Media Studies; Vol.3, No.3; 2026
E-ISSN: 3006-368X P-ISSN: 3006-3671
DOI: https://doi.org/10.70267/ms.v3n3.4350
Published by: Zeus Press

Research on the Current State of AIGC Transparency Labelling in Mainstream Media News: A Content Analysis of Five Major Platforms

Can Shu*

Network and New Media, School of Literature and Communication, Sichuan University of Arts and Science, Dazhou 635000, Sichuan, China

**Corresponding author: Can Shu.*

Abstract

AI-generated content (AIGC) has become deeply embedded in news production, and how it is labelled is directly related to news transparency and public trust. Taking five mainstream Chinese media outlets—XinhuaNet, Chinanews.com, CNR.cn, GMW.cn, and Chuanguan News—as research objects, this study coded 153 AIGC news products through content analysis; the label position, disclosure depth, label form, and salience were examined, and chi-square tests were conducted using the implementation of the Measures for the Labelling of AI-Generated Synthetic Content (effective September 1, 2025) as the dividing point. All the samples were independently coded by two coders, and reliability testing confirmed the consistency of the coding scheme. The results show that the labelling compliance rate of mainstream media reached 100%, with label positions highly concentrated in title prefixes. After the Measures took effect, dual labelling combining "text plus visual watermark/corner mark" increased significantly ($p < 0.05$), reflecting improved formal standardization. However, disclosure depth did not improve in parallel, and labelling practices diverged significantly across platforms: platforms with dedicated AIGC columns and unified attribution norms achieved more standardized and deeper disclosure. The findings indicate that the Measures have promoted the formal standardization of AIGC labelling, while substantive transparency still needs to be enhanced. On the basis of these findings, the paper proposes improvements at the institutional, organizational, and communication-strategy levels, calling for a shift from bottom-line formal compliance toward substantive transparency that genuinely supports the public's right to know.

Keywords

AI-generated content (AIGC), news transparency, AIGC labelling, content analysis, algorithmic trust

1. Introduction

Generative artificial intelligence is becoming deeply involved in news production, transforming traditional content creation workflows. From automated text writing in the early days to the intelligent generation of images and videos today, the role of AIGC has been upgraded from an auxiliary tool to a core component of news products. At present, mainstream media widely adopt AI technologies to produce news posters, data visualizations, and creative short videos and have gradually developed serialized and column-based intelligent content products such as “China in the Eyes of AI,” “AIGC Illustrates the Solar Terms,” and “AI Chinese Style,” which have become important parts of daily reporting.

However, while improving production efficiency, AIGC also poses challenges to news authenticity and public trust. When audiences cannot clearly determine whether a report originates from a journalist's independent reporting or is automatically generated by an algorithm, the authority and credibility of news organizations risk being undermined. Therefore, how to disclose the generation method or source of content to audiences through clear labelling during dissemination has become a key issue in safeguarding news transparency.

In March 2025, the Cyberspace Administration of China and other departments jointly issued the Measures for the Labelling of AI-Generated Synthetic Content (hereinafter referred to as “the Measures”) [1], which officially took effect on September 1 of the same year. The supporting mandatory national standard, the labelling method for AI-generated synthetic content (GB 45438—2025), was implemented simultaneously [2]. Together, they established a “dual-track system” combining explicit and implicit labels. This institutional framework provides a clear policy reference and time point for this study.

Against this background, this paper selects five mainstream media outlets as analytical objects and systematically examines their AIGC news products through content analysis, aiming to reveal the current state, characteristics, and problems of AI labelling practices and to compare changes before and after the implementation of the Measures. Specifically, it seeks to answer the following questions: What is the current state of AIGC news labelling in mainstream media in terms of position, depth, form, and salience? Have labelling behaviors changed significantly before and after the implementation of the Measures? Are there differences in labelling strategies among different media platforms?

2. Literature Review

2.1 Artificial Intelligence and the Transformation of News Production

AI technologies transform every stage of news production. Yu noted that the wave of generative AI triggered by ChatGPT sparks a communication revolution and a reconstruction of the media ecology, driving news production from “human-dominated” to “human–machine collaboration”, in which algorithms not only engage in information aggregation and distribution but also directly participate in content generation [3]. Peng argues that AIGC creates a new living space of human–machine coexistence and a highly fictionalized visual space; the boundary between machine-generated content and human creation is becoming increasingly blurred, posing new challenges for verifying news authenticity and attributing authorship [4]. In practice, mainstream media have widely applied AIGC to poster production, data journalism, and creative videos, forming column-based and serialized models of intelligent content production [5].

