https://doi.org/10.37420/j.cer.2026.007

# Research on the Impact of Algorithmic Bias in Generative Artificial Intelligence on Public Opinion Ecology from the Perspective of Media Ecology

**Fangchi Liu***
**School of Journalism and Communication, Beijing Institute of Graphic Communication, China**
***Corresponding author E-mail: liufangchi0108@163.com**

**Abstract:**
*With generative artificial intelligence (AI) deeply embedded in the production and dissemination of public opinion, its inherent algorithmic biases are gradually reshaping the mechanisms of public opinion generation and the public's cognitive structure. This paper, from the perspective of media ecology theory, uses content analysis and in-depth interviews to systematically compare the analytical texts of two generative AI models, Doubao and DeepSeek, in 30 highly discussed public opinion events. It also examines the impact of algorithmic biases on the public opinion ecosystem and individual cognition, incorporating the experiences of ordinary users. The study finds that generative AI exhibits a clear structural tendency in fact presentation, emotional expression, and value guidance. Its seemingly neutral expression, through repeated reinforcement, may influence the public's cognitive framework and value judgments. This paper argues that generative AI has transformed from an information tool into a significant mediating force influencing the public opinion ecosystem, and the long-term impact of its algorithmic biases on public opinion urgently requires continued attention and reflection.*

**Keywords:**
*algorithmic bias, generative artificial intelligence, media ecology, public opinion cognition, public opinion ecology*

## 1 Introduction

As generative AI technology becomes deeply embedded in news production and dissemination, generative AI, including platforms like Doubao and Deepseek, is playing an increasingly important role in public opinion. This information fragmentation dominated by generative AI not only changes the way public opinion is generated and spread but also weakens the consensus base for public discourse, increases the complexity of public opinion guidance and social governance, and leads to a polarized and fragmented public opinion ecosystem. So, what new changes are occurring in the impact of generative AI on the public opinion ecosystem? Can the biases of generative AI influence human biases ?

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

# 2 Literature Review

## *2.1 Relevant research on the media ecology school*

Media ecology theory originated in the mid-20th century, focusing on exploring the social impact of communication technologies, moving beyond research solely on media content. Numerous prominent figures represent this theory. Early proponents include Canadian scholar Marshall McLuhan, who in his 1964 book Understanding Media proposed that "the medium is the message" and argued that the form and environment of media influence culture. American scholar Neil Postman, in works such as Technological Monopoly: Culture Surrenders to Technology, emphasized the significant influence of media ecology on human emotional communication. More recently, active third-generation researchers, such as Paul Levinson, in Human History Revisited: The Evolution of Media, focused on the active choice of media by individuals with humanistic values. In 2013, Chen Lidan et al., in The Process of Media Ecology's Reception in China and its Social Context, detailed the localization process of media ecology and raised practical issues related to the theory. In 2022, Yang Jie, in her article A Study of Urban AI Sensory Media from the Perspective of Media Ecology, proposed that artificial intelligence sensory media, through technological innovation, has reshaped the media experience of urban individuals, promoted the formation of media cities, and driven changes in urban life and consumption patterns. However, most research on media ecology is limited to media aspects, and there is little research on the impact of algorithmic biases in generative artificial intelligence on the public opinion ecosystem.

## *2.2 Research on algorithmic bias in generative artificial intelligence*

Since its emergence in 2022, ChatGPT has garnered significant attention both domestically and internationally. It uses related technologies to collect, process, and summarize patterns to obtain data models. In recent years, facing the risks and challenges of artificial intelligence, European and American countries have begun to introduce ethical guidelines for AI. In 2023, the city of San Jose released the "Guidelines for Generative Artificial Intelligence," clarifying the local government's acceptance of generative AI, but also requiring everyone to minimize the risks of AI bias. Also in 2023, Zhou Ting and Pu Cheng, from the perspective of international communication, argued that generative AI has the potential risks of becoming a tool for propaganda warfare, delaying international conflicts, becoming a new conduit for extreme rhetoric, endangering network and data security, exacerbating global digital inequality, and weakening human cultural diversity. In 2025, Yang Xiaotong, in her article The Ideological Metaphors of Generative Artificial Intelligence and Its Concretization Risk Response, argued that countermeasures such as eliminating data bias and implementing technical governance through algorithmic monitoring, and building a collaborative mechanism with multi-party participation, should be taken to prevent the ideological risks of generative AI and promote the harmonious unity of technology and values. However, these studies did not examine the phenomenon of public opinion ecology from the perspective of algorithmic bias in generative artificial intelligence, and therefore did not answer questions about the new changes in the impact of generative artificial intelligence algorithms on the public opinion ecology, or whether the bias of generative artificial intelligence affects human bias.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

### *2.3 Raising the question*

This paper, supported by media ecology theory, attempted to answer the following questions by examining the technical aspects of algorithmic bias in generative artificial intelligence:

Q1: New characteristics of the public opinion ecosystem presented by the infiltration of generative artificial intelligence.

