Information Research - Vol. 31 No. iConf (2026)

How do users respond to AI fact-checkers?

Alton Y.K. Chua and Jiayu Han

DOI: https://doi.org/10.47989/ir31iConf64149

Abstract

Introduction. This paper aims to empirically validate a conceptual model that explains how users respond to AI fact-checkers originating from different countries. Guided by the country-of-origin effect, source credibility theory, and elaboration likelihood model, the model comprises five variables, namely, AI fact-checkers, fact-checker source credibility, perceived credibility of flagged news, issue involvement, and AI literacy.

Method. An online experiment was conducted to examine how participants responded to AI fact-checkers from two countries, namely the United States of America (U.S.) and China.

Analysis. A total of 139 responses were collected in this study. Data was analysed using a one-way analysis of variance (ANOVA), PROCESS Model 4 and 9.

Results. The results showed that AI fact-checkers (country of origin: U.S. vs. China) directly influenced the perceived credibility of flagged news. Fact-checker source credibility mediated the effects of AI fact-checkers. Issue involvement moderated the indirect effect of AI fact-checkers on perceived credibility of flagged news via fact-checker source credibility, whereas AI literacy did not.

Conclusion(s). Theoretically, this paper adds to the scholarly understanding of the effectiveness of AI fact-checkers from different countries of origin. Practically, it highlights the importance of considering the country-of-origin effect when deploying AI fact-checkers for social media platforms.

Introduction

Artificial intelligence (AI) empowers users to generate content with unprecedented ease and speed (Li et al., 2025). While this development democratises online expressions, it also creates a fertile ground for the rapid proliferation of fake news. Traditional fact-checkers are thus inundated by the relentless torrent of falsehoods. In addition, earlier machine learning–based fact-checking systems, which rely on predefined features, have limited adaptability to cope with the constant evolution of deceptive content. In response, AI fact-checkers driven by large language models (LLMs) have emerged (Kim & Lee, 2025). Besides having the capacity to process vast streams of content in real time, they outperform humans and older systems through their inbuilt advanced contextual reasoning (Augenstein et al., 2023).

Even as AI fact-checkers have gained popularity and begun to attract scholarly interest, at least three research gaps can be identified. First, prior studies tend to treat all AI fact-checkers as a single type. As technology progresses, AI from various countries has come onboard with different LLMs, each running on its own distinct data sources, algorithms, and design choices. Since news veracity judgments produced by AI fact-checkers are embedded in specific sociopolitical environments, including the media ecosystems and national censorship policies (Jiang et al., 2025), their credibility would likewise be influenced in part by the country from which they originate. This is known as the country-of-origin effect (Verlegh & Steenkamp, 1999; Yadav et al., 2025). Yet, the potential differences in response to AI fact-checkers across countries have not been studied.

Second, previous researchers largely focused on the direct effects of AI fact-checkers, overlooking the process through which their effectiveness is achieved. Source credibility theory (SCT) suggests that information is more persuasive if its source is perceived as highly credible (Ohanian, 1991). When an AI fact-checker is considered as a reliable source, users would be more likely to comply with its warning, such as reconsidering the news credibility (Chao et al., 2024). Although the importance of fact-checking source credibility has been recognised, the role it plays in the correction process has not been explored. Thus, there are calls for further research to uncover the '*black box*' of how AI fact-checkers exert their influence (Clayton et al., 2020; Gwebu et al., 2022).

Third, relatively scant attention has been paid to examining the role of users' characteristics. The elaboration likelihood model (ELM) identifies motivation and ability as key factors in determining how deeply users process information (Aghakhani et al., 2021; Petty & Cacioppo, 1986). When users hold a personal stake on the topic or possess some technical knowledge, they are more likely to scrutinise the authenticity of posts flagged by fact-checkers (McDermott & Lachlan, 2020; Miller et al., 2024). Nonetheless, prior studies in the domain of AI fact-checking tend to omit these user-related factors. This leaves a limited understanding of when and for whom AI fact-checking is more effective in decreasing perceived credibility of fake news.

For these reasons, the objective of this paper is to develop and empirically validate a conceptual model that explains how users respond to AI fact-checkers originating from different countries. Guided by the country-of-origin effect, SCT and ELM, the model comprises five variables, namely, AI fact-checkers, fact-checker source credibility, perceived credibility of flagged news, issue involvement, and AI literacy. Based on this model, four hypotheses are proposed. To test them, an online pre-test-post-test experiment was conducted, in which participants evaluated AI fact-checkers from two countries, namely the United States of America (U.S.) and China. These two global leaders in AI development make for an interesting comparison (Singh et al., 2025). Furthermore, they represent contrasting cases of information environments: The U.S. operates within a relatively open media context while China is characterised by a highly regulated information landscape (Harrison & Farn, 1990; Yang et al., 2014). A total of 139 responses were collected in this study. Data was analysed using a one-way analysis of variance (ANOVA), PROCESS Model 4 and 9.

