “Morgan Stanley: Samsung Electronics and SK Hynix Are Also AI Beneficiaries.”

Topic 4 addressed changes in the stock market, highlighting fluctuations in financial performance linked to GAI developments. Key terms included: profit, operating, increase, contrast, net profit, forecast value, and decrease. Relevant headlines include: “Gartner: Worldwide IT Spending Next Year to Increase 8% Over This Year, Led by AI Investments” and “OpenAI, Which Was in the Red, Expects 1.3 Billion Won in Annual Revenue on ChatGPT Jackpot.”

**Table 1.** Topic analysis of news articles.

Topic	Label	Weights	Documents	Keywords
0	Enterprise business	0.034	59,835	cloud, advertising, big, engine, forum, Kakao, open, office, startup, technology
1	GAI and robot	0.022	39,657	artificial intelligence, robot, intelligent, language, learning, image, English, interpreter, Siri
2	Game changer of GAI era	0.018	32,170	cloud, game, centre, Copilot, processing, ultra, data, chain, core
3	Samsung and Hynix	0.015	27,510	electronics, chairman, generation, Samsung, academic, Hynix, certification, group, session
4	Changes in the stock market	0.014	24,729	profit, operating, increase, contrast, net profit, forecast value, decrease
5	Stock investment	0.013	22,550	investment, stock, management, fund, investment trust, ant (small cap investors), dividend, share

Notes: “Documents” refers to the number of sentence-level articles assigned to each topic; “Weights” is the number of documents in each topic divided by the total number of documents ( $N = 1,781,121$ ).



**Figure 1.** Intertopic distance map of news articles. Note: The red circles are the top six topics.

Topic 5 covered stock investment, emphasizing investing in the stock market for the masses. Key terms were: investment, stock, management, fund, investment trust, ant (small cap investors), dividend, and share. Relevant headlines were: “Stock Investment AI Will Also Become a Game Changer” and “Amazon Invests in Companies Combining AI and Robots: Creates 1.3 Trillion Won Fund.”

Beyond these top six topics, additional themes such as chatbot services, smartphones, and information security also emerged prominently.

#### 4.1.2. Topic Analysis of News Comments

BERT model analysis of news comments was conducted using the same approach as for the news articles. While the labelling of news articles predominantly highlights industry-related topics such as semiconductors and smartphones, the comments are primarily dominated by negative themes, including gaming regulation, cryptocurrency losses, and fake news (see Table 2 and Figure 2).

Topic 0 contained the largest number of comments ( $n = 3,771$ ) and was labelled “short selling.” This topic reflects responses to the impact of the GAI outbreak on South Korean semiconductor companies. Key terms include: stock, short selling, ant (small cap investors), stock price, Samsung Electronics, semiconductor, Hynix, shareholder, stock market, and investment. Examples of comments within this topic include: “Korea’s Samsung and Hynix should support and grow alongside small Korean companies developing system AI and



semiconductors. This might be one way to stay ahead of the competition from Taiwan and the United States,” “I’m sure short stock sellers will soon exploit this article to incite people to short secondary batteries,” and “meanwhile, attention is being drawn to Nvidia and SK Hynix’s monopoly on production.”

Topic 1, labelled “iPhone and Galaxy,” focuses on the trends and implications of GAI adoption by major smartphone companies like Apple and Samsung. Key terms include: Apple, iPhone, Galaxy, Nvidia, Samsung, innovation, Google, smartphone, Jobs, and features. Example comments include: “When the iPhone was first released, I thought, What’s the big deal about having the internet on your phone?,” “when AI like ChatGPT becomes cheaper and apps using it become available, it will be a different world,” and “Samsung would be bigger than Nvidia if they went to the US, but the market is not big because of short stock selling on a tilted playing field.”