Q2:The impact of embedded algorithmic biases in generative artificial intelligence on individual cognitive attitudes and value judgments.

## 3 Research Methods

### *3.1 Content analysis method*

#### *3.1.1 Assumption Establishment*

Based on the questions raised above, we proposed the following hypothesis: generative artificial intelligence has a negative influence on the public opinion environment.

#### *3.1.2 Sampling Method*

We selected public opinion events from the *People's Daily Online Public Opinion Data Center's* official WeChat accounts that had generated significant public discussion and emotional engagement over the past six months. We conducted stratified sampling with a one-month cycle, ultimately selecting 30 public opinion events as research cases.

#### *3.1.3 Encoding table*

This study reduced the dimensionality of variable-generative artificial intelligence to Doubao and Deepseek. It also reduced the dimensionality of the variable-based public opinion ecology to the methods of fact presentation, the structure of public opinion presentation, the characteristics of emotional expression, value and normative orientation, public opinion guidance tendencies, and the characteristics of the AI role.

### *3.2 In-depth interview method*

#### *3.2.1 Selection of Interviewees*

The author selected ordinary users who frequently used Doubao and DeepSeek within the past six months as interview subjects, whose main purposes were information retrieval, event interpretation, opinion acquisition, or value judgment. The sample consisted of fifteen respondents aged 18-30, encompassing university students, graduate students, and young professionals. Interviews were conducted via telephone and WeChat text. Based on this, through a horizontal comparison of the viewpoints of different respondents, the main pathways and manifestations of how the biases of generative artificial intelligence embedded algorithms influence individual cognitive attitudes and value judgments were summarized.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

The interview results were compiled into a verbatim transcript, totaling 18 000 words. The entire research process strictly adhered to the principles of academic research ethics. All interviewees participated voluntarily after fully understanding the research objectives and procedures. The interview data was used solely for academic research, and personal information was anonymized.

### *3.2.2 Interview Outline*

The interview questions mainly revolve around respondents' understanding of public opinion events using artificial intelligence, the impact of generative artificial intelligence on respondents' perception of public opinion, the role of generative artificial intelligence in responding to respondents' judgment of public opinion, the specific ways of using artificial intelligence to deal with public opinion, and whether or not they have consciously adjusted their dependence on generative artificial intelligence and the way they have adjusted it. The research questions are simplified into easy-to-understand interview questions suitable for daily communication.

Throughout the interviews and research, the researchers took every effort to avoid the four ethical issues and transgressions emphasized by scholar Alan Bryman: (1) causing harm to research participants; (2) failing to use informed consent documents or materials; (3) violating the privacy of research participants; and (4) deceiving research participants. Furthermore, if respondents had any questions they did not wish to answer or expressed dissatisfaction during the interview, they could remain silent or withdraw midway. Interview materials that respondents stated they did not wish to disclose were not included or cited in this study.

## 4 Research Findings and Discussion Points

### *4.1 Sample processing method*

Thirty highly discussed public opinion events were selected from the WeChat official account *People's Daily Online Public Opinion Data Center* using stratified sampling. The same instructions (i.e., event keywords + please fully describe this public opinion event and analyze the social phenomena or trends behind it) were input, and two AI models, Deepseek and Doubao, analyzed the same public opinion event. Based on the analysis provided by the AI models, human evaluation was conducted according to six dimensions: factual presentation, public opinion structure, emotional expression characteristics, value and normative orientation, public opinion guidance tendency, and AI role characteristics.

### *4.2 Analysis of the intelligent large model*

### *4.2.1 Factual completeness*

Of the 60 samples, 51 contained complete factual information, indicating that both models performed well overall in terms of factual completeness. Doubao was more stable, achieving a completeness rate of 96.7%, while Deepseek achieved 73.3%. This suggests that Doubao has stronger information coverage and integration capabilities in extracting and presenting key factual information about events, with fewer information gaps.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

*Table 1 Factual integrity*

| Factual integrity | Deepseek | DOUBAO | total |
|---|---|---|---|
| **whole** | 22 | 29 | 51 |
| **part** | 6 | 0 | 6 |
| **Missing** | 2 | 1 | 3 |
| **total** | 30 | 30 | 60 |

### *4.2.2 Certainty of facts*

In terms of factual certainty, Doubao demonstrated high certainty, with 28 cases showing high certainty and the remaining 2 showing medium certainty. While Deepseek had 22 cases showing high certainty, it also had 6 cases showing low certainty. This suggests that Doubao uses more definitive language when outputting factual judgments, while Deepseek exhibits ambiguity in factual boundaries in some events, potentially reflecting room for improvement in its factual inference mechanism for complex public opinion events.