This paper holds both theoretical and practical significance. Theoretically, this paper adds to the scholarly understanding of the effectiveness of AI fact-checkers from different countries of origin. The proposed model reveals their differences through both mediating and moderating mechanisms. It also extends the application of SCT and ELM to the context of AI fact-checking. Practically, it highlights the importance of taking into account the country-of-origin effect when deploying AI fact-checkers for social media platforms. Furthermore, it also encourages social media users to critically use fact-checkers (Gilchrist, 2018).

Literature review and hypothesis development

The direct and indirect effects of AI fact-checkers

Prior studies on the country-of-origin effect have demonstrated that evaluations of AI are influenced by the location in which it is developed (Pinarbasi, 2023). At the same time, news authenticity judgments are often closely connected to national contexts, including media environment, political orientation, and cultural values. As a result, users would react differently to AI fact-checkers from different countries. For example, AI fact-checkers originating in the U.S. are often associated with openness, whereas those from China are more likely to be perceived as shaped by state regulation and censorship practices (Harrison & Farn, 1990; Yang et al., 2014). Thus, such country-specific perceptions will affect how users assess the credibility of news flagged by AI fact-checkers. The first hypothesis is proposed:

H1: AI fact-checkers (country of origin: U.S. vs. China) directly influence the perceived credibility of flagged news.

Fact-checker source credibility refers to the degree to which users perceive the fact-checking source as reliable (Moon & Kahlor, 2025). According to SCT, information from credible sources is more persuasive, which shapes subsequent attitudes (Chao et al., 2024; Ohanian, 1991). Based on this, the country-of-origin effect may also operate indirectly through perceived source credibility. Specifically, AI fact-checkers developed in different countries may elicit varying levels of credibility among users. These perceptions can, in turn, influence users' beliefs in news (Carpenter et al., 2017). For example, when an AI fact-checker is regarded as highly trustworthy, they will be less willing to believe the suspicious content (Koch et al., 2023). Thus, the second hypothesis is proposed:

H2: Fact-checker source credibility mediates the effects of AI fact-checkers on the perceived credibility of flagged news.

The moderating roles of issue involvement and AI literacy

ELM suggests that the depth of elaboration in information processing depends on two individual factors. The first is users' motivation, defined as the extent to which individuals are willing to invest effort in processing information (Petty & Cacioppo, 1986). In this study, it is driven by the degree of personal relevance users attach to the news topic, namely, issue involvement (Bae, 2008). When involvement is high, users are more likely to engage in systematic processing, rather than relying on emotions or intuition. As a result, users place greater weight on the fact-checking source credibility when assessing news accuracy (Sun & Dong, 2024). By contrast, when involvement is low, users are more likely to process information peripherally, and the fact-checker may not achieve its intended effectiveness (Park & Young Yoon, 2025).

The second factor highlighted by ELM is users' ability, which reflects their cognitive capacity to comprehend, analyse, and critically evaluate information (Aghakhani et al., 2021; Sun & Dong, 2024). In this study, it refers to users' knowledge and skills to scrutinise judgments provided by AI fact-checkers, namely, AI literacy (El-Sayed et al., 2025). Users with higher levels of AI literacy are better able to discern how AI fact-checkers function, making perceived source credibility more decisive for news credibility. Conversely, low AI literacy limits users' capacity to interpret fact-checkers'

outputs, which weakens the effects of source credibility on belief change. Thus, the third and fourth hypotheses are proposed:

H3: Issue involvement moderates the indirect effect of AI fact-checkers on the perceived credibility of flagged news via fact-checker source credibility.

H4: AI literacy moderates the indirect effect of AI fact-checkers on the perceived credibility of flagged news via fact-checker source credibility.

Figure 1 illustrates the conceptual model guiding our research hypotheses.