Topic 2, which focuses on “ICT companies,” discusses the challenges and opportunities faced by firms such as Naver, Kakao, and Google in the GAI era. Key terms include: Naver, Kakao, search, Google, advertising, blog, stock listing, Coupang, shopping, and search engine. Example comments include: “The metaverse may not have shaken any major companies, but ChatGPT has sparked concerns that even prominent firms like Naver, Kakao, and Google might struggle to survive,” “Bard or GPT shows a lot of hallucinations and performance drops for Korean prompts. Even if it’s Konglish [Korean English], Bard shows good performance for the same English prompt,” and “the lack of Korean data is more of a problem with Naver than with Google or OpenAI looking down on Korea.”

Topic 3, labelled “game regulation,” explores public opinions on the regulation of gaming and related technologies. Key terms include: drawing, game, regulation, author, web comics, copyright, technology, graphics, cloud, and work (of art). Example comments are: “All those who advocate for AI regulation that will never happen will be labelled as enemies of AI and disappear,” “is there a gaming service that lets you play with an AI that learns without a player?,” and “comic and web comic authors are worried about copyright. While they’re happy about the progress in AI, they want to talk about the copyright problems that come with it.”

Topic 4 addresses “cryptocurrencies and damages” and focuses on issues such as fraud, financial losses, and compensation linked to cryptocurrencies. Key terms include: coin, compensation, bitcoin, bank, principal, disaster, fraud, people, impeachment, and finance. Some comment examples are: “Is Nvidia stock selling well now, or did it sell well during the coin craze 4 years ago?,” “labor industry will gradually reduce jobs by robots, and AI will reduce jobs in white-colored jobs such as simple office work, etc. Banks, media companies are overflowing,” and “that ChatGPT is going to be a ball of fire, a human-made disaster. It reminds me of the movie Terminator. A terrible world where machines overpower humans and keep them as servants!”

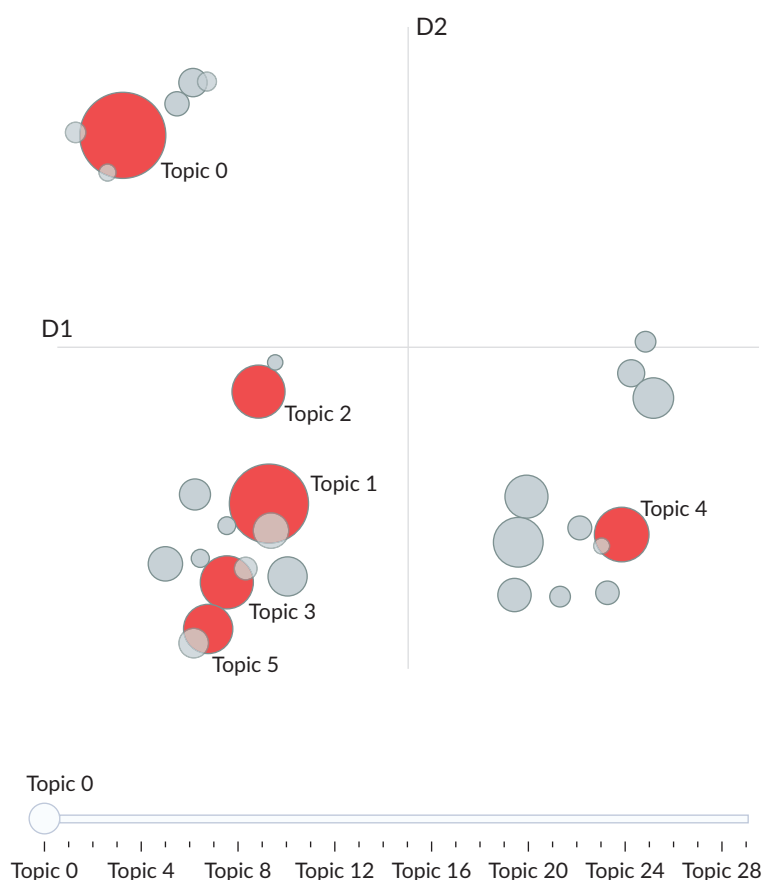
Topic 5, labelled “mobility,” discusses the advancement of autonomous driving technology as electric cars become more widespread. Key terms were: Tesla, electric car, bus, metaverse, driving, battery, self-driving, car, taxi, and battery. Some examples follow: “If you want to invest in real AI, buy Tesla stock,” “GAI will allow us to create an infinite amount of VR AR content in the Metaverse. GAI is the key to the metaverse, and once the device revolution comes, we’ll never see humans crossing the street with their necks craned,” and “in a few years, we can imagine wearing Vision Pro and taking Tesla into self-driving mode and if we get in an accident: who’s to blame? The driver, Tesla, Apple?”

