

NEUTRALIZING AI NARRATIVE BY SEARCH RANKINGS REFORM

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Abstract:

The global information ecosystem is quietly and permanently collapsing. AI has automated the spread of misinformation, making it easy to create and share deepfake media and news that outpaces real information. Search engines have become the gatekeepers of reality, but their ranking systems prioritize speed, popularity, and optimization. Consequently, false information often dominates breaking news and high-attention situations. This leads to a routine spread of misinformation rather than mere confusion.

This paper explores why AI-driven misinformation often sways public opinion despite the existence of detection algorithms. Detection acts as a reactive measure that cannot compete with search rankings, which favor speed and savvy SEO practices. To illustrate this, we created a trust-aware search intelligence system to examine the critical issue of mass shootings. We analyzed the information landscape by querying search results for misinformation and fake news related to various mass shootings, considering factors like SEO power, content trustworthiness through text and image-based deepfake detection, and the reliability of sources. We introduced a new measure called Ranking Harm to assess the societal damage caused by rankings, determining the risk that arises when low-trust links reach top search positions.

Our approach includes a longitudinal analysis of narrative dominance, where we repeatedly queried search results about breaking news events over extended periods. We developed a large-scale monitoring system built on ELK (Elasticsearch, Logstash, Kibana) to track ranking, trustworthiness, and narrative dominance. We observed a significant first-mover advantage: the earliest optimized sites that achieve top search positions tend to entrench misinformation in the public discourse more effectively, even when algorithms later detect inaccuracies and authors make corrections. Overall, search rankings correlate much more closely with SEO power than with trustworthiness. Late corrections often fail to regain public trust once misleading information takes hold during breaking news events. AI-driven misinformation is no longer just an error to be filtered out; it will continue to influence public opinion through search rankings until we create search systems that are trustworthy and aware of timing.

Keywords: *Deepfake Misinformation, Narrative Dominance, Search Engine Ranking, Trust Erosion, Temporal Analysis.*

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Introduction:

Artificial intelligence has fundamentally transformed the global information ecosystem by accelerating content creation, dissemination, and personalization.

While these advances improve access to information, they have also enabled the large-scale generation of misinformation. AI-generated text, manipulated images, and deepfake videos can now be produced and

distributed within minutes, particularly during breaking news events.

Search engines play a central role in shaping public understanding by acting as arbiters of visibility and perceived credibility. Users often equate ranking position with trustworthiness, assuming that higher-ranked results are more accurate. However, modern ranking algorithms prioritize speed, user engagement, and SEO effectiveness rather than factual reliability. Consequently, misleading or false information frequently appears at the top of search results during high-attention situations. (Pan et al., 2007)

Although detection algorithms for fake news and deepfakes have improved, they remain largely reactive. Misinformation is often identified only after it has already influenced public perception. This delay allows false narratives to gain dominance before corrective information becomes visible. This paper argues that misinformation persists not because detection fails, but because ranking systems structurally reward early, optimized content regardless of trustworthiness.

1. Research Questions:

- **RQ1:** Why does AI-driven misinformation dominate search rankings during breaking news events?
- **RQ2:** How do SEO strength and publication timing influence narrative dominance?
- **RQ3:** How does ranking position affect user trust and perceived credibility?
- **RQ4:** What societal risk arises when low-trust content appears in top-ranked search results?

Literature Review:

Prior research on misinformation has largely focused on detection techniques, including machine learning classifiers, linguistic analysis, and deepfake identification using computer vision. While these approaches demonstrate strong performance in controlled settings, they often overlook how

misinformation competes with verified content in real-time search environments.