*Table 2 Certainty of facts*

| Certainty of facts | Deepseek | DOUBAO | total |
|---|---|---|---|
| **high** | 22 | 28 | 50 |
| **middle** | 6 | 2 | 6 |
| **Low** | 2 | 0 | 4 |
| **total** | 30 | 30 | 60 |

### *4.2.3 Diversity of viewpoints*

Both models performed well in presenting the diversity of viewpoints. Deepseek had 28 samples demonstrating diverse viewpoints, while Doubao had 29, with only a few cases showing a relatively singular viewpoint. This indicates that both models can cover different stances and opinions in public opinion analysis, possessing a certain degree of multi-angle analytical capability, which is beneficial for users to obtain a more comprehensive perspective on public opinion.

*Table 3 Diversity of viewpoints*

| Diversity of viewpoints | Deepseek | DOUBAO | total |
|---|---|---|---|
| **yes** | 28 | 29 | 57 |
| **no** | 2 | 1 | 3 |
| **total** | 30 | 30 | 60 |

### *4.2.4 Balance of positions*

In terms of balance of stance, Doubao performed exceptionally well, with all samples showing a balanced stance. Deepseek, on the other hand, had 28 balanced samples and 2 unbalanced samples. This indicates that Doubao prioritizes balance when expressing different stances and is less prone to significant bias. Deepseek also maintains neutrality in most cases, but may exhibit bias in a very few instances.

*Table 4 Balance of positions*

| Balance of positions | Deepseek | DOUBAO | total |
|---|---|---|---|
| **balanced** | 28 | 30 | 58 |
| **Imbalance** | 2 | 0 | 2 |
| **total** | 30 | 30 | 3 |

### *4.2.5 Emotional intensity*

Both models tend to output high emotional intensity results. Deepseek had 28 cases of high emotional in-

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

tensity, while Doubao had 27, with fewer cases of medium to low intensity. This indicates that in the analysis of current public opinion events, the models are more inclined to identify and highlight emotional expressions in public issues, reflecting their high sensitivity to the emotional structure of public opinion. This tendency may further amplify the emotional mobilization effect in the public opinion field, pushing public discussion away from factual statements and towards emotional resonance.

*Table 5 Emotional intensity*

| Emotional intensity | Deepseek | DOUBAO | total |
|---|---|---|---|
| **high** | 28 | 27 | 55 |
| **middle** | 2 | 3 | 5 |
| **Low** | 0 | 0 | 0 |
| **total** | 30 | 30 | 60 |

### *4.3.6 Emotion-oriented*

In terms of emotional guidance, both models were dominated by positive emotions, with Deepseek exhibiting one instance of negative emotion and Doubao one instance of neutral emotion. Overall, the AI models tended to convey positive or neutral emotions in interpreting public opinion, with negative emotions being extremely rare. This suggests that intelligent models may intentionally reinforce the spread of positive emotions when participating in public opinion construction, thereby subtly influencing the public's emotional perception of public events. However, it is important to be wary that this phenomenon may also weaken the necessary critical and reflective aspects of public opinion supervision to some extent.

*Table 6 Emotion-oriented*

| Emotion-oriented | Deepseek | DOUBAO | total |
|---|---|---|---|
| **positive** | 29 | 29 | 58 |
| **neutral** | 0 | 1 | 1 |
| **negative** | 1 | 0 | 1 |
| **total** | 30 | 30 | 60 |

### *4.2.7 Clarity of responsibility attribution*

In terms of the clarity of responsibility attribution, Doubao slightly outperformed Deepseek, with 29 cases showing clear responsibility attribution and 1 case showing ambiguity; Deepseek had 28 cases showing clear responsibility attribution and 2 cases showing ambiguity, and neither showed any instances of responsibility avoidance. This indicates that in the analysis of public opinion events, large AI models generally tend to clearly identify the responsible party.

*Table 7 Clarity of responsibility attribution*

| Clarity of responsibility attribution | Deepseek | DOUBAO | total |
|---|---|---|---|
| **clear** | 28 | 29 | 57 |
| **Vague** | 2 | 1 | 3 |
| **avoid** | 0 | 0 | 0 |
| **total** | 30 | 30 | 60 |

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

### *4.2.8 Normative Implications*

The two models showed a high degree of consistency in normative cues, with all samples exhibiting strong cues. This indicates that during the interpretation of public opinion events, the AI model continuously guides users to focus on social norms, moral principles, or legal frameworks, demonstrating a clear value-guiding tendency.

*Table 8 Normative implications*

| Normative implications | Deepseek | DOUBAO | total |
|---|---|---|---|
| **Strong reminder** | 30 | 30 | 60 |
| **Weak prompts** | 0 | 0 | 0 |
| **No prompt** | 0 | 0 | 0 |
| **total** | 30 | 30 | 60 |

### *4.2.9 Enhanced Agenda Framework*

Regarding the elevation of the issue framing, the vast majority of samples exhibited strong elevation characteristics, meaning they were able to interpret specific events within a broader social or cultural context. Specifically, all 30 samples from Deepseek showed strong elevation, while Doubao showed 29. This indicates that the intelligent big data model possesses a strong ability to elevate issues in public opinion analysis, helping to shift public attention from individual events to broader social problems.

