# Social Media Algorithms and the Spread of Misinformation: A Data-Driven Survey Study of User Perceptions

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**Abstract —** Social media platforms use recommendation algorithms to decide which content each user sees. Because many of these systems rank content by predicted engagement, concerns have been raised that they may increase the visibility of false or misleading information. This study investigates how social media users perceive the relationship between recommendation algorithms and misinformation. A structured questionnaire of ten questions was administered through Google Forms and 62 responses were collected. The questionnaire covered platform usage, daily usage time, awareness of algorithmic recommendation, exposure to suspected misinformation, sharing behaviour, verification habits, perceived effects of emotional content and repeated exposure, and preferred countermeasures. Responses were analysed using descriptive statistics (frequencies and percentages) and summarised with charts. The results show that 90.3% of respondents were aware of algorithmic recommendation, 50.0% encountered suspected false content often or very often, and 71.0% agreed that algorithms increase the visibility of misinformation. A further 71.0% agreed that emotionally engaging content spreads faster, and 58.1% agreed that repeated exposure can make misinformation more believable. Improving algorithmic detection (29.0%) and warning labels (22.6%) were the most preferred measures. Notably, 80.6% of respondents reported always verifying information before sharing, while 30.6% admitted having shared content later found false, which suggests self-report bias. The study measures perceptions, not platform data, so it does not establish that algorithms cause misinformation to spread. Machine learning analysis of engagement data is proposed as future work.

**Keywords —** Social Media Algorithms; Misinformation; Recommendation Systems; User Engagement; Survey Research; Data Analytics; Fact-Checking; Echo Chambers

## I. INTRODUCTION

Social media platforms such as Instagram, YouTube, Facebook, WhatsApp and X (formerly Twitter) use recommendation algorithms to show users personalised content. These algorithms consider likes, comments, shares, watch time, followed accounts and previous interests to decide which posts, videos and news appear in a user's feed. As a result, users receive different content based on their online activities and preferences.

Social media algorithms often promote content that receives more likes, comments, shares and views. When a post gets more engagement, it may reach a larger audience. Research shows that emotional content spreads quickly on social media and false news can spread farther and faster than true news on Twitter [1], [2]. Therefore, misleading information may also receive greater visibility through engagement-based recommendations.

Misinformation is false or misleading information shared without the intention to cause harm, whereas disinformation is deliberately created and shared to mislead people [3]. Both can influence public health, elections, financial decisions and social harmony [4], [5]. Understanding users' awareness of misinformation and recommendation algorithms helps explain their online behaviour, trust and information-sharing decisions.

This study examines users' perceptions of social media recommendation algorithms and misinformation through survey responses. It focuses on users' awareness, experiences and opinions about personalised content and misleading information. It does not analyse platform engagement data or the internal working of proprietary algorithms.

## II. RELATED WORK

### 1. Social Media Algorithms and Content Recommendation

Social media platforms such as Instagram, YouTube, Facebook and X use recommendation algorithms to display personalised content to users. These algorithms analyse user activities, including likes, comments, shares, watch time and previous interests, to rank and recommend posts. Previous research has shown that engagement-based algorithms influence the visibility and distribution of online information. Vosoughi et al.

[1] found that false news spread farther, faster and more widely than true news on Twitter. Similarly, research by Brady et al. [2] showed that emotional and moral-emotional language increases the spread of content on social networks.

### 2. Misinformation and User Behaviour

Misinformation has become a major concern on social media because false or misleading information can influence people's opinions and decisions. Researchers have studied how users interact with online information and how repeated exposure can affect their beliefs. Pennycook and Rand [3] highlighted the role of analytical thinking in identifying false news. Research also suggests that users may share misleading information without checking its accuracy. User awareness, online behaviour and information verification are therefore important factors in understanding the spread of misinformation.