Beyond the top six topics, additional themes emerged, including judgment and politics, fake news, marriage and childbirth, and English and GAI.

**Table 2.** Topic analysis of public comments.

Topic	Label	Weight	Documents	Keywords
0	Short selling	0.081	3,771	stock, short selling, ant (small cap investors), stock price, Samsung electronics, semiconductor, Hynix, shareholder, stock market, Investment
1	iPhone and galaxy	0.065	3,035	Apple, iPhone, Galaxy, Nvidia, Samsung, innovation, Google, smartphone, (Steve) Jobs, features
2	ICT companies	0.031	1,442	Naver, Kakao, search, Google, advertising, blog, stock listing, Coupang, shopping, search engine
3	Game regulation	0.030	1,400	drawing, game, regulation, author, web comics, copyright, technology, graphics, cloud, work (of art)
4	Cryptocurrencies and damages	0.028	1,325	coin, compensation, bitcoin, bank, principal, disaster, fraud, people, impeachment, finance
5	Mobility	0.027	1,253	Tesla, electric car, bus, metaverse, driving, battery, self-driving, car, taxi, battery

Notes: “Documents” refers to the number of comments assigned to each topic; “Weights” is the number of documents in each topic divided by the total number of documents ( $N = 46,662$ ).



**Figure 2.** Intertopic distance map of the top 30 topics in news comments. Note: The red circles are the top six topics.

## 4.2. Identified Risk and the Public

BERT model analysis identified the communication flows in news articles and public comments that act as amplification stations in the Korean public sphere. However, this analysis was limited in its ability to pinpoint the processes underlying the amplification or attenuation of activity within the SARF. To adopt a more empirical approach, we assessed the relevance of the analysis results regarding established GAI-related risk factors.

We began by identifying GAI-related risk factors through a literature review. Wach et al. (2023) outlined seven controversies and threats associated with GAI from a management and economics perspective. Similarly, Beltran et al. (2024) analyzed government-issued guidelines for GAI usage in Australia, Canada, New Zealand, the United Kingdom, and South Korea, identifying 22 risk factors. Beltran et al. (2024) further measured how these guidelines reflected the risk factors, finding that the South Korean government's guidelines weighted leakage (41.7%) and hallucination (25%) most heavily, followed by privacy, intellectual property, and bias concerns (see Table 3).

Building on these studies, we empirically measured the differences in risk perceptions between media, which reflects expert perspectives, and public discourse from a SARF perspective. This involved comparing their alignment with the analysis results and the risk factors defined by Wach et al. (2023) and Beltran et al. (2024). We vectorized Korean data from news articles and comments within each topic. We also vectorized the 22 risk factors' names and definitions. The cosine similarity between these vectors was then calculated using the following formula where A = vector of the 22 risk factors and B = vector of BERT model results:

$$\text{cosine}_{\text{similarity}(A,B)} = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^n A_i \times B_i}{\sqrt{\sum_{i=1}^n A_i^2} \times \sqrt{\sum_{i=1}^n B_i^2}}$$

**Table 3.** Risks related to GAI.

Controversies and risks of GAI	Identified risk	Definition
Poor quality, lack of quality control, disinformation, deepfake content, algorithmic bias	Authenticity	GAI can intensify the spread of fake information.
	Explainability	Difficulty interpreting and understanding GAI outputs, leading to challenges in identifying errors and trust issues.
	Hallucination	GAI may generate nonsensical or incorrect outputs.
	Harmful content	Content produced by GAI could be violent, offensive, or harmful.
	Public trust	The use of GAI raises significant concerns about public trust and may lead to its erosion.
	Quality of training data	GAI can produce erroneous outputs due to inadequate or low-quality training data.
	Misuse	Potential for using GAI in plagiarism or cheating. GAI may exacerbate the digital divide, impacting individuals and communities with varying access to and acceptance levels of this technology.

