

Review

A Review of the Relationship Between the Transparency of AIGC News Content and Audience Trust

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Abstract: After generative artificial intelligence is used in news production, whether content identification can win the trust of the audience has become the focus of academic circles. This article focuses on three questions: Does tagging AI identity make the audience more trusted or more skeptical? Can unmarked be detected, and what are the consequences once found? Where is the boundary of effective transparency? Integrated multidisciplinary research reveals that disclosure of AI identity generally leads to a decline in trust, which is due to users' lack of empathy for machines and stereotypes of machines. At present, it is difficult for the audience to identify the unmarked content, and it is found that the deception will seriously damage the credibility of the media; there are boundaries in transparency, and hierarchical disclosure and traceability mechanisms are superior to single identification. Transparency is not the goal, from transparency to credibility is the key. This paper reviews the contributions and shortcomings of the existing research, and puts forward the prospect.

Keywords: AIGC, News Transparency, Audience Trust, Information Disclosure, Human-Machine Collaboration

1. Introduction

News production is undergoing revolutionary changes, and the content generated by artificial intelligence (that is AIGC) has penetrated into daily life. The Reuters Institute's "Journalism, Media, and Technology Trends and Predictions 2026" shows that news organizations are facing a double squeeze of generative AI and the creator economy, and the search flow is expected to decline by 40 % in the next three years (Newman, 2026). Imagine that you are scrolling on a mobile phone, a news headline is very attractive, click in to find a line of small words at the end: "This article is generated by AI." Will you continue to read it, or cut it off immediately? Trust is tested in this moment. And even if the media does not label AI identity, can readers detect it? Once it is found to be hidden, how much damage to the long-term trust of the media? Is the simple "AI generated" enough? These problems constitute the core of this paper. Luo et al. found that the disclosure of the identity of the chatbot caused a 79.7 % drop in the customer purchase rate, due to the user's perception of the lack of knowledge and empathy of the machine (Luo et al., 2019). However, in some scenarios, increased transparency can enhance trust - a paradox worthy of further study.

In this study, credibility is defined as the cognitive evaluation of source expertise and message accuracy, whereas trust is conceptualized as the behavioral intention to accept the AI's output despite uncertainty. Transparency primarily builds the former, which serves as a foundational component of the latter.

In addition, in order to enhance the repeatability and rigor of this review, I adopted a systematic search method. Search databases included Web of Science, Scopus, CNKI, PsycINFO, and Communication & Mass Media Complete; the time span is from January 2019 to March 2026 (before and after the large-scale application of generative AI). Keyword combinations are ("AI-generated content" or "AIGC" or "artificial intelligence" or "chatbot") and ("transparency" or "disclosure" or "labeling") and ("trust" or "credibility" or "user perception"). A total of 1,247 articles were initially obtained, and 210 articles were included after title/abstract screening (excluding non-empirical, non-English/Chinese, and papers not directly related to news/media). After reading the full text, a total of 23 empirical studies, theoretical reviews, and policy analysis directly related to transparency-trust were selected as the core references. In addition, reports from authoritative institutions (such as the Reuters Institute, the Pew Research Center) and case studies from major media were supplemented. (See Figure 1. Paper review literature screening flow chart)

It should be noted that this review goes beyond other previous reviews on artificial intelligence and trust. It has a unique interdisciplinary synthesis and the argument that “transparency is not the ultimate goal, but the means to obtain audience trust.” The research on the relationship between the transparency of AIGC news content and audience trust has unique research value.