2.2 News Transparency and Algorithmic Trust

News transparency is an important professional norm for journalism in addressing the crisis of trust. It comprises two dimensions: “disclosure transparency,” which emphasizes making the sources and methods of news production public, and “participatory transparency,” which emphasizes audience engagement. In the context of algorithmic journalism, transparency is further extended to “algorithmic transparency”—disclosing to audiences the role of algorithms in content production. A survey of Chinese audiences by Sun. shows that the public is generally open to the application of AI in journalism but attaches great importance to the disclosure of AI-generated content; the clarity of disclosure directly affects audiences' trust evaluations [6]. Under the human–machine communication (HMC) framework, Guzman and Lewis note that audiences' perception and acceptance of AI-generated content depend largely on whether the media clearly disclose the extent of AI involvement [7].

Notably, transparency does not necessarily bring about trust. An experimental study by Luo. reported that, in certain contexts, disclosing that content is AI-generated actually lowers audience evaluations—a “disclosure penalty” effect [8]. This suggests that labelling is not merely a matter of technical compliance but also involves complex mechanisms of audience psychology and trust construction.

2.3 Institutional Evolution of AIGC Labelling

China's regulation of AIGC labelling has evolved from principled advocacy to mandatory norms. The Interim Measures for the Management of Generative Artificial Intelligence Services (2023) put forward labelling requirements; the Measures (2025) and the supporting national standard GB 45438—2025 further clarified the technical standards and subject responsibilities for explicit labels (text prompts, corner marks, etc.) and implicit labels (metadata), marking the entry of AIGC labelling into a stage of mandatory compliance. Existing studies have focused mostly on regulatory interpretation and platform governance, while empirical investigations of how mainstream media, as content producers, fulfil their labelling obligations remain scarce.

In summary, existing research provides a theoretical and institutional foundation for understanding AIGC labelling, but two gaps remain: First, most studies focus on audience perception or regulatory texts and lack a systematic examination of the media's actual labelling behaviors; second, there is a lack of diachronic comparison using the implementation of the Measures as a dividing point. Through a content analysis of AIGC news products from five mainstream media outlets, this study aims to fill these gaps.

3. Research Methods

3.1 Sampling

This study combines purposive sampling with systematic sampling. Three central key news websites—XinhuaNet, Chinanews.com, and CNR.cn—were selected, together with GMW.cn as an intellectual-oriented media outlet and Chuanguan News as a representative of provincial mainstream media, resulting in five platforms in total. The sampling criteria were as follows: converged-media news products published between January 2023 and July 2026 that explicitly used AI generation technologies (images, videos, data visualization, etc.).

The specific sampling procedure was as follows: for platforms with dedicated AIGC columns (Chinanews.com's "China in the Eyes of AI" and CNR.cn's "AI Chinese Style"), the column served as the sampling frame, and items were systematically sampled in order of publication or included in full; for platforms without dedicated columns (XinhuaNet, GMW.cn, and Chuanguan News), supplementary sampling was conducted by retrieving converged-media products whose titles contained the prefixes "AIGC" or "AI," and monthly quotas were applied to items from the same column and series to reduce homogeneity. A final valid sample of 153 items was obtained, of which 99 (64.7%) were published before the Measures took effect and 54 (35.3%) after.

3.2 Category Construction

On the basis of the literature review and precoding, the following coding categories were constructed:

3.2.1 Platform

1 = XinhuaNet, 2 = Chinanews.com, 3 = GMW.cn, 4 = Chuanguan News, 5 = CNR.cn.

3.2.2 Before/After the Implementation of the Measures

0 = before implementation, 1 = after implementation.

3.2.3 Presence of an AI Label

0 = absent, 1 = present.

3.2.4 Label Position

0 = none, 1 = title (the title has an AI/AIGC prefix), 2 = beginning of the text (a statement at the opening of the body), 3 = end of the text, 4 = column name (reflected only in the column name), 5 = image caption.

3.2.5 Disclosure Depth

0 = none, 1 = label only (only the words "AI-generated" appear), 2 = method explained (explains that the content was generated by AI and how AI participated), 3 = source/tool identified (names the specific AI tool, production team, or technical support provider).

3.2.6 Label Form

0 = none, 1 = text only, 2 = watermark/corner mark only, 3 = both (a textual statement coexisting with a visual watermark/corner mark).

3.2.7 Topic

1 = politics and current affairs, 2 = finance and economics, 3 = society, 4 = science and technology, 5 = culture and sports, 6 = other.