**Table 3. (Cont.) Risks related to GAI.**

Controversies and risks of GAI	Identified risk	Definition
Widening socio-economic inequalities	Bias	GAI may show unfair favouritism or discrimination against certain individuals or groups.
	Digital divide	GAI may exacerbate the digital divide, impacting individuals and communities with varying access to and acceptance levels of this technology.
	Environmental	GAI incurs a substantial environmental cost, mainly due to the significant greenhouse gas emissions associated with its development and use.
	Income inequality and monopolies	GAI exacerbates income disparities by favouring those with AI proficiency and resources and potentially leading to resource and power monopolization by large companies.
	Industry disruption	GAI can transform competitive dynamics across industries, potentially leading to market dominance by a few players.
	Over-reliance	Users can become extremely dependent on GAI, hindering critical thinking and problem-solving skills.
Personal data violation, social surveillance, and privacy violation	Cybersecurity	The vulnerability of GAI to unauthorized access, manipulation, and data theft poses significant threats to the integrity and confidentiality of operations and sensitive data.
	Leakage	Dissemination of sensitive information or intellectual properties of the organization.
	Privacy	GAI may lead to the loss, alteration, or unauthorized disclosure of personal data and infringe on individuals' privacy rights.
AI-related technostress	Governance	Issues with human control over AI behaviour, interoperability, and data fragmentation. The use of GAI raises significant concerns about public trust and may lead to its erosion.
	Prompt engineering	The quality of prompts can lead to errors or misunderstandings in AI responses.
Automation-spurred job losses	Labor market	Potential for job displacement and unemployment as a consequence of the integration and advancement of GAI in various sectors.
	Professional standards	Using GAI to complete tasks requiring a professional license (e.g., medical diagnosis or legal advice) can breach regulations or professional guidelines.
No regulation of the AI market and urgent need for regulation	Intellectual property	GAI can contravene copyrights, trademarks, or patents.
Social manipulation, weakening ethics, and goodwill	Liability and accountability	Using GAI can involve an unclear assignment of responsibility for GAI errors or harm.

Notes: "Controversies and risks of GAI" was cited in Wach et al. (2023) and "Identified risk and Definition" was cited in Beltran et al. (2024).

The analysis revealed noticeable differences in the similarity scores between news articles and comments, as outlined in Table 4. For news articles, the topic with the highest similarity score was cybersecurity, which

**Table 4.** Differences in GAI risk perception by amplification station.

Rank	Korea's government	News articles	Comments
1	Leakage	Cybersecurity (0.576)	Misuse (0.507)
2	Hallucination	Misuse (0.558)	Industry disruption (0.506)
3	Privacy	Industry disruption (0.518)	Governance (0.492)
4	Intellectual property	Governance (0.510)	Labor market (0.483)
5	Bias	Hallucination (0.508)	Leakage (0.482)

Note: The numbers in parentheses are the cosine similarity between the data and the identified risk.

scored 0.576. This was followed by misuse with a similarity score of 0.558, industry disruption at 0.518, governance at 0.510, and hallucination at 0.508. In contrast, for comments, the highest similarity score was observed for misuse, with a score of 0.507. This was closely followed by industry disruption, which scored 0.506, and governance, which had a similarity score of 0.492. Furthermore, the topics of labor market and leakage were significant, with scores of 0.483 and 0.482, respectively.