*Table 9 Enhanced Agenda Framework*

| Enhanced Agenda Framework | Deepseek | DOUBAO | total |
|---|---|---|---|
| **Strong enhancement** | 30 | 29 | 59 |
| **weak improvement** | 0 | 1 | 1 |
| **No improvement** | 0 | 0 | 0 |
| **total** | 30 | 30 | 60 |

### *4.2.10 Risk adjustment tendency*

Regarding risk mitigation tendencies, both models exhibited a clear tendency to amplify risk, with Deepseek showing 27 cases and Doubao showing 29. This suggests that in interpreting public opinion events, the models tend to emphasize the risk and conflict factors within the event.

*Table 10 Risk adjustment tendency*

| Risk adjustment tendency | Deepseek | DOUBAO | total |
|---|---|---|---|
| **enlarge** | 27 | 29 | 56 |
| **neutral** | 2 | 1 | 3 |
| **easing** | 1 | 0 | 1 |
| **total** | 30 | 30 | 60 |

### *4.2.11 Mediating role*

All samples exhibited a mediating role, primarily serving the function of information transmission and interpretation, rather than directly advocating for a stance. This indicates that in the analysis of public opinion events, intelligent large-scale models are generally designed to remain neutral, acting as information intermediaries rather than discourse agents.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

*Table 11 mediator role*

| mediator role | Deepseek | DOUBAO | total |
|---|---|---|---|
| **yes** | 30 | 30 | 60 |
| **no** | 0 | 0 | 0 |
| **total** | 30 | 30 | 60 |

### *4.2.12 Judgmental Tendency*

Regarding the adjudicative tendency, Doubao exhibited an adjudicative tendency in all samples, meaning it explicitly offered judgments of right and wrong or suggested solutions. While 28 samples from Deepseek showed an adjudicative tendency, all of Doubao's samples did. This indicates that the model, in analyzing public opinion events, not only provides factual descriptions but also tends to output clear value propositions. This adjudicative tendency may lead to a rapid consensus among the public and guide public opinion, but it may also weaken the openness and diversity of the public opinion field.

*Table 12 Judgmental sexual orientation*

| Judgmental sexual orientation | Deepseek | DOUBAO | total |
|---|---|---|---|
| **yes** | 28 | 30 | 58 |
| **no** | 2 | 0 | 2 |
| **total** | 30 | 30 | 60 |

## *4.3 Description of content analysis results*

This study uses content analysis to analyze highly discussed public opinion events from the *People's Daily Online Public Opinion Data Center*. The analysis compares six dimensions: factual presentation , public opinion structure, emotional expression characteristics, value and normative orientation, public opinion guidance tendency, and AI role characteristics. Lower scores in each dimension indicate a negative influence of generative artificial intelligence on the public opinion ecosystem. The research data is as follows:

From the above analysis results of the intelligent big data model, Deepseek's analysis scored an average of 2.6 (3) in fact presentation, 0.93 (1) in public opinion structure presentation, 2.93 (3) in emotional expression characteristics, 2.97 (3) in value and norm orientation, 2.93 (3) in public opinion guidance tendency, and 2.97 (3) in AI role characteristics. Meanwhile, Doubao's analysis scored an average of 2.93 (3) in fact presentation, 0.98 (1) in public opinion structure presentation, 2.93 (3) in emotional expression characteristics, 2.98 (3) in value and norm orientation, 2.97 (3) in public opinion guidance tendency, and 3 (3) in AI role characteristics.

By comparing the analysis of public opinion events by different intelligent models, using the scoring criteria of this coding study, it is evident that Doubao outperforms Deepseek across all dimensions of its analysis, indicating that Doubao's impact on the public opinion ecosystem is more positive. Specifically, Doubao's analysis of 30 samples provides a more complete and accurate narrative in terms of factual presentation , while Deepseek exhibits some degree of incompleteness and inaccuracy in its narrative. The differences in information integration, factual presentation, and language expression among the different models suggest that, in the context of generative AI's intervention in public opinion events, due to the imperfections in its algorithmic logic, the facts presented may contain omissions, inaccuracies, or even both. Faced with the massive amounts of fragmented and distorted information produced by generative AI, the public is highly likely to de-

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

velop cognitive biases regarding events through long-term use of algorithmic models. Conversely, when users receive a more complete, coherent, and definitive narrative of public opinion events from generative AI, it is easier to cultivate a holistic mindset, enabling the public to make dialectical value judgments and take practical actions based on this foundation. Therefore, it can be concluded that the presentation of facts in intelligent large-scale models should enhance the completeness and certainty of the text to guide the public in forming correct public opinion perceptions and value judgments. Furthermore, when inputting commands to Doubao and Deepseek, Doubao's accuracy in capturing a small number of keywords is greater than Deepseek's.