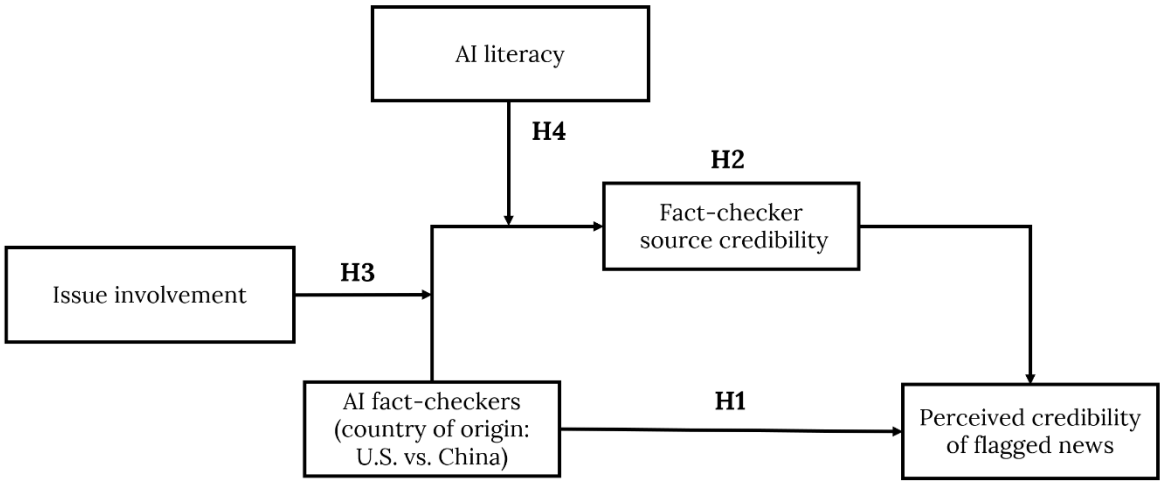

Figure 1. Conceptual model.

Method

Research design and experimental stimuli

To test four proposed hypotheses, this study adopted a pre-test–post-test design. In the pre-test, participants viewed four social media news posts without AI fact-checker claims, two of which were fake and two were real, which were presented in random order. In the post-test, they were re-exposed to one of the fake news posts with an AI fact-checker claim. And they were randomly assigned to conditions where the AI fact-checker originated from either the U.S. or China. Participants' task was to rate credibility on the news post after each exposure. The lower the credibility ratings after the post-test compared to the pre-test, the more effective the fact-checker is considered. Hence, the effectiveness of AI fact-checker was computed by taking the difference between the mean pre-test and post-test scores (Pareek & Goncalves, 2024).

All experimental materials used the typical format of social media news posts. As shown in Figure 2, each post included a poster image and its name at the top. The main news content was presented in the middle, including a headline, a picture, and a brief description. Four health-related news posts were obtained from well-known fact-checking websites, such as Snopes and FullFact. The topics were about the side effects of chemotherapy, the harm of laptop use, mRNA COVID-19 vaccines, and the risks of Bluetooth earbuds. These were selected because of their sensational nature that easily grabs attention (Pal et al., 2020). Regarding the fact-checked news, the AI fact-checker claim appeared below the news content, as shown in Figure 3. It featured a red triangle with an exclamation mark on the left and the message '*marked fake by the U.S.-based AI model*' or '*marked fake by the China-based AI model*'. Interactive features such as like, comment, and share buttons were incorporated at the bottom to enhance ecological validity (Han & Chua, 2025).