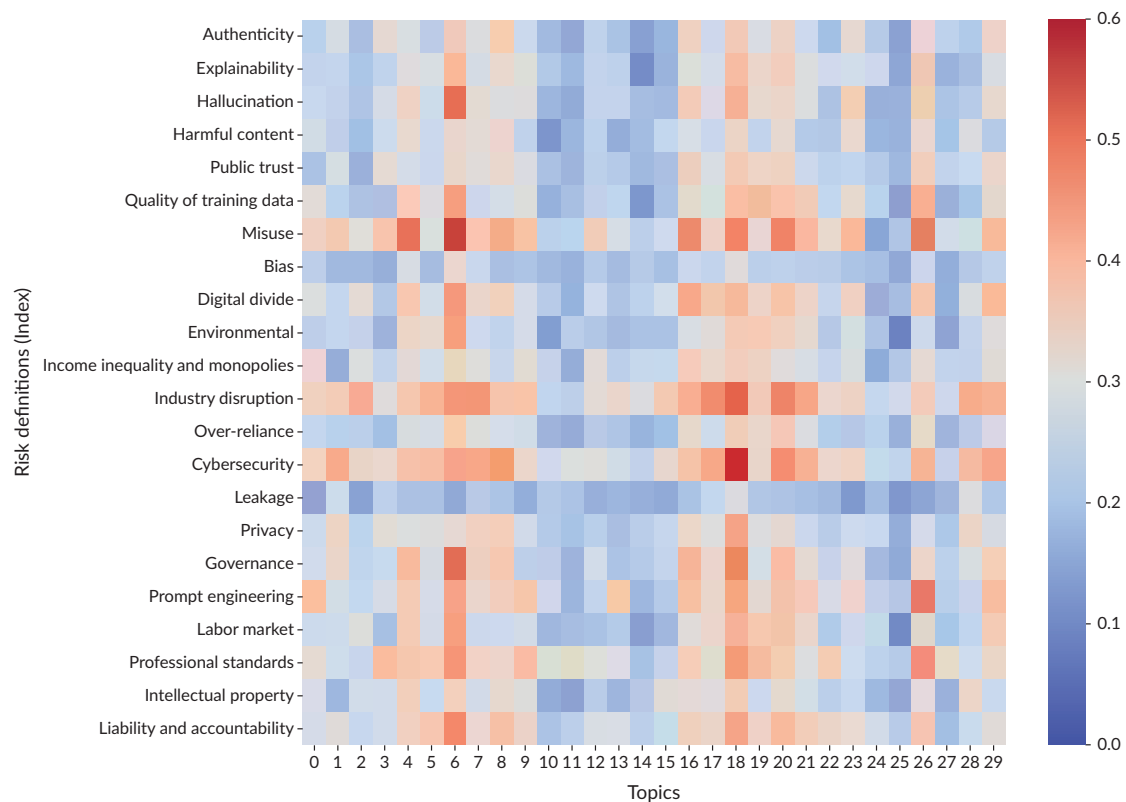
These results highlight the differing emphases placed on specific risk factors by news articles and public comments, reflecting variations in the perception and prioritization of GAI-related risks between these two amplification stations.

The average similarity value across all topics was higher for news articles (0.280) than for comments (0.212). Among news articles, the highest average similarity scores were observed for misuse (0.294), followed by cybersecurity (0.257), prompt engineering (0.257), professional standards (0.251), and industry disruption (0.245). In the case of comments, the highest averages were noted for industry disruption (0.366), cybersecurity (0.360), misuse (0.350), professional standards (0.325), prompt engineering (0.312), and liability and accountability (0.311). However, these results are not significant since similarity is generally considered meaningful only when the measure is greater than or equal to 0.5.