### *4.4 Interview analysis and conclusions*

The previous section, through content analysis, analyzed the intelligent big data model and concluded that generative artificial intelligence (AI) has a negative influence on the public opinion ecosystem. Building upon this foundation, this section further explores the impact of generative AI on individual public opinion cognition through in-depth interviews. Fifteen individuals were interviewed, focusing on their use of generative AI to understand public opinion events, their stance and attitude when using the intelligent big data model, the impact on their exposure to diverse information, and their perception of algorithmic bias. Basic information about the interviewees is shown in the table below.

*Table 13 A Fuzzy Relation Rs*

| serial number | gender | age | Profession |
|---|---|---|---|
| S1 | male | 22 | college students |
| S2 | female | 22 | reporter |
| S3 | female | 23 | edit |
| S4 | female | 25 | postgraduate |
| S5 | female | 22 | civil servants |
| S6 | female | 27 | human Resources |
| S7 | female | 23 | teacher |
| S8 | female | 23 | college students |
| S9 | male | 26 | postgraduate |
| S10 | female | 23 | postgraduate |
| S11 | male | 24 | postgraduate |
| S12 | male | 23 | Advertising planning |
| S13 | male | 23 | postgraduate |
| S14 | female | 23 | Media Operations |
| S51 | female | 22 | civil servants |

#### *4.4.1 Individual attitudes towards generative artificial intelligence*

The interview results show that the attitudes of the fifteen respondents toward using generative artificial intelligence to understand the ins and outs of public opinion events can be roughly divided into three categories: active use, passive exposure, and no use.

"Yes, I feel that artificial intelligence will be faster and more convenient than traditional search. I only need to enter the question I want to ask, and artificial intelligence will help me summarize the answers obtained from traditional search and give me what I want directly, instead of spending most of the day searching for the useful information I need, and sometimes even spending time verifying the authenticity of the information ." (S12)

"Generally speaking, when searching for related events on Weibo, it seems that AI automatically generates

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

a rough outline of the events, including timelines and some event details. Sometimes I'll click on it to take a look, but most of the time I don't actively use AI to understand the background of an event. ”(S9)

“No. AI is too easily corrupted; information is a mixture of truth and falsehood, and it is not entirely reliable.”(S10)

The aforementioned differences indicate that generative AI has not yet exerted a singular influence on individual public opinion perception; its strength and impact path largely depend on individual agency. Specifically, respondents who actively use generative AI typically perceive it as efficient, comprehensive and convenient. Those who do not use it show a clear distrust of generative AI, relying more on authoritative official media or manually filtered information. Respondents who are passively exposed to it often encounter generative AI content “incidentally” within the platform environment, such as automatically generated event summaries on Weibo’s intelligent search, Xiaohongshu, or search pages. This type of use is not based on a clear tool selection but rather is a result of the platform's algorithm being embedded in the public opinion acquisition process.

### *4.4.2 The impact of generative artificial intelligence on individual cognition*

The interviews aimed to investigate the impact on individual cognition by asking questions about the respondents' stance on generative AI analysis, their attitudes toward obtaining information from multiple channels, and their level of trust in generative AI.

Regarding whether generative AI analysis carries a specific bias, five respondents believed it did not. Their main view was that generative AI is simply an integration and summary of data, without subjective interpretation.

“Personally, I think the analyses on Weibo are relatively neutral because most of them use very careful wording and the content is relatively short and objective, such as ‘it sparked heated discussions among some netizens’ and ‘it caused the situation to deteriorate to some extent,’ etc. However, there are also some intelligent interpretations on Weibo that involve in-depth thinking and may be biased.” (S8)

“I don’t think AI will be too biased. I think it will mainly interpret things in terms of positive and negative perspectives. Because I think that AI, when trained, won’t have too many biases except for politically sensitive issues.” (S9)

Conversely, respondents who held a stance on generative artificial intelligence believed that this stance could stem from the public opinion structure of the training data itself, or be influenced by platform norms, ideological constraints, or business logic.

“Generative AI's analysis of public opinion events is entirely biased and cannot be neutral. Firstly, it depends on the technology... secondly, it depends on the user's questioning style and proficiency... Therefore, the stance of the AI's response is determined by the technology itself and influenced by the user’s own guidance . It can never be completely neutral.” (S11)

On the other hand, regarding whether respondents were influenced by generative artificial intelligence and thus reduced their access to information, the interview results showed that most respondents did not reduce

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

their willingness to obtain information from other channels, either because they were willing to accept different viewpoints or because they believed that generative artificial intelligence was insufficient to cover everyone's views and had a strong willingness to verify and supplement information on their own.

“Personally, I wouldn't be skeptical because while the analysis is comprehensive, it’s not necessarily absolutely accurate, and third-party perspectives might also be unclear. For example, after watching the AI analysis, if I come across related videos and comments, I'll still watch them to see if they correspond to the AI analysis.” (S13)

A minority of respondents believed that generative artificial intelligence, being objective and comprehensive, could reduce the time spent searching for information.