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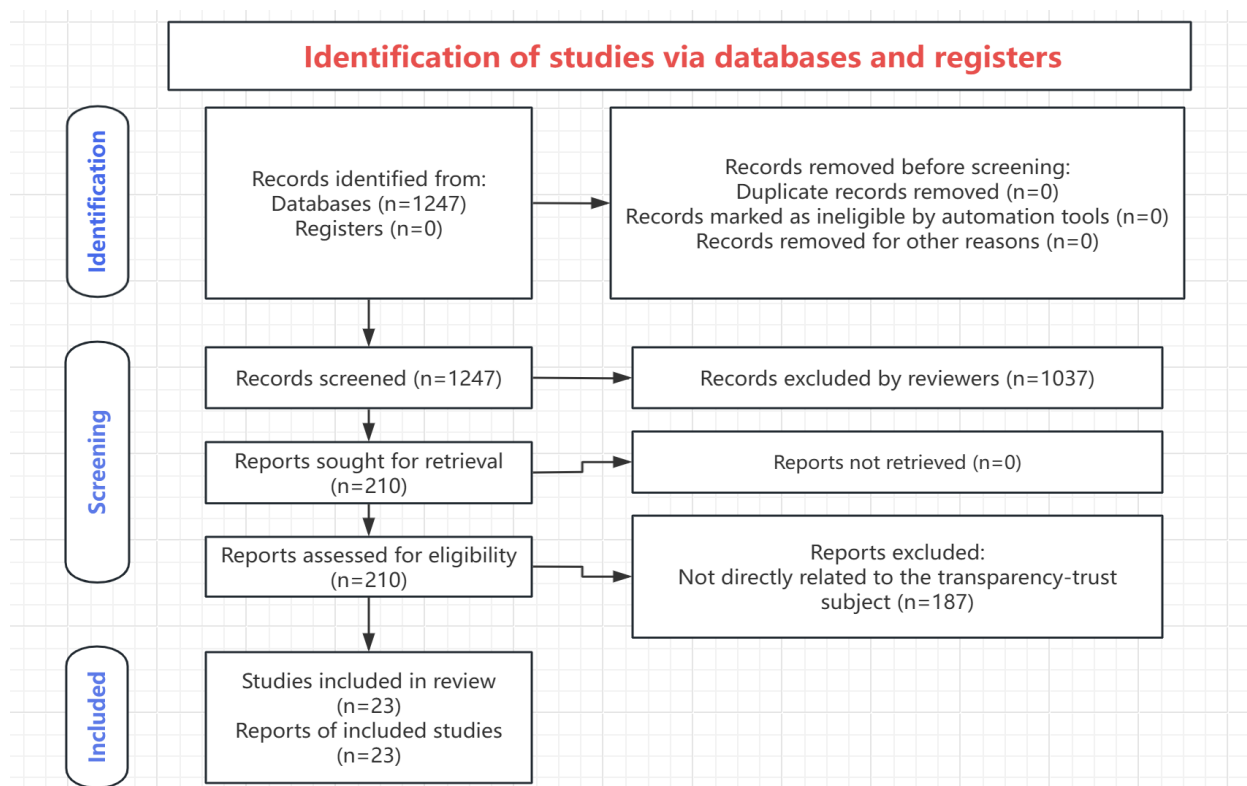


Figure 1. Paper review literature screening flow chart

2. Theoretical Basis and Practical Dilemma of Transparency

The principle of transparency bridges the information gap between content producers and recipients by disclosing information, enabling audiences to make independent judgments with full knowledge (Shao, 2024). The theoretical basis of this principle can be traced back to communication ethics and information economics: from the perspective of ethics, the audience has the right to know the source of information and the way of generation; from an economic point of view, transparency helps to solve the problem of information asymmetry and maintain market efficiency. In the context of AI-generated content, the principle of transparency is endowed with new connotations: it is not only related to the transparency of information sources, but also involves complex elements such as the degree of technical intervention, algorithm logic, and data sources.