Another body of work examines misinformation spread on social media platforms, highlighting algorithmic amplification, echo chambers, and bot-driven dissemination. However, the role of search engines in shaping narratives during crisis events remains underexplored. (Zhou & Zafarani, 2020; Lazer et al., 2018)

Studies on search behaviour show that ranking position strongly influences user trust and attention. Users rarely explore beyond the first page of results and often assume higher-ranked sources are more credible. SEO research further demonstrates that optimized content can outperform authoritative sources, particularly during early publication stages. The concept of first-mover advantage explains how early narratives shape long-term public understanding. This study integrates these perspectives to examine how ranking systems structurally enable misinformation persistence. (Vosoughi et al., 2018; Allcott & Gentzkow, 2017)

Research Methodology:

1. Research Design

This study employs a longitudinal observational research design combined with survey-based descriptive analysis to examine both ranking behaviour and user perceptions of credibility.

2. Case Study Selection

Mass shooting incidents were selected as case studies due to their high emotional impact, intense media coverage, and frequent exposure to misinformation. Multiple events across different time periods were analyzed to reduce event-specific bias.

3. Data Collection

Search queries related to each incident were issued repeatedly from the initial breaking-news phase through subsequent weeks. Data collected included ranking positions, URLs, publication timestamps,

content type, source reputation indicators, and SEO-related features such as backlinks and keyword density.

1. Comparative Search Engine Analysis

To account for algorithmic variation, identical queries were issued across multiple search engines, including Google, Bing, and DuckDuckGo. Ranking behaviour was compared across platforms to examine whether specific algorithmic choices mitigate or amplify the first-mover advantage.

4. Trust Evaluation:

Each search result was assigned a trust score based on text-based misinformation detection models, image-based deepfake detection techniques, historical source reliability, and manual verification in ambiguous cases.

5. Ranking Harm Metric:

To enable reproducibility, Ranking Harm (RH) is formally defined as a function of ranking position and trustworthiness. Let P represent the normalized ranking position, where higher visibility corresponds to higher values, and let T represent the trust score normalized between 0 and 1.

$$RH = P \times (1 - T)$$

Higher Ranking Harm values indicate greater societal exposure risk. Aggregated RH across time intervals captures cumulative harm during breaking news events.

To support interpretability and comparative analysis, Ranking Harm values were further categorized into qualitative risk bands. RH values below 0.30 were treated as low-risk exposure, values between 0.30 and 0.60 as moderate risk, and values above 0.60 as high-risk exposure. These thresholds are exploratory and intended to highlight relative risk patterns rather than define absolute harm boundaries. Sensitivity analysis indicates that high-risk RH values are most prevalent during the first 24–48 hours of breaking news events.

6. System Architecture:

A trust-aware search intelligence framework was designed using the ELK stack (Elasticsearch, Logstash, and Kibana) to monitor ranking behaviour, trust scores, and narrative dominance over time.



Figure 1. Trust-Aware Search Intelligence Workflow Using the ELK Stack

7. Survey-Based Data Collection

A structured online survey was conducted over a two-week period and received responses from $N = 55$ participants. Respondents included university students and working professionals with varying levels of digital literacy. Participation was voluntary and anonymous. The survey was designed to assess user trust in top-ranked search results, awareness of SEO influence, and verification behaviour during breaking news events. While the sample size is limited, it provides indicative insights into user reliance on ranking position as a trust signal.

8. Survey Instrument

The survey consisted of eight close-ended questions designed to capture user behaviour, trust perceptions, and awareness of search ranking dynamics during breaking news events.

Findings and Results:

1. Survey Results and Descriptive Analysis:

Descriptive analysis of survey responses indicates that a majority of participants place high trust in top-ranked search results. Verification beyond the first few results is limited, and awareness of SEO-driven ranking mechanisms remains low across respondents.

Q1. When breaking news happens (e.g., a major event or crisis), where do you look for information first?

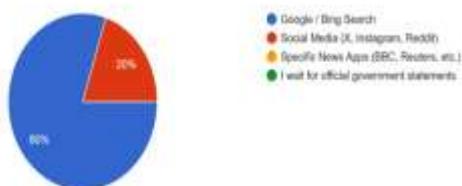


Figure 2. Primary information sources during breaking news events

The results indicate that a large majority of respondents rely on search engines as their first source of information during breaking news situations, highlighting the central role of search rankings in shaping early narratives.