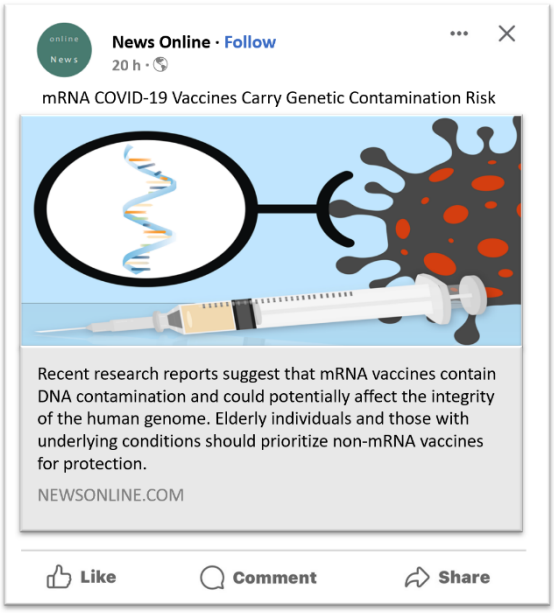

Figure 2. Example of a pre-test stimulus

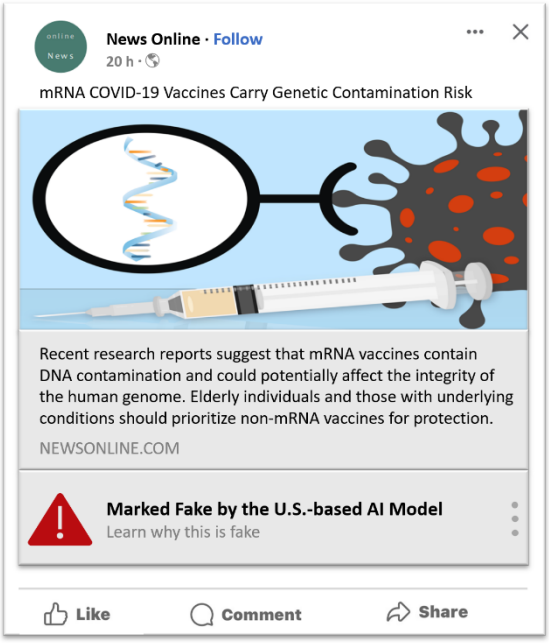

Figure 3. Example of a post-test stimulus

Data collection and measures

This study was conducted in Singapore. Participants were recruited using a combination of purposive and snowball sampling (Banerjee & Chua, 2025). Two inclusion criteria were imposed. First, they had to be over 21 years old to avoid including vulnerable populations such as minors. The second was that participants had to be frequent social media users for news consumption, which guaranteed their ability to comprehend the social media content and fact-checking information presented in the study. Participants were anonymised and were assured they could withdraw from the study at any point of time.

After obtaining informed consent, participants were guided through three steps. In the first step, they were asked to go through four social media news posts. After each post, they were required to answer a 3-item questionnaire, which was used to measure perceived credibility of news (Gupta et al., 2023). In the second step, participants were reintroduced to one of the fake news posts that they had seen earlier, but with an AI fact-checker claim. The perceived credibility of news was reported again. Third, they were asked to complete an 18-item questionnaire. Fact-checker source credibility was measured with nine items (Chao et al., 2024), while issue involvement and AI literacy were measured with three items each (Lam et al., 2022), resulting in a total of 15 items (9 items + 3 items x 2 variables). Participants indicated their level of agreement on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The last three items on the questionnaire collected demographic information, including participants' gender, age group, and educational qualification.

Data analysis

Data was analysed using ANOVA, PROCESS Model 4 and 9 with SPSS software. First, to ensure the reliability of the measures, Cronbach's alpha was used. Second, the assumptions of one-way ANOVA were checked to ensure the validity of the analysis, including normality and homogeneity of variances. Specifically, normality was tested using Probability-Probability Plot (P-P Plot), and homogeneity of variances was tested using Levene's test. Third, a paired-samples t-test was performed to examine changes in perceived credibility of flagged news from pre-test to post-test, which aims to evaluate the effectiveness of the presence of AI fact-checkers. Fourth, a one-way ANOVA was conducted to examine significant differences between group means, testing H1. Fifth, PROCESS Model 4 was used to examine the mediation effects within SPSS software, testing H2. Last, PROCESS Model 9 was used to examine the moderated mediation effects within SPSS software, testing H3 and H4.

Results

Sample, descriptive statistics, and preliminary analyses

An initial pool of 154 participants was invited to this study. Of these, 15 did not meet the inclusion criteria. Complete responses from 139 (154 - 15) participants were thus admitted for analysis. Specifically, 63 participants were assigned to the U.S. AI fact-checker condition, while 76 were assigned to the China AI fact-checker condition.

In terms of demographics, 59 (42.4%) were male and 68 (48.9%) were female. 8 (5.8%) were non-binary gender, and 3 (2.2%) prefer not to say. The dominantly represented age groups were 21-30 years (45.3%), followed by 31-40 years (27.3%). In terms of educational qualification, 57 participants (41.0%) had a bachelor's degree, 32 participants (23.0%) had attended some college but did not obtain a degree, 30 participants (21.6%) had a master's degree, 13 participants (9.4%) had a high school diploma or less, and the other 6 participants (4.3%) had a doctoral degree or higher.

The Cronbach's α value of all variables ranged from 0.753 to 0.920, which exceeded the threshold of 0.7, and thus ensured the internal consistency of the items for each of the constructs. The P-P Plot results for all variables closely aligned with the diagonal line, indicating that all variables followed the normal distribution (Nunnally, 1978). Moreover, the p-value of Levene's Test of Equality of Variances for all variables was also greater than 0.05, suggesting that the variances were homogeneously distributed (Lim & Loh, 1996). Thus, the sample met the basic assumptions for conducting subsequent analysis.