“Yes. While the public opinion analysis generated by AIGC may not be entirely objective and accurate, it can greatly save time and energy spent searching online. In today's fast-paced society, people generally lack the patience to personally investigate and sort out the causes and consequences of events from a sea of complex information.” (S2)

Overall, generative AI does not necessarily weaken access to diverse information; its effect depends on an individual's media literacy and critical awareness. However, when generative AI is embedded in a platform's default interface and presented as an “authoritative summary,” its tendency to weaken the complexity and conflict of public opinion becomes more pronounced.

In terms of the degree of trust individuals place in generative artificial intelligence, respondents were able to trust it mainly in areas that do not involve social controversies, emotional stances, relatively simple public opinion events, and some areas that they were not very familiar with.

“Frankly speaking, I trust the judgment of generative artificial intelligence more when it comes to issues that are not related to me. That is to say, if it is entertainment gossip, as long as it is not a star I follow, I will almost always believe what the artificial intelligence says and will not deliberately search for it. If it involves my idol, I will start to search for it myself. The same is true for some hot topics. I am not easy to trust artificial intelligence when it is related to my life and study, but I am casual about it when it is not related to me.” (8)

“From a time perspective, we tend to trust AI more in urgent problems that need to be solved immediately. From a knowledge category perspective, we tend to trust AI more in areas of knowledge we are less familiar with. When time is tight, there is no time to compare and verify, but in areas we are very familiar with, we can naturally raise questions about the answers provided by AI.” (11)

### *4.4.3 The complex impact of generative artificial intelligence on individual public opinion perception*

The vast majority of respondents were aware that generative artificial intelligence might be influenced by algorithmic settings, training data, or value biases. However, this awareness remained superficial and did not necessarily translate into strong cognitive resistance to algorithmic biases in generative AI. Several respondents admitted that even knowing the existence of algorithmic biases, long-term use could still subtly influence their own cognitive framework regarding public opinion.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

"I can recognize that. Because when using AI software developed by different companies, they give different answers to the same question, sometimes even with significant discrepancies. I believe this is due to the influence of the companies behind them, who, during development and operation, prioritize their own interests or are limited by technology, resulting in AI-generated content that is not entirely objective." (S2)

"Yes, because if you keep refreshing the same viewpoint, my homepage will keep pushing the same viewpoint to me. It will assume that I agree with the viewpoint. But sometimes I may disagree, or I may be refreshing repeatedly out of curiosity. If it keeps pushing the same viewpoint to me too much, I will also feel annoyed."(S3)

"Yes, there is a bias. On the one hand, its creators will have some emotional bias in the initial state. On the other hand, there are acquired influences. Open source AI training information comes from the public opinion field, and the strength of the voice will affect the AI's response and cognition."(S10)

Some respondents explicitly pointed out that generative AI language models themselves have the function of guiding emotions and suggesting values. This shows that individual-level "conscious vigilance" cannot completely offset the structural influence of generative AI on public opinion; its influence is more of a slow, subtle, and non-coercive process of value shaping.

Based on the comprehensive interview results, the impact of generative artificial intelligence on individual public opinion cognition cannot be simply categorized as positive or negative. Its effect is more of a complex process interwoven across different stages of use and specific contexts. On the one hand, generative AI effectively reduces individuals' time and cognitive costs in acquiring and organizing public opinion information. On the other hand, the methods it employs for filtering, integrating, and summarizing events in their initial presentation may subtly influence individuals' understanding of the events and potentially guide subsequent value judgments. This influence does not appear in the form of explicit persuasion or intervention, but rather gradually embeds itself into individuals' public opinion cognition through a relatively neutral narrative style. Therefore, the role of generative AI in the public opinion field is no longer limited to an information tool, but is gradually becoming an important factor influencing the structure of public opinion cognition.

## 5 Technical characteristics of generative artificial intelligence and its impact on public opinion

As generative artificial intelligence is increasingly embedded in the social information dissemination process, its role in the fermentation and spread of public opinion is becoming increasingly prominent, and it is having a significant impact on the cognitive construction of the audience. Unlike the information production mode dominated by editors and reporters in the era of mass communication, generative AI mainly relies on large-scale data training and model generation mechanisms to integrate, reorganize, and re-express existing information. Although its output content often presents a neutral and objective form, it may still exhibit varying degrees of bias in the specific presentation process. Based on the content analysis of the public opinion texts of generative large-scale models such as DeepSeek and Doubao mentioned above, this paper summarizes the formation mechanism of content bias in generative AI into the following three main ways.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

### *5.1. Bias information from algorithm engineers*

Because algorithm engineers operate within society, their own biases inevitably embed themselves into the model architecture, training objectives, and output rules of generative artificial intelligence. Specifically, they may intentionally or unintentionally incorporate personal perceptions, values, or interests into algorithm design, leading to biased processing of specific information. Furthermore, during model training, they may influence the model's output by selectively choosing data, setting filtering standards based on specific interests , and avoiding risky content detrimental to certain groups. This influence is a form of implicit bias, subtly affecting users' understanding of public opinion events through seemingly reasonable information ranking and discourse selection.