China has made a positive response to this at the regulatory level. The “Internet information service deep synthesis management regulation” clearly requires the identification of deep synthetic content, and the “artificial intelligence generates synthetic content identification method (draft)” further proposes the identification obligation and explores the establishment of a dual-track identification mechanism combining “explicit + implicit” (National Internet Information Office, 2024). Explicit identification refers to the AI generation attribute that explicitly prompts the content to the user in the form of text, sound, etc. Implicit identification is to record and generate information in the background through metadata, watermarks, and other technologies for retrospective use. The design idea of this dual-track mechanism reflects the regulators’ understanding of the multidimensionality of transparency.

At the same time, Western countries have also taken a series of measures. The EU’s Artificial Intelligence Act also establishes transparency as a cornerstone of AI governance, requiring providers of high-risk AI systems to ensure sufficient transparency in their operations (Morosoli et al., 2026). However, the Dutch citizen focus group study found that the lack of substantive public participation in the formation of the existing regulatory framework may lead to the final design deviating from the real needs of society. Citizens who participated in the study said they want to have more say in AI regulation and hope that regulatory measures will effectively respond to their concerns about a credible information environment (Morosoli et al., 2026).

The consensus at the institutional level has not been translated into effective operation in practice. Shao Zijie pointed out that the current labeling scheme only requires labeling “AI generation”, does not involve substantive information such as AI participation

and rights declaration, and is difficult to meet the deep needs of secondary use of content and infringement relief (Shao, 2024). For example, when a news article labeled “AI generation” is reprinted, the reprinter cannot know the specific generation parameters, training data sources, and copyright restrictions, which brings legal risks to subsequent dissemination. Users also cannot judge whether AI content is manually reviewed and whether it represents the media’s position, which greatly reduces the significance of the “AI generation” logo.

Cao Xinming and Fan Guo emphasized that in the field of academic publishing, the transparency obligation also needs to disclose the specific division and interaction process of human-computer contributions (Cao & Fan, 2025). They pointed out that when AI is involved in research design and writing, the author is obliged to explain the degree of AI involvement so that readers can evaluate the reliability of the research. This view also applies to the field of journalism: if AI only assists in collecting data, the final manuscript is written by a human journalist, and labeling “AI generation” may cause misunderstanding; if the manuscript is completely automatically generated by AI, it needs to be clearly explained. Qian (2026) pointed out that the current AI governance faces structural problems such as algorithm black box, interactive security risk, unstable corpus quality, and unclear ownership. These dilemmas respond to the core concern: is a single “AI generation” logo sufficient to help the audience form a rational judgment? From the current research, the answer is obviously negative.

3. After Labeling, Why Does Trust Not Increase but Decrease?

Luo et al. found that disclosing the identity of the robot before the dialogue would reduce the customer purchase rate by nearly 80 %. Mechanism analysis shows that this is because users activate negative presuppositions about machines: they think they lack empathy, have low emotional intelligence, and are difficult to understand the complex needs of human beings (Luo et al., 2019). This negative presupposition stems from the stereotype of AI, which is stubborn and difficult to eliminate in the short term even if the machine performs well.

The findings in the field of marketing have also been confirmed in the field of news communication. With the help of drift diffusion model, Yang Juan and other scholars found that compared with non-authority, the audience showed lower trust rate and longer decision-making response time to the AI generated news of authoritative institutions (Yang et al., 2026). This finding is called “the paradox of trust between authority and AI-generated content”: people expect authority endorsement to enhance trust, but when authority uses AI-generated content, audience trust is lower. Researchers believe that this may be because readers have established higher quality standard expectations for authoritative institutions, and AI is considered difficult to meet this expectation, which will lead to greater disappointment.

The Pew Research Center survey shows that there is a complex differentiation in the attitude of the American public towards AI. The public who know more about AI is more cautious about AI, indicating that knowledge does not necessarily bring trust (Tyson & Kikuchi, 2023). Lalot et al.’s research revealed that the credibility perception of AI is closely related to its perceived ability and integrity, and the degree of personification significantly affects the willingness to use. When AI shows a more human-like way of communicating, users are more likely to trust it, but this trust may also collapse instantaneously by realizing that the other person is a machine (Lalot & Bertram, 2025).