### 3. Impact of Algorithms and Strategies to Reduce Misinformation

Previous studies have examined how social media algorithms, emotional content and repeated exposure influence the visibility of misinformation. Research on warning labels and fact-checking has shown that providing users with additional information can help reduce belief in false news [4]. Other approaches include improving algorithmic detection, promoting verified information, removing confirmed false content and educating users about fact-checking. These studies provide a foundation for understanding the relationship between recommendation algorithms and misinformation.

### 4. Research Gap

Although previous research has examined the spread of false news and the role of social media algorithms, there is a need to understand how ordinary users perceive these algorithms and their influence on misinformation. This study addresses this gap through a survey-based approach involving 62 respondents. It examines users' awareness of recommendation algorithms, exposure to misinformation, information-sharing and verification behaviour, and opinions about measures to reduce misinformation. The study focuses on user perceptions rather than analysing the internal working of social media algorithms.

## III. METHODOLOGY

**1.Research Design:** A quantitative, descriptive, cross-sectional survey design was used.

**2.Data Collection:** Primary data were collected using a ten-question structured questionnaire created in Google Forms. All questions were closed-ended (single choice or five-point agreement scale). A total of 62 responses were received. Google Forms generated a summary of each question as a pie chart with percentages, and these summaries are the data source for this paper.

**3.Data Preparation**: Ever shared information later found false Emotional content spreads faster through likes, comments and shares Frequency of verifying before sharing Repeated exposure increases belief in misinformation Most effective measure to reduce misinformation The Google Forms summary reports counts as percentages. Each percentage was converted into an approximate number of respondents by multiplying by 62 and rounding to the nearest whole number (for example, 50% of 62 = 31). Slices without printed labels in the charts (very small categories) were estimated from slice size and the requirement that each question's responses total 62; these are marked with "~" in Section 10. Duplicate and missing-value checks are not needed for a form where each question is mandatory, but the raw response sheet should be checked for duplicate submissions before final submission.

**4.Analysis Procedure:** The following steps were applied: (1) frequency and percentage calculation for each question; (2) grouping of agreement categories (Strongly agree + Agree) for comparison; (3) visualisation using pie and bar charts (Google Forms, Microsoft Excel; Matplotlib may be used for final figures); (4) 4interpretation against the objectives and prior literature.

**5.Proposed but Not Yet Implemented Steps:** The following steps from the original research plan were not implemented because no engagement dataset was analysed: classification of posts into reliable, false and misleading categories using verified labels; feature extraction from views, likes, comments, shares, topic and content type; correlation analysis of engagement variables; and machine learning classification with Scikit-learn. These are described in Sections 8 and 11 as future work.

## IV. RESULTS AND DISCUSSION

All results are based on Google Forms responses collected from 62 respondents (n = 62). Values marked approximately (~) are estimated.

**1.Platform Usage and Time Spen:** The survey found that Instagram was the most frequently used platform, with 31 respondents (50%), followed by YouTube (21%), WhatsApp (16.1%) and Facebook (9.7%). Regarding daily usage, 45.2%

spent 1–2 hours and 43.5% spent 3–4 hours on social media. This shows that most respondents regularly use social media.

**2.Awareness of Algorithms and Exposure to Misinformation:** The results show that 54.8% of respondents were completely aware of recommendation algorithms, while 35.5% had some awareness. Regarding misinformation, 50% encountered it often or very often, while 35.5% encountered it sometimes. This indicates that most respondents have experienced misleading information on social media.

**3.Perceptions of Algorithms, Emotional Content and Repeated Exposure:** Around 71% of respondents agreed that algorithms increase the visibility of misinformation. Similarly, 71% believed that emotional content spreads faster through likes, comments and shares. Additionally, 58.1% agreed that repeated exposure can make misinformation more believable. These findings highlight users' concerns about the influence of social media algorithms.

**4.Sharing and Verification Behaviour:** The survey found that 30.6% of respondents had shared information that was later found to be false, while 50% had not. Another 19.4% were unsure. Although 80.6% reported always verifying information before sharing, these results suggest that misinformation can still be shared unknowingly.