When receiving the same instructions and analyzing the same public opinion event, Doubao and DeepSeek often exhibit similar processing methods for key expressions, such as downplaying conflicting statements and presenting extreme viewpoints in a vague or generalized manner. This convergence does not entirely stem from the event itself, but is more likely related to the model's avoidance mechanisms during the design phase for content such as “risky public opinion” “negative emotions” and “unstable factors”. Under the premise of emphasizing safety and controllability, the algorithm effectively defines implicit boundaries for public opinion expression. Therefore, this bias is not a subjective stance in an individual sense, but a value orientation embedded in the technological system and continuously replicated, enabling generative artificial intelligence to gradually form a relatively stable information output tendency in the public opinion field.

### *5.2. Universal information in the new normal sense*

Heidegger’s description of the “ordinary person” is simply that of the general public. Chatgpt-like generative AI surpasses Heidegger’s mediocre “ordinary person” because it possesses a massive corpus roughly equivalent to all human knowledge and computational capabilities exceeding 1750 trillion parameters. Its breadth of knowledge and reasoning ability also surpasses the average human level. Therefore, such an entity can be called a “new ordinary person”. On the one hand, its knowledge is based on the probabilistic average of human knowledge, lacking creativity and risk-taking in the eyes of experts; but on the other hand, its breadth of knowledge surpasses that of any ordinary person, and even many experts.

Generative AI analysis of public opinion events often presents a generalized perspective from the viewpoint of ordinary people. This type of information is not entirely neutral; it involves sifting through and integrating complex texts to selectively output content that is highly stable, low-risk, and less controversial. These viewpoints often appear with vague expressions such as “most people believe” “some netizens say” or “widespread social concern”, seemingly inclusive of diversity but actually reinforcing the mainstream voice.

Repeated comparative analysis of interview texts reveals that generative AI outputs highly similar viewpoints in its analysis of public opinion events, almost completely omitting any novel perspectives. The “common perspective” constructed by generative AI cannot encompass all public opinions, and in the long run, this universal narrative may lead users to equate “majority voices” with “rational voices”, thus trapping them in an “information cocoon”.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

### *5.3 Information that has been vetted*

The term “gatekeeping” was first coined by Lewis in *Ecological Psychology* to describe the role of individuals in screening and filtering information during dissemination. In the new media era, the gatekeeping power of professional communicators has been partially delegated to platforms, self-media bloggers , and so on. Today, generative AI - generated information is essentially a highly gated form of information. Unlike the gatekeeping of traditional information producers , generative AI does not make judgments in the sense of fact-checking, but rather technically reprocesses public opinion texts through rule restrictions, keyword filtering, and content rewriting. This is a structural reorganization, reconstructing the narrative framework of public opinion events by selecting which information can be integrated, which viewpoints can be presented side by side, and which emotions need to be weakened. Once this framework is presented to users in the form of an “authoritative summary”, it may invisibly enhance the legitimacy of the discourse.

A comparison of the public opinion events handled by Deepseek and Doubao reveals that generative artificial intelligence often adopts a highly cautious expression strategy when it comes to moral evaluation, attribution of responsibility, or institutional criticism, tending to use vague references and neutral wording. This “technical gatekeeping” is not entirely equivalent to information censorship, but its result can still change the original form of public opinion expression, causing some sharp issues to be “de-sharpened” in the reproduction process.

## 6 Enhancing the effect and netizens’ approval: The struggle for perception during the fermentation of online public opinion

The widespread embedding of generative artificial intelligence (AI) into various platforms has become a common trend. The large amount of AI-generated text, images, and videos surrounding the same public opinion event is gradually creating a highly repetitive information environment at the dissemination level. This repetition does not rely on continuous updates of facts, but rather on the repeated presentation of existing viewpoints, thus amplifying the post-truth effect during the fermentation of public opinion. In the post-truth context, the influence of public opinion no longer depends primarily on the accuracy of the facts themselves, but rather on the frequency and degree of acceptance of information being repeatedly encountered. Generative AI, through the efficient and low-cost production of content, enables a certain type of viewpoint to gain extremely high exposure in a short period of time, thereby forming a "false consensus" at the cognitive level.

### *6.1 Persuasion techniques of artificial intelligence: Appealing to emotions and reasoning with the author*

Hovland, in his persuasion theory, points out that communicators can achieve the effect of “moving people with emotion and reasoning with them” by using both rational and emotional appeals. Similarly, the attitude and logic of generative artificial intelligence in its content presentation make its viewpoints more readily accepted by the audience. Compared to emotionally charged comments or lengthy articles with strong stances published by real humans, AI-generated content is often objective, concise, and logically clear. Even when value judgments are involved, they are often presented through analysis and summarization. This style of

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

expression lowers the audience's psychological defenses, making the viewpoints more easily perceived as rational and objective conclusions, thus gaining an advantage in the competition for public opinion. Conversely, viewpoints with stronger emotional expressions or more complex logical structures are more likely to be selectively ignored or skipped in users' media consumption experience.