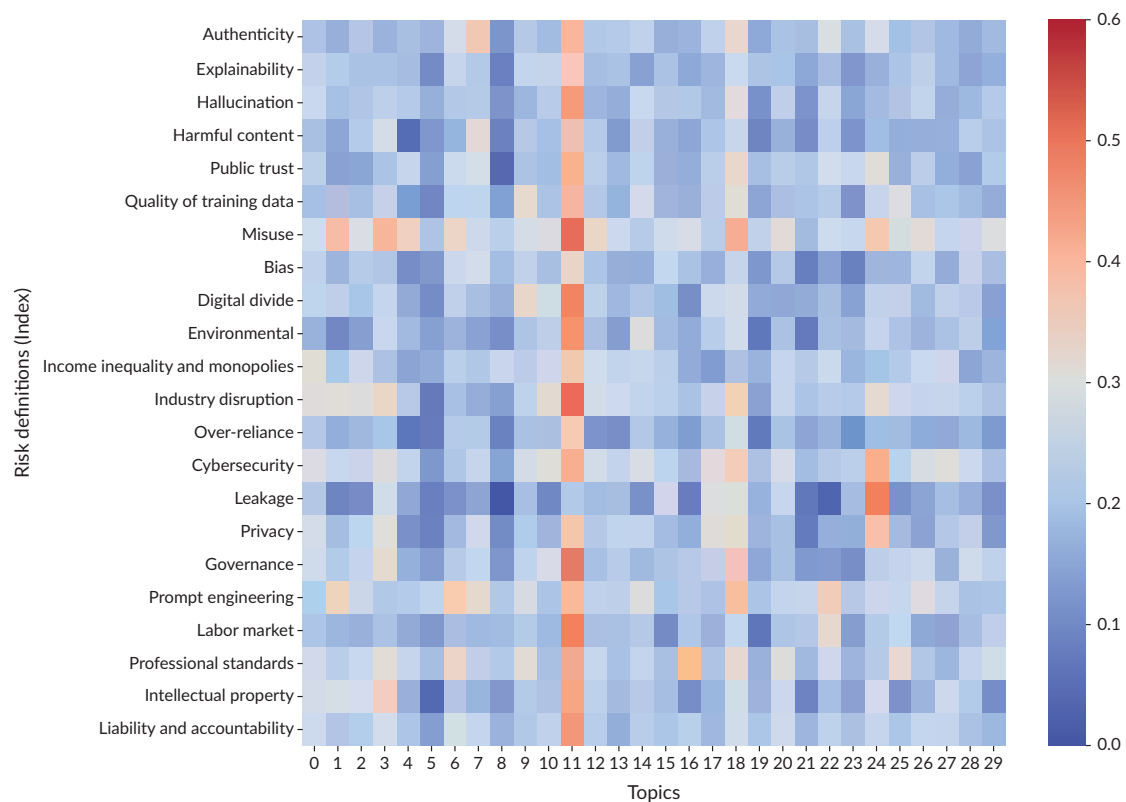
Upon visualizing the similarity analysis results through heatmaps, notable differences emerged (see Figures 3 and 4). The similarity results between comments and risk factors showed relatively high similarity to specific topics (Topic 11), but overall low similarity between other topics. Conversely, the heatmap between articles and risk factors demonstrated a relatively distinct pattern of similarity across many topics.

From a qualitative perspective, there were also notable differences in how risk factors were prioritized by the two amplification stations. Analysis of news articles identified cybersecurity as the most significant risk factor, while comments highlighted misuse as the top concern, alongside labor market and leakage issues. Both news articles and comments recognized misuse and industry disruption as key concerns. However, neither amplification station gave significant attention to the South Korean government's top-ranked risk factors: leakage, hallucination, privacy, intellectual property, and bias.

Despite these differences, the two amplification stations demonstrated some alignment in their classifications of risk factors. The controversies and risks of GAI, as outlined by Wach et al. (2023), were addressed in both stations within five overarching categories: (a) poor quality, lack of quality control, disinformation, deepfake content, and algorithmic bias; (b) widening socio-economic inequalities; (c) personal data violations, social surveillance, and privacy breaches; (d) AI-induced technostress; and (e) job losses driven by automation. This



**Figure 3.** Similarity analysis: Identified risk keywords and BERT model of the top 30 topics in news articles.



**Figure 4.** Similarity analysis: Identified risk keywords and BERT model of the top 30 topics in comments.

alignment underscores shared concerns about certain critical risks, even as the emphasis on specific factors varies between news articles and public comments.