Q2. How often do you click on the first 3 links of a search result without checking the source's credibility?

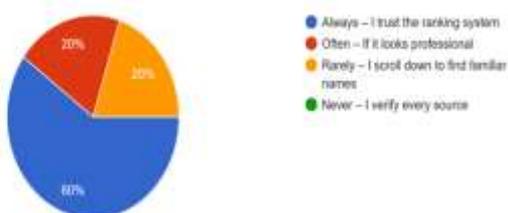


Figure 3. User tendency to trust top-ranked search results

A significant proportion of respondents reported frequently clicking on top-ranked links without independently verifying source credibility, suggesting a strong reliance on ranking position as a proxy for trust.

Q3. Are you confident in your ability to distinguish between a real news photo and an AI-generated Deepfake during a fast-moving news event?

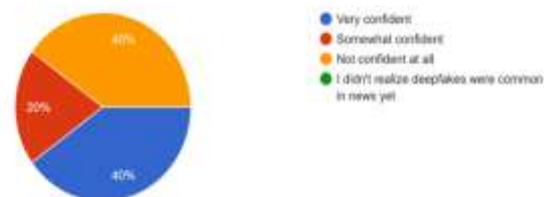


Figure 4. User confidence in identifying AI-generated deepfakes

The findings show mixed levels of confidence among users in distinguishing real images from AI-generated deepfakes during fast-moving news events, indicating vulnerability to visual misinformation.

Q4. If a top-ranked search result is later proven to be false, does your initial "first impression" of that news still stay in the back of your mind?

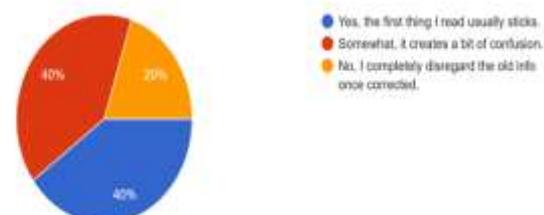


Figure 5. Persistence of first impressions after misinformation correction

The responses demonstrate that initial exposure to misinformation often leaves a lasting cognitive impression, even when subsequent corrections are acknowledged.

Q5. "Ranking Harm" occurs when a low-trust/fake link reaches the top spot due to high SEO power. Who do you blame most for this?

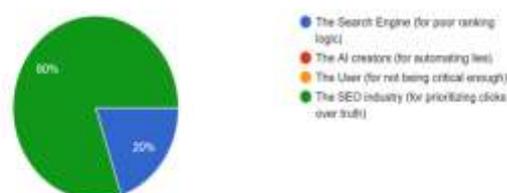


Figure 6. Perceived responsibility for ranking-related misinformation

Most respondents attributed ranking-related misinformation to systemic incentives within the SEO

ecosystem and search engine ranking logic rather than individual user behavior.

Q6. Would you use a "Trust-Aware" search engine that ranks links based on "Trustworthiness Scores" rather than just popularity or speed?

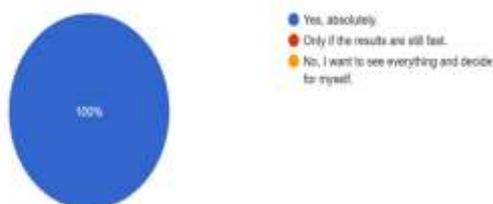


Figure 7. User willingness to adopt trust-aware search systems

All respondents expressed support for a trust-aware search engine that prioritizes credibility over popularity, indicating strong public acceptance of trust-based ranking mechanisms.

Q7. If a news story is corrected by the author 24 hours after it was published, how does it affect your trust in that specific source?