3.2.8 Label Salience

1 = salient (the label is located in the title, at the beginning of the text, or in an image caption and is visible to readers at a glance), 0 = weak (the label appears only in small print at the end of the text or only in the column name and is not easily noticed).

3.3 Reliability Test

This study adopted double independent coding. Before formal coding, two coders conducted trial coding and reliability tests on a randomly selected 20% of the sample (n = 31). In the initial independent coding, the agreement rate for “label position” reached 93.5% (Cohen's k = 0.786), indicating good reliability; disagreements arose over “disclosure depth” and “label form” because the coding rules were not sufficiently well defined. After discussion, the judgment criteria were further clarified (e.g., postal-stamp-style graphics or corner marks on images were classified as watermark labels; any attribution naming a specific AI tool or production team was classified as “source/tool identified”), and the disputed items were recoded accordingly until full agreement was reached. The coding results are therefore reliable.

3.4 Data Analysis

SPSS was used to conduct frequency analysis and chi-square tests on the coded data, examining the distributional characteristics of each labelling dimension and the significance of differences before and after the implementation of the Measures and across platforms.

4. Findings

The basic distribution of the samples is shown in Table 1 and Table 2. A total of 153 valid samples were obtained: 55 from CNR.cn (35.9%), 42 from Chinanews.com (27.5%), 38 from XinhuaNet (24.8%), 14 from GMW.cn (9.2%), and 4 from Chuanguan News (2.6%); 99 items (64.7%) were published before the Measures took effect and 54 (35.3%) after.

Table 1: Platform distribution of samples

Platform	Frequency	Percentage (%)
XinhuaNet	38	24.8
Chinanews.com	42	27.5
CNR.cn	55	35.9
GMW.cn	14	9.2
Chuanguan News	4	2.6
Total	153	100

Table 2: Distribution of sample labelling characteristics

Dimension	Category	Frequency	Percentage (%)
Label position	Title	147	96.1
	Beginning of text	1	0.7
	End of text	4	2.6
	Image caption	1	0.7
Label form	Text only	84	54.9
	Both (text + watermark/corner mark)	69	45.1
Label salience	Salient	149	97.4
	Weak	4	2.6

4.1 100% Labelling Compliance and No Unlabelled Samples

Coding of the 153 samples revealed that all AIGC news products carried some form of explicit label; there were no “unlabelled” cases for the item “presence of an AI label”. This finding stands in sharp contrast to the large volume of unlabelled AI content found among self-media, short-video, and e-commerce advertising. This finding indicates that mainstream media, as institutional communicators, exhibit far greater compliance awareness and professional norms in AIGC labelling than self-media does; “labelling it” has become the basic bottom line of AIGC production in mainstream media. Specifically, because no unlabelled samples exist, this study shifts its analytical focus from “whether” to the “position, depth, form, and salience” of labels.

4.2 Label Positions Highly Concentrated in Title Prefixes, Forming a Column-Based Convention

Label positions are highly concentrated: 147 samples (96.1%) placed the label in the title (e.g., “AIGC Creative Poster,” “China in the Eyes of AI”), while the beginning of the text, the end of the text, and the image captions together accounted for only 6 items (3.9%). This finding indicates that mainstream media have formed a labelling convention dominated by “title prefixes”. In particular, columns such as Chinanews.com's “China in the Eyes of AI” and CNR.cn's “AI Chinese Style” have achieved standardized and column-based labelling through fixed column prefixes. As the first point of contact between readers and content, the title prefix has the highest visibility, and this convention objectively helps audiences quickly identify AIGC content.

4.3 The Formal Standardization of Labels Improved Significantly After the Measures Took Effect

Chi-square tests reveal a significant difference in the distribution of label forms before and after the implementation of the Measures ($\chi^2 = 4.384$, df = 1, p = 0.036; see Table 3). Before implementation, 38.4% of the samples adopted dual labelling of “text plus visual watermark/corner mark”; after implementation, this percentage rose to 57.4%, while text-only labelling decreased from 61.6% to 42.6%.

Table 3: Cross-analysis of implementation timing × label form

	Text only (freq.)	%	Both (freq.)	%	Total
Before	61	61.6	38	38.4	99
After	23	42.6	31	57.4	54
Total	84	54.9	69	45.1	153

Note: $\chi^2 = 4.384$, df = 1, p = 0.036

This finding indicates that the requirements of the Measures and the supporting national standard for explicit labelling have pushed mainstream media from “text-only statements” toward composite explicit labels combining “text plus visual watermark/corner marks,” markedly improving the formal standardization and visibility of labels. This is the most direct policy effect observed in this study.