## 5. Conclusion and Discussion

### 5.1. Implications of Research

Using the framework of the SARF, this study examined how the risks associated with GAI are amplified or attenuated within the Korean public sphere. Specifically, to evaluate differences in risk perception between the media and the public, we employed the BERT model analysis to identify themes in news articles and public comments. The findings yield several important implications for understanding risk dynamics.

First, the analysis of news articles and comments reveals that perceptions of GAI-related risks differ based on the amplification station. From the SARF perspective, media outlets—often shaped by expert contributions—traditionally act as amplification stations. The BERT model results show that media coverage has largely focused on keywords highlighting the impacts of GAI on various industries. Specifically, the most prominent topics in news articles include robotics, semiconductors, and smartphones, reflecting the media's emphasis on industry-level consequences of GAI. In contrast, public comments, which function as a public amplification station, set an alternative agenda for GAI-related risks, spotlighting issues such as gaming regulations, cryptocurrency concerns, and the spread of fake news. Moreover, they also reflect doubts about the relevance of learning foreign languages in an era dominated by GAI technologies. This contrast highlights the divergence in focus between media narratives and public discourse.

Second, the definition of risk factors for GAI further supports the idea that the public's perception of risk differs significantly from that of the media. To objectively identify these differences, we applied a similarity measure for each topic instead of relying solely on thematic analysis. Both the public and the media, as amplification stations, address major risk themes associated with GAI but differ in the specific risks they prioritize. Notably, the public tends to amplify concerns about misuse and labor market disruptions, whereas the media and government emphasize other risks such as cybersecurity and industry disruption.

Third, the study found that the amplification effect of news media within the amplification station was limited. Consistent with prior SARF-based studies, the topics amplified by news media were not always reflected in public comments. This suggests that the risk agenda set by the media does not necessarily align with the risk perceptions expressed in public discourse.

This selective amplification and attenuation of risk, arising from the interaction between news articles and comments, is likely to influence the public forum's response to GAI-related risks. These dynamics will, in turn, shape the subsequent phases of the SARF, including the ripple effects and impact phase. Based on the findings, public debate on the risks of GAI is expected to converge around specific topics and is likely to prioritize the impacts of industry changes over broader issues such as the ethics of AI, global regulatory frameworks, or transformations in the knowledge economy.

## 5.2. Limitations and Suggestions

This study builds upon existing academic research to identify new dimensions of social risk perception. However, several limitations should be acknowledged. First, this study did not establish a fully objective metric to quantify the degree of risk amplification or attenuation in news articles and comments. Although the SARF inherently lacks tools for measuring the extent of these processes, we attempted to address this gap by using word similarity as a quantitative measure. While this approach offered a partial solution, future research could benefit from incorporating more diverse and robust methodologies to enhance the analysis and provide a clearer understanding of amplification and attenuation dynamics.

Second, the study relied on risk factors identified in prior studies to measure the similarity between news articles and comments. While this approach yielded valuable insights, it may not have captured the broader or evolving spectrum of risks discussed in public forums. Public perceptions of risk are dynamic and multifaceted, often influenced by emerging issues and contextual shifts. Future studies could develop improved metrics and frameworks that account for the variability and complexity of public discourse on risk-related topics.

Third, the role of social media as an amplification station remains a significant challenge in risk communication research. This study focused on analyzing news comments, which are inherently shaped by the agendas set by news agencies. As a result, they may not fully reflect the public's active, autonomous responses to risk signals. To overcome this limitation, future research could expand in scope to include other social media. Platforms such as X, Facebook, or YouTube may provide a more comprehensive and diverse perspective on public engagement with risk-related issues, offering insights into how risks are perceived and debated across different digital spaces.

By addressing these limitations, future studies can contribute to a more nuanced and holistic understanding of how risks are communicated, perceived, and amplified in the public sphere. This understanding can in turn inform more effective strategies for risk management and communication.

## Acknowledgments

The authors used generative artificial intelligence (ChatGPT 4.0; DeepL) partly for the coding in Python, translating, and proofreading.

## Conflict of Interests

The authors declare no conflict of interests. In this article, editorial decisions were undertaken by Jeong-Nam Kim (University of Oklahoma).

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