Inferential statistics

Before testing H1, a paired-samples t-test was conducted to examine whether perceived credibility of flagged news differed between the pre-test (without AI fact-checker) and the post-test (with AI fact-checker). The results showed a significant decrease in perceived credibility of flagged news from the pre-test to the post-test ($M_{pre\text{-}test} = 4.32 \pm 0.63$ vs. $M_{post\text{-}test} = 1.54 \pm 0.57$; $t = 50.96$; $p < 0.001$).

Then, a one-way ANOVA test was performed to test H1. The results showed that there is a significant difference between the effectiveness of the U.S. AI fact-checker and China AI fact-checker on decreasing perceived credibility of flagged news ($F = 9.00$; $p < 0.001$). H1 was supported.

The mediation effect proposed in H2 was tested using PROCESS Model 4. All analyses used 5,000 bootstrap samples to estimate bias-corrected bootstrap confidence intervals. The model considered the AI fact-checkers as the independent variable, fact-checker source credibility as the mediator, and perceived credibility of flagged news as the dependent variable. As shown in Table 1, results indicated an indirect effect such that the AI fact-checkers decreased perceived credibility of flagged news through fact-checker source credibility (Effect = -0.163, 95% confidence interval (CI) [-0.281, -0.062]). Since the direct effect of the AI fact-checkers on the perceived credibility of flagged news was not significant (Effect = -0.156, 95% CI [-0.346, 0.034]), perceived credibility of flagged news fully mediated the relationship of AI fact-checkers on perceived credibility of flagged news when included in the model, supporting H2.

	Effect	Bias-Corrected 95%CI	
		Lower	Upper
Total effect	-0.319	-0.529	-0.109
Indirect effect	-0.163	-0.281	-0.062
Direct effect	-0.156	-0.346	0.034

Table 1. The mediation effect of fact-checker source credibility

The moderated mediation effects proposed in H3 and H4 were tested using PROCESS Model 9. The model considered AI fact-checkers as the independent variable, fact-checker source credibility as the mediator, perceived credibility of flagged news as the dependent variable, issue involvement and AI literacy as the moderators, gender, age, and educational level as the covariates. The results showed that issue involvement moderates the indirect effect of AI fact-checkers on perceived credibility of flagged news via fact-checker source credibility (B = 0.173, Boot SE = 0.054, 95% Boot CI [-0.065, -0.280]). H3 was supported. However, AI literacy does not moderate the indirect effect of AI fact-checkers on perceived credibility of flagged news via fact-checker source credibility (B = -0.110, Boot SE = 0.074, 95% Boot CI [-0.266, 0.025]). H4 was not supported.

Discussion and conclusion

Key findings

Three major findings could be gleaned from this research. First, AI fact-checkers (country of origin: U.S. vs. China) will directly influence perceived credibility of flagged news (H1). In other words, there is a significant difference between the effectiveness of AI fact-checkers from the U.S. and China. This means that the country-of-origin effect (Verlegh & Steenkamp, 1999; Yadav et al., 2025) also applies to the context of AI fact-checking. Users form an impression of an AI fact-checker based on the national context in which it was created. The U.S. is generally associated with an open media environment, whereas China is characterised by a more regulated information system (Harrison & Farn, 1990; Yang et al., 2014).

Second, fact-checker source credibility mediates the effects of AI fact-checkers on perceived credibility of flagged news (H2). This is consistent with SCT, which posits that information persuasiveness depends on the perceived trustworthiness of its source (Chao et al., 2024; Zha et al., 2018). In this study, after users encountered AI fact-checkers, they would evaluate their source credibility. Highly reliable sources are more likely to gain users' compliance, making them more receptive to corrections and more willing to revise their mistaken beliefs. This finding confirms

the important role of fact-checker source credibility in shaping users' judgements on news accuracy.

Third, issue involvement moderates the indirect effect of AI fact-checkers on perceived credibility of flagged news via fact-checker source credibility (H3), whereas AI literacy does not (H4). Prior studies have emphasised the roles of both motivation and ability factors in users' information elaboration (Aghakhani et al., 2021; Lam et al., 2022). However, this study provides evidence only for the role of motivation. One possible explanation lies in nature of using AI-related services. Users never have to possess a high level of technical knowledge before they can process AI fact-checking information. Still, future studies are needed to explore why ability factors such as AI literacy play a limited role in this context.