Because AI-generated content uses gentler language to evoke stronger emotional resonance in users, they are less likely to consult different information sources after reading summaries from generative AI. This is because users believe they have "already grasped the full picture of the event in a short time", which is related to the AI's mode of expression. Thus, generative AI not only participates in information dissemination but also preemptively "encapsulates meaning" at the level of public opinion perception. When users are repeatedly exposed to AI content with similar stances and tones, even if this content does not provide new facts, it reinforces dominant viewpoints and further marginalizes weaker ones. This reinforcement process is not based on factual accuracy but relies more on netizens' emotional resonance and cognitive comfort. Generative AI often presents viewpoints in a relatively clear and mild-toned manner, making them easier to accept and share, thus gaining a dissemination advantage in the competition for public opinion. In contrast, viewpoints with stronger emotional expressions, sharper stances, or more complex logical structures are more easily weakened in the process of algorithmic recommendation and AI content integration.

### *6.2 Artificial intelligence persuasion techniques: Audience selection in a droplet-like information environment*

In the new media era, information exhibits a droplet-like characteristic, meaning that information has become like droplets in the air.

Faced with a complex and conflicting information environment, audiences tend to read condensed versions of content generated by platforms or AI systems. This selective exposure, understanding, and memorization behavior is not based on judgments of the correctness of a particular viewpoint, but rather stems more from considerations of cognitive load and emotional comfort.

Today, with the combined influence of generative artificial intelligence and algorithmic recommendation mechanisms, opinions in the public sphere are profoundly affected by the form of content expression and the logic of its integration. Generative AI plays an intermediary role in the fermentation of public opinion. It does not directly create false information, but rather reshapes the rules of public opinion competition by selecting, integrating, and repeatedly presenting existing information. Under this mechanism, repeatedly generated and integrated opinions are more likely to become widely accepted, while voices in a weaker position are gradually marginalized in the process of algorithmic recommendation and AI content integration.

## 7 Summary and Reflection

This paper, through in-depth interviews with fifteen respondents, further confirms the reinforcing effect of generative artificial intelligence on public opinion cognition. Through implicit technological means, it subtly alters public perception of public opinion, perceiving repeatedly generated and integrated viewpoints as universally accepted. In this process, while the diversity of public opinion does not completely disappear,

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

its visibility and influence are redistributed. In short, the role of generative AI in the public opinion field has transcended its function as a mere information tool, becoming a crucial variable influencing public cognitive structures. In the post-truth dissemination environment, its cognitive reinforcement effect warrants continued attention and reflection in future research.

## References

[1].Li, J. (2023). Research on the Relationship between Human and Technology in Micro-lectures from the Perspective of Media Ecology. Master's thesis.China:Guangxi Normal University.(in Chinese)

[2].Yang, J. (2022). Research on Urban AI Sensory Media from the Perspective of Media Ecology.Master's thesis,.China:Soochow University.(in Chinese)

[3].Teng, J. (2021). Research on Content Dissemination of Short Videos from the Perspective of Media Ecology,Master's thesis.China:Chengdu University of Technology.(in Chinese)

[4].Zhang, H. (2025). Research on the Impact of Algorithmic Bias on Media Content Diversity: Based on an Analysis of Social Representations in Generative AI Images. Journal of News Research, 16(17), 23-28.(in Chinese)

[5].Carah, N. (2022). Media & society: Power, platforms, & participation (2nd ed.). China Communication University Press.

[6].Liu, H., & Lian, X. (2023). The advent of the rule of the "New Normal" ChatGPT and communication research. Journalism Review, (06), 11-20.(in Chinese)

[7].Yang, X. (2025). Ideological Metaphors of Generative Artificial Intelligence and Countermeasures for Reification Risks. Studies on Marxism, (09), 133-144.(in Chinese)

[8].Agnieszka Hess ,Elena Negrea Busuioc ,Anita Ciunova Shuleska ,Nikolina Palamidovska Sterjadovska ,Agnieszka Stępińska ,Anna Bączkowska ... & Ardita Reçi.(2026).Rethinking Public Opinion Studies in the Digital Era: Expert Discourse on the Theoretical and Methodological Challenges of Public Opinion Research. International Journal of Public Opinion Research,38(1).

[9].Bodó, B., Helberger, N., Farkas, S., & Müller, J. (2019). The role of user attitudes, algorithmic feedback loops, and policy in news personalization. Digital Journalism, 7(2), 206-229.

[10].Thurman, N., Moeller, J., Helberger, N., & Tilling, D. (2019). My friends, editors, algorithms, and I: Examining audience attitudes to news selection. Digital Journalism, 7(4), 447–469.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)