**5.Preferred Countermeasures:** Improving algorithms to detect misinformation was the most preferred measure, selected by 29% of respondents. Adding warning labels was selected by 22.6%, followed by action against accounts spreading misinformation (16.1%). Other suggestions included promoting verified information, educating users about fact-checking and removing false information. These findings show that respondents prefer stronger platform-level measures.

**5.Relationship to the Objectives and Prior Research:** The findings support the first research objective at the level of user perception, as most respondents believe algorithms increase misinformation visibility. The results are consistent with previous research on engagement-based sharing [1], [2] and repeated exposure [12], [13]. Some objectives were partially supported because the study collected opinions rather than actual engagement data.

**6.Limitations and Alternative Explanations:** The study has a limited sample size of 62 respondents, so the findings cannot represent all social media users. Instagram was the most commonly used platform, which may influence the results. The study is based on self-reported opinions rather than actual platform data and cannot establish a direct causal relationship between algorithms and misinformation. Additionally, self-report bias, closed-ended questions and the absence of demographic analysis are other limitations.

## VI. CONCLUSION

This study examined how social media users perceive the link between recommendation algorithms and misinformation, using a Google Forms survey of 62 respondents and descriptive statistical analysis. Main findings. (1) Algorithmic awareness was high (90.3% at least somewhat aware; none unaware). (2) Exposure to suspected misinformation was common: half encountered it often or very often. (3) A clear majority (71.0%) agreed that algorithms increase the visibility of misinformation and that emotional content spreads faster, and 58.1% agreed that repeated exposure increases belief in it. (4) Self-reported verification was very high (all respondents always or often), yet 30.6% had shared content later found false and 19.4% were unsure, indicating a gap between reported and actual practice. (5) Respondents most preferred platform-side measures, led by better algorithmic detection (29.0%) and warning labels (22.6%). Contribution. The study provides small-scale evidence on user perceptions and a documented gap between verification claims and sharing outcomes, and it links the questionnaire themes to established research. What the study does not show. The results are perceptions from a limited sample. They do not prove that recommendation algorithms cause misinformation to spread faster; they are consistent with, and motivate, such a hypothesis. Recommendations. • For platforms: improve detection of misleading content, apply clear warning labels with links to fact-checks, reduce the amplification of repeatedly flagged accounts, and add accuracy prompts before sharing [14], [15]. • For researchers: combine survey data with platform engagement data, use verified labels, and use designs (such as experiments) that can test causal effects. • For users: pause before sharing emotionally charged posts, check the original source, and diversify information sources to reduce repeated exposure to one narrative. Future work. Collect a larger, demographically described sample; analyse subgroup differences by platform, usage time and age; use open-ended questions; and conduct the planned classification and 9correlation analysis of engagement data with Python, Pandas, NumPy, Matplotlib and Scikit-learn [19] using a verified, labelled dataset.

## VII. REFERENCES

1. W. J. Brady, J. A. Wills, J. T. Jost, J. A. Tucker, and J. J. Van Bavel, "Emotion shapes the diffusion of moralized content in

social networks," Proc. Natl. Acad. Sci. U.S.A., vol. 114, no. 28, pp. 7313–7318, 2017, doi: 10.1073/pnas.1618923114.

2. S. Vosoughi, D. Roy, and S. Aral, "The spread of true and false news online," Science, vol. 359, no. 6380, pp. 1146–1151, 2018, doi: 10.1126/science.aap9559.

3. C. Wardle and H. Derakhshan, Information Disorder: Toward an Interdisciplinary Framework for Research and Policymaking. Strasbourg, France: Council of Europe, 2017..

4. D. M. J. Lazer et al., "The science of fake news," Science, vol. 359, no. 6380, pp. 1094–1096, 2018, doi: 10.1126/science.aao2998.

5. H. Allcott and M. Gentzkow, "Social media and fake news in the 2016 election," J. Econ. Perspect., vol. 31, no. 2, pp. 211–236, 2017, doi: 10.1257/jep.31.2.211.