Contributions and implications

The theoretical contributions of this paper are two-fold. First, this paper advances scholarly understanding by comparing the effectiveness of AI fact-checkers originating from different countries. Prior researchers often assumed that users perceived AI fact-checkers equally, which overlooks the potential variations among them (Kim & Lee, 2025; Liu et al., 2023; Moon & Kahlor, 2025). This paper demonstrates that users' evaluations of AI fact-checks are affected by their countries of origin. In doing so, it represents an initial attempt to explore the country-of-origin effect in a relatively uncharted research area.

Second, it extends the applicability of SCT and ELM in the context of AI fact-checking. It develops a research model to examine the underlying mechanism of how AI fact-checkers work on perceived credibility of flagged news. Specifically, fact-checker source credibility mediates the effects of AI fact-checkers on perceived credibility of flagged news. Issue involvement moderates the indirect effect of AI fact-checkers on perceived credibility of flagged news via fact-checker source credibility. Furthermore, this paper also contributes to ELM by revealing a divergence from its traditional proposition that both motivation and ability shape information elaboration (Aghakhani et al., 2021; Lam et al., 2022).

On the practical front, this paper offers implications for social media platforms. The findings underscore the importance of considering the country-of-origin effect when deploying AI fact-checkers. Social media can reduce potential national bias through transparent disclosure of fact-checking procedures and collaborating with international organisations (Park & Young Yoon, 2025). In addition, they should also take individual factors into account. For example, they could design fact-checker presentations that stimulate users' issue involvement, thereby encouraging deeper engagement with corrective information.

This paper also encourages social media users to engage critically with AI fact-checking information rather than relying solely on national labels. Since fact-checker source credibility plays a decisive role in whether users accept corrections, users are advised to judge fact-checkers by the quality of supporting evidence, rather than by their countries of origin. Moreover, users should remain attentive to news issues that matter to them, as higher personal involvement makes them more receptive to corrections. Developing a habit of cross-checking news with multiple sources can further strengthen their ability to resist misinformation (Beer & Matthee, 2020).

Limitations and future research directions

Two limitations in this paper need to be acknowledged. One, it focuses specifically on AI fact-checkers originating from the United States and China. While they represent two contrasting cultural contexts in the world, the findings may not be generalisable to AI fact-checkers developed in other nations. Future research can consider comparing the effectiveness of AI fact-checkers from a wider range of countries to provide a more comprehensive understanding.

Another limitation is the methodological parsimony of the experimental setup. No full social media browsing experience was replicated in the experiment. Participants could neither scroll through the feed nor interact with the posts. A suggestion for future studies is to adopt a more realistic context that better simulates real-world social media environments.

About the authors

Alton Y.K. Chua is an Associate Professor at the Wee Kim Wee School of Communication and Information, Nanyang Technological University, Singapore. His research interests include online rumors, user reviews of products and services, question and answering system, and information and knowledge management. He can be contacted at altonchua@ntu.edu.sg

Jiayu Han is a PhD candidate at the Wee Kim Wee School of Communication and Information, Nanyang Technological University, Singapore. Her research interests include fact-checking, online misinformation, and tourism live-streaming. She can be contacted at jiayu002@e.ntu.edu.sg

References

Aghakhani, N., Oh, O., Gregg, D. G., & Karimi, J. (2021). Online Review Consistency Matters: An Elaboration Likelihood Model Perspective. Information Systems Frontiers, 23(5), 1287–1301. https://doi.org/10.1007/s10796-020-10030-7

Augenstein, I., Baldwin, T., Cha, M., Chakraborty, T., Ciampaglia, G. L., Corney, D., DiResta, R., Ferrara, E., Hale, S., Halevy, A., Hovy, E., Ji, H., Menczer, F., Miguez, R., Nakov, P., Scheufele, D., Sharma, S., & Zagni, G. (2023). Factuality Challenges in the Era of Large Language Models (No. arXiv:2310.05189). arXiv. https://doi.org/10.48550/arXiv.2310.05189

Bae, H.S. (2008). Entertainment-Education and Recruitment of Cornea Donors: The Role of Emotion and Issue Involvement. Journal of Health Communication, 13(1), 20–36. https://doi.org/10.1080/10810730701806953

Banerjee, S., & Chua, A. Y. K. (2025). Effect of autonomous vehicle-related eWOM on (fe)males' attitude and perceived risk as passengers and pedestrians. Internet Research, 35(2), 841–859. https://doi.org/10.1108/INTR-10-2023-0912