Through large-scale experiments, Hoq et al. found that the influence of AI credibility signals in shaping users’ perception of political news transcends traditional factors such as likes, sharing, and media institutional reputation (Hoq et al., 2025). This finding not only confirms the powerful effect of labeling, but also highlights its “double-edged sword” characteristics. In the experiment, when the political news is labeled “generated by AI,” the credibility evaluation of the news will decrease significantly even if the user trusts the media before.

4. Unmarked Cost: Short-Term Convenience and Long-Term Risk

When the media chooses not to label, the audience may not be aware of it in the short term. Based on three years of interview data from six countries, Thomson et al. found that only 25 % of news audiences are convinced that they have encountered content produced by generative AI (Thomson et al., 2025). This shows that the vast majority of the audience lacks a clear understanding of the actual content of AI news, and may unknowingly consume a large amount of AI content. When researchers showed typical AI news to respondents and asked if they had read similar content, many people realized that they may have been exposed to AI news before.

Park and Thomson based on Australian survey data also show that nearly half of respondents believe that AI news is more untrustworthy than human news (Park & Thomson, 2025). However, one interviewee said the key: I don’t know where AI is used, and I can’t tell whether an article is written by people or by AI (Hong & Chang, 2025). This sentence reveals the fundamental dilemma of the audience: they may have a negative attitude towards AI news, but due to the lack of recognition ability, they cannot implement the attitude into reading practice. This disconnect makes it difficult to translate attitudes into pressure to monitor the media.

But in the long run, there is a high risk afterwards. Erlei found that concealing the use of AI can seriously damage consumer trust, and the cost of repair is extremely high once the truth is exposed (Erlei, 2025). This plays an important warning role for news

agencies. In the experiment, when consumers find that the information obtained before is generated by AI rather than provided by human experts, the trust in the entire platform drops sharply, even if the information quality is high. Trust loss will be generalized to the evaluation of the entire organization and is difficult to repair.

Dai's research also shows that consumers are subjectively more inclined to seek human services, especially in scenarios involving emotional support and complex communication (Dai et al., 2025). This preference stems from deep-rooted social needs: people want to interact with their peers and gain empathy and understanding. In news consumption, readers also want to feel the emotional connection with journalists.

Zajmi reported that AI-generated scams and "fake freelancers" impersonating human identities appeared in well-known media, exacerbating public distrust of the industry (Zajmi, 2026). For example, in an event in 2025, a technology media published a number of false interviews generated by AI, in which the cited "experts" did not exist. After the incident was exposed, the trust of the media readers decreased by more than 30 % (Zajmi, 2026). Once this trust erosion occurs, the repair cost is much higher than the prior transparent investment.

5. The Boundary of Effective Transparency: Not the More Transparent the Better

Do and Geyer (2025) compared four disclosure strategies—transparency, attention, ambiguity, and opacity through a Q & A scenario experiment, and came to an unexpected conclusion: ambiguity and opacity strategies bring higher trust while maintaining users' perception of the quality of answers (Do & Geyer, 2025). This challenges the intuition of "the more transparent, the better," and fits the psychological nature of trust: people need a sense of dependence, not infinite information bombing. When the system explicitly informs that the answer is generated by AI and explains the generation process in detail, users begin to question the reliability of the answer instead.

This finding is not an isolated case. Prajod et al. (2026) found that not all AI disclosures lead to a transparency dilemma, which reflects the trade-off between readers' need for greater transparency and their trust in AI-assisted journalism (Prajod et al., 2026). When AI is less involved (such as only for grammar checking), disclosure may enhance trust, because it indicates that the media attaches importance to content quality; when AI is deeply involved (e.g., generated entirely by AI), disclosure is more likely to trigger distrust.