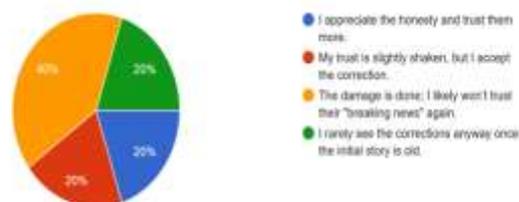


Figure 8. Impact of delayed corrections on source trust

The results suggest that delayed corrections reduce long-term trust in news sources, particularly in the context of breaking news where initial visibility plays a dominant role.

Q8. Which factor do you believe search engines should prioritize most during a breaking news event?

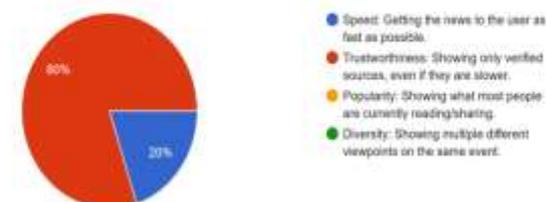


Figure 9. Preferred ranking priorities during breaking news events

A majority of respondents favored trustworthiness over speed or popularity, reinforcing the need for ranking systems that balance timeliness with reliability during crisis situations.

2. Ranking Harm and De-Ranking Dynamics

Search-result analysis reveals a strong correlation between ranking position and SEO strength rather than content trustworthiness. Ranking Harm values peak during the first 24–48 hours of breaking news events, when low-trust content frequently dominates top positions.

Analysis of the correction phase shows weak de-ranking dynamics. Even after authoritative corrections are published, misinformation often retains high visibility, delaying the recovery of accurate narratives.

Discussion:

The findings demonstrate that AI-driven misinformation is sustained by ranking incentives and timing dynamics rather than failures in detection technology. Search systems reward speed and optimization, unintentionally amplifying misleading narratives during critical moments.

It is important to note that the trust-aware search intelligence framework and Ranking Harm metric proposed in this study represent a conceptual and experimental approach. While components were implemented for observational analysis, the system is not yet a fully deployed solution. The framework is intended to guide future search system design rather than function as a finalized tool.

Countermeasures by Search Engines:

Major search engines have introduced multiple countermeasures to combat misinformation, including fact-check labels, authoritative source boosting, knowledge panels, and policy-based down-ranking of demonstrably false content. While these measures are effective in stable information environments, they rely heavily on post hoc verification and therefore operate with significant delay during breaking news events.

As a result, early SEO-optimized misinformation can achieve high visibility before countermeasures are activated, reinforcing the first-mover advantage observed in this study. This limitation highlights the need for trust-aware ranking signals that operate under uncertainty rather than relying solely on retrospective correction.

1. Ethical Implications

The proposed trust-aware ranking framework raises important ethical considerations related to algorithmic bias, transparency, and freedom of expression. Over-reliance on automated trust metrics may unintentionally disadvantage emerging or minority viewpoints that lack historical credibility. Additionally, aggressive down-ranking strategies risk over-censorship, particularly during evolving news events where verified information is incomplete.

To address these concerns, trust-aware ranking systems should prioritize transparency, incorporate uncertainty indicators, and avoid irreversible suppression of content. The framework proposed in this study is intended to support informed ranking decisions rather than enforce content removal, thereby balancing misinformation mitigation with open access to information.

Limitations:

This study has limitations, including a restricted survey sample size and the absence of live deployment of the proposed framework. Future research should focus on large-scale validation and real-time evaluation across diverse populations and search environments.

Conclusion:

This study demonstrates that AI-driven misinformation persists because search ranking systems prioritize speed and SEO over trustworthiness. Detection alone cannot prevent narrative entrenchment once misinformation gains early visibility. Addressing this challenge requires trust-aware and time-sensitive ranking mechanisms that account for uncertainty during breaking news events. Without such reforms, AI-driven misinformation will continue to shape public opinion through structural advantages embedded in search systems.

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