Beer, D. de, & Matthee, M. (2020). Approaches to Identify Fake News: A Systematic Literature Review. Integrated Science in Digital Age 2020, 136, 13. https://doi.org/10.1007/978-3-030-49264-9_2

Carpenter, S., Zhu, F., Zeng, M., & Shreeves, M. (2017). Expert Sources in Warnings May Reduce the Extent of Identity Disclosure in Cyber Contexts. International Journal of Human–Computer Interaction, 33(3), 215–228. https://doi.org/10.1080/10447318.2016.1232909

Chao, F., Zhou, Q., Zhao, J., Xu, Y., & Yu, G. (2024). Trustworthiness matters: Effect of source credibility on sharing debunking information across different rumour types. Information Processing & Management, 61(4), 103747. https://doi.org/10.1016/j.ipm.2024.103747

Clayton, K., Blair, S., Busam, J. A., Forstner, S., Glance, J., Green, G., Kawata, A., Kovvuri, A., Martin, J., Morgan, E., Sandhu, M., Sang, R., Scholz-Bright, R., Welch, A. T., Wolff, A. G., Zhou, A., & Nyhan, B. (2020). Real Solutions for Fake News? Measuring the Effectiveness of General Warnings and Fact-Check Tags in Reducing Belief in False Stories on Social Media. Political Behavior, 42(4), 1073–1095. https://doi.org/10.1007/s11109-019-09533-0

El-Sayed, B. K. M., El-Sayed, A. A. I., Alsenany, S. A., & Asal, M. G. R. (2025). The role of artificial intelligence literacy and innovation mindset in shaping nursing students' career and talent self-efficacy. Nurse Education in Practice, 82, 104208. https://doi.org/10.1016/j.nepr.2024.104208

Gilchrist, A. D. (2018). Post-Truth: An outline review of the issues and what is being done to combat it. Ibersid: Revista de Sistemas de Información y Documentación, 12(2), 13–24. https://doi.org/10.54886/ibersid.v12i2.4601

Gupta, M., Dennehy, D., Parra, C. M., Mäntymäki, M., & Dwivedi, Y. K. (2023). Fake news believability: The effects of political beliefs and espoused cultural values. Information & Management, 60(2), 103745. https://doi.org/10.1016/j.im.2022.103745

Gwebu, K. L., Wang, J., & Zifla, E. (2022). Can warnings curb the spread of fake news? The interplay between warning, trust and confirmation bias. Behaviour & Information Technology, 41(16), 3552–3573. https://doi.org/10.1080/0144929X.2021.2002932

Han, J., & Chua, A. Y. K. (2025). The Power of Warning: Unpacking the Impact of Fact-Checking Flag on News Sharing and Verification. In G. Oliver, V. Frings-Hessami, J. T. Du, & T. Tezuka (Eds.), Sustainability and Empowerment in the Context of Digital Libraries (pp. 291–304). Springer Nature. https://doi.org/10.1007/978-981-96-0865-2_24

Harrison, W. L., & Farn, C.K. (1990). A comparison of information management issues in the United States of America and the Republic of China. Information & Management, 18(4), 177–188. https://doi.org/10.1016/0378-7206(90)90038-J

Jiang, Q., Gao, Z., & Karniadakis, G. E. (2025). DeepSeek vs. ChatGPT vs. Claude: A comparative study for scientific computing and scientific machine learning tasks. Theoretical and Applied Mechanics Letters, 15(3), 100583. https://doi.org/10.1016/j.taml.2025.100583

Kim, Y., & Lee, J. (2025). Balancing Artificial Intelligence and Human Expertise: Ideal Fact-Checking Strategies for Hard and Soft News. Journalism & Mass Communication Quarterly, 10776990251325875. https://doi.org/10.1177/10776990251325875

Koch, T. K., Frischlich, L., & Lermer, E. (2023). Effects of fact-checking warning labels and social endorsement cues on climate change fake news credibility and engagement on social media. Journal of Applied Social Psychology, 53(6), 495–507. https://doi.org/10.1111/jasp.12959

Lam, C., Huang, Z., & Shen, L. (2022). Infographics and the Elaboration Likelihood Model (ELM): Differences between Visual and Textual Health Messages. Journal of Health Communication, 27(10), 737–745. https://doi.org/10.1080/10810730.2022.2157909

Li, C., Lin, Y., Chen, R., & Chen, J. (Elaine). (2025). How do users adopt AI-generated content (AIGC)? An exploration of content cues and interactive cues. Technology in Society, 81, 102830. https://doi.org/10.1016/j.techsoc.2025.102830