The hierarchical disclosure scheme proposed by Shao Zijie is consistent with this logic: according to the different needs of the three stages of training, generation, and dissemination, different types of information are disclosed separately, and the "attached + query" dual-track approach is adopted (Shao, 2024). Incidental disclosure refers to the direct inclusion of basic information in the content, such as "this article is generated by AI"; query-based disclosure provides users with in-depth needs to further query detailed information, such as training data sources, generation parameters, etc. This hierarchical design not only respects the limited information processing ability of ordinary users, but also meets the information needs of deep users.

Through interviews with 75 user focus groups, Nserat found that tagging behavior itself is perceived as a trust-enhancing factor, but this perception is shaped by tagging functionality, credibility, content relevance, media participation, and user AI literacy (Nserat, 2025). Participants said that they trust the media that actively annotate AI content, because it shows that the media is responsible; but at the same time, it is hoped that the annotation does not interfere with the reading experience.

Gamage et al.'s research on the perception of social media content annotations shows that the specific design of annotations affects user trust. They compared a variety of annotation designs and found that users prefer concise and clear ways to consume content without interfering with content consumption (Gamage D et al., 2025). A simple "AI" logo is more acceptable than a detailed description.

Hong Jiewen and Chang Jingyi proposed to establish an accident disclosure and traceability mechanism to achieve "accident traceability" by embedding watermarks and retaining logs (Hong & Chang, 2025). When there is a problem with AI content, the root cause of the problem can be traced through technology to show transparency to the public and reduce the loss of trust. Qian (2026) proposes to build a "human-machine collaboration" governance pattern, which needs to be promoted from four dimensions: technical governance, resource construction, user literacy, and ecological collaboration (Qian, 2026).

Guo Jinbo's research found that there is a significant threshold effect of digital literacy: low-literacy groups have limited response to changes in transparency, and the marginal effect of high-literacy groups is significantly enhanced (Guo, 2026). Similarly, transparency measures have different effects on different literacy groups. For low-literacy groups, more simple and direct transparency design is needed; for high-literacy groups, more information choices can be provided. Research on Dutch citizens also shows that the public wants to participate in the regulatory process, prefers standardized transparency measures, such as source disclosure, and wants to be held accountable for violations (Morosoli et al., 2026).

Table 1. Summary of Key Empirical Studies

Author (Year)	Study Field	Method (Sample)	Core Discovery
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Luo et al. (2019)	Marketing	Field Experiment (customer service dialogue)	Revealed that the purchase rate of AI identity decreased by 79.7 %, due to the lack of empathy in the perception machine.
Yang et al. (2025)	Psychology	Drift Diffusion Model Experiment	AI news trust of authoritative institutions is lower and decision-making time is longer.
Hoq et al. (2025)	Communication Studies	Social Media Experiment (large sample)	AI credibility signal influence beyond traditional participation indicators
Erlei (2025)	Economics	Trust Market Experiment	Conceals the use of AI, and the cost of post repair is extremely high.
Cornelio et al. (2025)	Human-Computer Interaction	Question Answering Scene Experiment	Fuzzy strategy brings higher trust than complete transparency.
Shao (2024)	Jurisprudence	Policy Analysis	Proposes a dual-track mechanism of hierarchical disclosure and “accompanying + inquiry”.
Nserat (2025)	Information Management	Focus Group (75 people)	Annotations are perceived as trust enhancements, but are moderated by multiple factors

6. Research Review and Future Prospect

In summary, existing research has made important progress in the relationship between AIGC transparency and audience trust. At the theoretical level, multidisciplinary perspectives reveal the complex mechanism of trust formation: psychological research deepens understanding from negative presupposition, cognitive decision-making process, multiple psychological mechanisms and credibility dimension; communication studies have found that the influence of AI credibility signals exceeds traditional participation indicators; marketing experiments show that the efficiency of human-machine collaborative market can exceed that of pure human market, and there are differentiated trust paths in different fields (Liu et al., 2025); some studies challenge the intuition of “the more transparent, the better,” and explore the challenges of interactive transparency (Molina & Sundar, 2022) and content review (Fisher et al., 2024). Methodologically, experiments, questionnaires, and focus groups are used together to provide support for the research conclusions.