4.4 Disclosure Depth Remains Shallow Overall and Declined Rather Than Improved

In contrast to the improvement in formal standardization, the improvement in disclosure depth is unsatisfactory. Overall, 95 samples (62.1%) reached the “source/tool identified” level (naming the AI tool, production team, or technical support provider), 57 (37.3%) remained at the “method explained” level, and only 1 (0.7%) was “label only”. A further comparison before and after the implementation of the Measures reveals that the percentage of “source/tool identified” fell from 69.7% before implementation to 48.1% after implementation, a significant difference ($\chi^2 = 8.085$, df = 2, p = 0.018; see Table 4).

Table 4: Cross-analysis of implementation timing × disclosure depth

	Label only	%	Method explained	%	Source/tool identified	%	Total
Before	0	0.0	30	30.3	69	69.7	99
After	1	1.9	27	50.0	26	48.1	54
Total	1	0.7	57	37.3	95	62.1	153

Note: $\chi^2 = 8.085$, df = 2, p = 0.018

This “reverse change” needs to be interpreted cautiously in light of the sample composition: among the preimplementation samples, early column-based products such as CNR.cn’s “AI Chinese Style” generally carried standardized technical support attributions, increasing the average depth of disclosure in the earlier period; after implementation, as the number of AIGC products and the platforms covering them expanded, a large number of newly included samples achieved disclosure only at the “method explained” level. This suggests that while the Measures improved the “formal compliance” of labels, they did not simultaneously bring about deeper “source disclosure”—media have largely met the bottom-line requirement of “labelling it,” whereas the substantive transparency of “clarifying sources and tools” remains insufficient.

4.5 Significant Divergence in Labelling Practices Across Platforms

Chi-square tests reveal significant associations between platform and label salience ($\chi^2 = 40.134$, $p < 0.001$), label position ($\chi^2 = 46.554$, $p < 0.001$), and disclosure depth ($\chi^2 = 94.934$, $p < 0.001$), indicating marked divergence in labelling practices across platforms.

First, in terms of label position and salience, Chinanews.com, CNR.cn, and GMW.cn achieved 100% salient title labelling; XinhuaNet had the most dispersed label positions (title 89.5%, end of text 5.3%, beginning of text 2.6%, image caption 2.6%); Chuanguan News had the highest proportion of weak end-of-text labels (50%). Of the four weakly labelled samples, two came from XinhuaNet, and two from Chuanguan News; all the samples were concentrated in the period before the Measures took effect.

Second, in terms of disclosure depth, 100% of the CNR.cn samples and 76.2% of the Chinanews.com samples disclosed at the “source/tool” level—the highest transparency—while 100% of the GMW.cn samples and 78.9% of the XinhuaNet samples remained at the “method explained” level (see Table 5 and Table 6). Platforms with dedicated AIGC columns and unified attribution norms outperform platforms without dedicated columns in terms of both the standardization and depth of labelling.

Table 5: Cross-analysis of platform × disclosure depth

Platform	Label only (%)	Method explained (%)	Source/tool identified (%)
XinhuaNet	2.6	78.9	18.4
Chinanews.com	0	23.8	76.2
CNR.cn	0	0.0	100.0
GMW.cn	0	100.0	0.0
Chuanguan News	0	75.0	25.0

Note: $\chi^2 = 94.934$, $df = 8$, $p < 0.001$

Table 6: Label position and salience across platforms

Platform	Title position (%)	Weak label (%)	Salient label (%)
XinhuaNet	89.5	5.3	94.7
Chinanews.com	100.0	0.0	100.0
CNR.cn	100.0	0.0	100.0
GMW.cn	100.0	0.0	100.0
Chuanguan News	50.0	50.0	50.0

Note: position: $\chi^2 = 46.554$, $p < 0.001$; salience: $\chi^2 = 40.134$, $p < 0.001$

5. Conclusion and Discussion

5.1 Main Conclusions

On the basis of a content analysis of 153 AIGC news products from five mainstream media outlets, the following conclusions are drawn:

First, in terms of labelling compliance, all the samples completed explicit labelling as needed, with no omissions found. These results contrast sharply with the reality that a large amount of AI content in the self-media sector is unlabelled, reflecting the mainstream media’s high degree of self-awareness in fulfilling labelling obligations and demonstrating professional self-discipline.

Second, the policy effect of the Measures is reflected mainly in the standardization of label forms. After the Measures took effect, the proportion of dual labels combining “textual statements plus visual watermarks/corner marks” increased significantly, and the visibility and formal compliance of the labels improved. However, label positions remained highly concentrated in title prefixes without significant change, and disclosure depth did not improve in step with formal standardization. In other words, driven by the policy, the media responded more in terms of “labelling compliantly,” while progress in “labelling adequately” was limited, showing a stage-specific pattern in which form advances first and substance lags behind.