Lim, T.S., & Loh, W.Y. (1996). A comparison of tests of equality of variances. Computational Statistics & Data Analysis, 22(3), 287–301. https://doi.org/10.1016/0167-9473(95)00054-2

Liu, X., Qi, L., Wang, L., & Metzger, M. J. (2023). Checking the Fact-Checkers: The Role of Source Type, Perceived Credibility, and Individual Differences in Fact-Checking Effectiveness. Communication Research, 00936502231206419. https://doi.org/10.1177/00936502231206419

McDermott, K. C. P., & Lachlan, K. A. (2020). Polarising Organisations and Image Repair: The Effects of Extreme Disposition and Ego-Involvement on ELM Processing Routes for Organisational Responses. Communication Studies, 71(2), 332–350. https://doi.org/10.1080/10510974.2020.1733039

Miller, S., Menard, P., Bourrie, D., & Sittig, S. (2024). Integrating truth bias and elaboration likelihood to understand how political polarisation impacts disinformation engagement on social media. Information Systems Journal, 34(3), 642–679. https://doi.org/10.1111/isj.12418

Moon, W.K., & Kahlor, L. A. (2025). Fact-checking in the age of AI: Reducing biases with non-human information sources. Technology in Society, 80, 102760. https://doi.org/10.1016/j.techsoc.2024.102760

Nunnally, J. C. (with Internet Archive). (1978). Psychometric theory. New York : McGraw-Hill. http://archive.org/details/psychometrictheo00nunn

Ohanian, R. (1991). The Impact of Celebrity Spokespersons' Perceived Image on Consumers' Intention to Purchase. Journal of Advertising Research, 31(1), 46–54.

Pal, A., Chua, A. Y. K., & Hoe-Lian Goh, D. (2020). How do users respond to online rumor rebuttals? Computers in Human Behavior, 106, 106243. https://doi.org/10.1016/j.chb.2019.106243

Pareek, S., & Goncalves, J. (2024). Peer-supplied credibility labels as an online misinformation intervention. International Journal of Human-Computer Studies, 188, 103276. https://doi.org/10.1016/j.ijhcs.2024.103276

Park, K., & Young Yoon, H. (2025). AI algorithm transparency, pipelines for trust not prisms: Mitigating general negative attitudes and enhancing trust toward AI. Humanities and Social Sciences Communications, 12(1), 1160. https://doi.org/10.1057/s41599-025-05116-z

Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. In L. Berkowitz (Ed.), Advances in Experimental Social Psychology (Vol. 19, pp. 123–205). Academic Press. https://doi.org/10.1016/S0065-2601(08)60214-2

Pinarbasi, F. (2023). Country-of-Origin Effect and Digital Marketing: Evaluating Current and Future of Marketing. In Origin and Branding in International Market Entry Processes (pp. 117–137). IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-6684-6613-1.ch006

Singh, S., Bansal, S., Saddik, A. E., & Saini, M. (2025). From ChatGPT to DeepSeek AI: A Comprehensive Analysis of Evolution, Deviation, and Future Implications in AI-Language Models (No. arXiv:2504.03219). arXiv. https://doi.org/10.48550/arXiv.2504.03219

Sun, M., & Dong, X. (2024). Factors influencing correction upon exposure to health misinformation on social media: The moderating role of active social media use. Online Information Review, ahead-of-print(ahead-of-print). https://doi.org/10.1108/OIR-09-2023-0505

Verlegh, P. W. J., & Steenkamp, J.-B. E. M. (1999). A review and meta-analysis of country-of-origin research. Journal of Economic Psychology, 20(5), 521–546. https://doi.org/10.1016/S0167-4870(99)00023-9

Yadav, S., Koushik, K., & Kishor, N. (2025). The state of country-of-origin research: A bibliometric review of trends and future. Asia Pacific Management Review, 30(1), 100337. https://doi.org/10.1016/j.apmrv.2024.12.001

Yang, Z. J., Kahlor, L., & Li, H. (2014). A United States-China Comparison of Risk Information–Seeking Intentions. Communication Research, 41(7), 935–960. https://doi.org/10.1177/0093650213479795

Zha, X., Yang, H., Yan, Y., Liu, K., & Huang, C. (2018). Exploring the effect of social media information quality, source credibility and reputation on informational fit-to-task: Moderating role of focused immersion. Computers in Human Behavior, 79, 227–237. https://doi.org/10.1016/j.chb.2017.10.038