However, the lack of existing research is equally obvious. First, the correlation between research fields is weak. Communication focuses on how transparency affects credibility, psychology focuses on how people view machines, and marketing focuses on whether users pay. These studies can confirm each other, but they are still “separate” and lack an integrated theoretical framework. Second, the research scenario is too single. Most of the experiments are one-time cross-sectional studies, lack of longitudinal tracking research, and cannot answer dynamic changes. At the same time, although some studies cover European and American countries, there is a serious lack of attention to the local situation in China. How do Chinese readers view AI news? Is the trust mechanism consistent with Western countries? These problems are still lack of systematic research. Third, some core mechanisms are still vague. We know that tagging AI can lead to distrust, but how does this psychological change occur? If the quality of AI content is high enough, can the initial distrust be reversed? These deep-seated problems have not yet been truly clarified.

Future research can be deepened in the following directions. First of all, a more complete theoretical framework is constructed, which includes key factors such as information sources, content characteristics, audience differences, and AI labeling methods, and systematically examines interactions to explore the optimal transparency strategies in different contexts. Secondly, carry out long-term follow-up study. Through follow-up survey, observe whether the length and frequency of contact with AI news promote their attitude change. A multi-wave longitudinal study was designed to capture the dynamic change process of trust at the initial contact, after a period of contact, and after the trust crisis event. Again, deepen the field of human-machine cooperation. Future news production is likely to be a product of human-machine collaboration. How to label, how to allocate responsibilities, and how to maintain trust are worthy of further study. Compare the impact of different annotation methods (such as “human writing” and “AI generation, human editing”) on trust. Finally, pay more attention to China’s local situation. How do Chinese readers accept AI news? Do differences in cultural traditions and media environments lead to different trust mechanisms? Comparative methods can be used to simultaneously collect Chinese and Western samples in the same research design to reveal cross-cultural similarities and differences.

7. Conclusion: From Transparency to Credibility

Back to the first three questions. First, labeling AI identity generally leads to a decline in trust, which is rooted in the user’s stereotype of the lack of empathy and knowledge of the machine. Second, the current audience generally lacks the ability to identify AIGC, and if it is later found to be hidden, it will seriously damage the long-term credibility of the media. Third, it is not the more transparent the better-the combination of fuzzy strategy, hierarchical disclosure, traceability mechanism, and capacity building can achieve an effective transformation from transparency to credibility.

To operationalise this, we propose a concrete two-layer “incidental + queryable” label design: a subtle badge (e.g., “AI-assisted” with an icon) sits below headlines, with a clickable panel revealing AI’s specific role, human editorial review, and data timestamp.

Newsrooms could pilot this via A/B testing. Likewise, rather than merely urging more Chinese studies, we advance three testable cross-cultural hypotheses—cultural collectivism may weaken the trust penalty, platform type (super-apps vs. traditional sites) may moderate label effects, and framing as “assisted” may provoke less distrust than “generated”. These can be tested through parallel experiments with eye-tracking, clarifying whether transparency effects are universal or culturally contingent.

Ultimately, transparency is never an end, but a path to credibility. What readers really care about is not whose name is written on the “birth certificate” of an article, but whether it is worth entrusting their own judgment. This may be the core proposition that future research needs to answer: how to ensure transparency without weakening the precious trust in people’s hearts? As Euractiv commented: “AI promises speed and scale, but its risk lies in misplaced trust”. After all, what the readers ultimately care about is not who wrote it, but whether the news is worth believing. Future research needs to further explore the optimal solution of transparency boundaries in different scenarios, and provide theoretical support and practical guidance for credible news production in the intelligent era.

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