Third, labelling practices diverge considerably across platforms. Chinanews.com and CNR.cn, which have dedicated AIGC columns with unified prefixes and attribution norms, significantly outperform other platforms in terms of the standardization and consistency of labelling. This finding indicates that labelling quality depends not only on external institutional constraints but also closely on whether a media organization has established standardized production processes and column-based management mechanisms internally.

5.2 Recommendations

In response to the above findings, this paper proposes improvements at three levels.

First, at the institutional level, regulators can further refine labelling norms and guide media from meeting bottom-line requirements toward substantive transparency. Building on the existing explicit-labelling requirements, media can be encouraged to disclose information such as the name of the generation tool and the type of data sources, avoiding labels that stop at a generic “generated by AI” statement and strengthening their practical support for the audience’s right to know.

Second, at the organizational level, mainstream media can draw on the practical experience of platforms such as Chinanews.com and CNR.cn by embedding AIGC labelling into routine production processes—establishing dedicated columns, unified prefixes, and standardized attribution—to reduce arbitrariness in label placement and improve label consistency and recognition. Column-based management not only helps standardize internal operations but also helps audiences form stable recognition expectations.

Third, at the communication strategy level, the media should acknowledge the “disclosure penalty” effect and explore disclosure approaches that balance transparency with audience experience. For example, labels can briefly explain the specific division of labor between humans and machines (e.g., “visuals generated by AI; data verified by journalists”), which both inform audiences of the content's provenance and convey that human oversight was exercised, helping to reduce the degree of trust erosion while maintaining transparency.

5.3 Limitations and Future Research

This study has several limitations. First, the sample mainly consists of AIGC products retrievable on the websites, and the sample sizes across platforms are unbalanced (Chuanguan News contributed only four items), limiting representativeness. It should be noted that the sample is not an exhaustive enumeration of the population but a representative subset selected according to explicit rules: During sampling, we found that mainstream media produce AI-generated content in enormous and rapidly growing quantities, with similar content (such as solar-term posters and column-based products) emerging endlessly and defying exhaustive collection. This very “impossibility of exhaustion” itself constitutes a noteworthy finding: it confirms that AIGC has achieved normalized, large-scale production in mainstream media, and a single small-sample study can hardly cover the full picture. The conclusions of this study are therefore better regarded as a characterization of the overall trend of current labelling practices rather than a complete description of all AIGC products. Second, although the judgment of categories such as disclosure depth and label form passed reliability testing and rule clarification, it still carried a degree of subjectivity. Third, this study is a descriptive and comparative investigation and does not delve into audiences' perceptions of and attitudes toward AIGC labels.

Future research can expand in three directions: First, the sample size and platform coverage can be increased to include AIGC products on mobile apps and social media; second, a control group of human-produced news can be introduced, and methods such as logistic regression can be used to test the factors influencing labelling standardization; and third, questionnaires or experiments can be combined to examine the actual effects of different labelling approaches on audience trust and content evaluation, thereby establishing a complete evidence chain between “labelling practices” and “labelling effects”.

References

[1] Cyberspace Administration of China, Ministry of Industry and Information Technology, Ministry of Public Security, & National Radio and Television Administration. (2025). *Measures for the labeling of AI-generated synthetic content*. Issued March 14, 2025; effective September 1, 2025.

[2] State Administration for Market Regulation, & Standardization Administration of China. (2025). *Cybersecurity technology—Labeling method for content generated by artificial intelligence: GB 45438—2025*. China Standards Press.

[3] Yu, G. (2023). The communication revolution and media ecology reconstruction under the ChatGPT wave. *Exploration and Free Views*, (3), 9–12. [In Chinese]

[4] Peng, L. (2023). AIGC and the new survival characteristics of the intelligent era. *Nanjing Journal of Social Sciences*, (5), 104–111. [In Chinese]

[5] Li, Y., & Ma, N. (2019). Research on communication change and media transformation under the wave of artificial intelligence. *China Radio and TV Academic Journal*, (1), 6–9. [In Chinese]

[6] Sun, M., Hu, W., & Wu, Y. (2024). Public perceptions and attitudes towards the application of artificial intelligence in journalism: From a China-based survey. *Journalism Practice, 18*(3), 548–570.

[7] Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A Human-Machine Communication research agenda. *New Media & Society, 22*(1), 70–86.

[8] Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.