6. E. Pariser, The Filter Bubble: What the Internet Is Hiding from You. New York, NY, USA: Penguin Press, 2011.

7. E. Bakshy, S. Messing, and L. A. Adamic, "Exposure to ideologically diverse news and opinion on Facebook," Science, vol. 348, no. 6239, pp. 1130–1132, 2015, doi: 10.1126/science.aaa1160.

8. A. M. Guess et al., "How do social media feed algorithms affect attitudes and behavior in an election campaign?," Science, vol. 381, no. 6656, pp. 398–404, 2023, doi: 10.1126/science.abp9364.

9. M. Del Vicario et al., "The spreading of misinformation online," Proc. Natl. Acad. Sci. U.S.A., vol. 113, no. 3, pp. 554–559, 2016, doi: 10.1073/pnas.1517441113.

10. A. Guess, J. Nagler, and J. Tucker, "Less than you think: Prevalence and predictors of fake news dissemination on Facebook," Sci. Adv., vol. 5, no. 1, eaau4586, 2019, doi: 10.1126/sciadv.aau4586.11

11. M. Cinelli, G. De Francisci Morales, A. Galeazzi, W. Quattrociocchi, and M. Starnini, "The echo chamber effect on social media," Proc. Natl. Acad. Sci. U.S.A., vol. 118, no. 9, e2023301118, 2021, doi: 10.1073/pnas.2023301118.

12. L. Hasher, D. Goldstein, and T. Toppino, "Frequency and the conference of referential validity," J. Verbal Learn. Verbal Behav., vol. 16, no. 1, pp. 107–112, 1977, doi: 10.1016/S0022-5371(77)80012-1.

13. G. Pennycook, T. D. Cannon, and D. G. Rand, "Prior exposure increases perceived accuracy of fake news," J. Exp. Psychol. Gen., vol. 147, no. 12, pp. 1865–1880, 2018, doi: 10.1037/xge0000465.

14. K. Clayton et al., "Real solutions for fake news? Measuring the effectiveness of general warnings and fact-check tags in reducing belief in false stories on social media," Polit. Behav., vol. 42, pp. 1073–1095, 2020, doi: 10.1007/s11109-019-09533-0.

15. G. Pennycook et al., "Shifting attention to accuracy can reduce misinformation online," Nature, vol. 592, pp. 590–595, 2021, doi: 10.1038/s41586-021-03344-2.

16. K. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu, "Fake news detection on social media: A data mining perspective," ACM SIGKDD Explor. Newsl., vol. 19, no. 1, pp. 22–36, 2017, doi: 10.1145/3137597.3137600.

17. A. J. Nederhof, "Methods of coping with social desirability bias: A review," Eur. J. Soc. Psychol., vol. 15, no. 3, pp. 263–280, 1985, doi: 10.1002/ejsp.2420150303.

18. L. Breiman, "Random forests," Mach. Learn., vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

19. F. Pedregosa et al., "Scikit-learn: Machine learning in Python," J. Mach. Learn. Res., vol. 12, pp. 2825–2830, 2011.

20. F. Huszar, S. I. Ktena, C. O'Brien, L. Belli, A. Schlaikjer, and M. Hardt, "Algorithmic amplification of politics on Twitter," Proc. Natl. Acad. Sci. U.S.A., vol. 119, no. 1, e2025334119, 2022, doi: 10.1073/pnas.2025334119.

21. S. Flaxman, S. Goel, and J. M. Rao, "Filter bubbles, echo chambers, and online news consumption," Public Opin. Q., vol. 80, no. S1, pp. 298–320, 2016, doi: 10.1093/poq/nfw006.

22. N. Walter, J. Cohen, R. L. Holbert, and Y. Morag, "Fact-checking: A meta-analysis of what works and for whom," Polit. Commun., vol. 37, no. 3, pp. 350–375, 2020, doi: 10.1080/10584609.2019.1668894.

23. J. Roozenbeek and S. van der Linden, "Fake news game confers psychological resistance against online misinformation," Palgrave Commun., vol. 5, art. 65, 2019, doi: 10.1057/s41599-019-0279-9.

24. X. Zhou and R. Zafarani, "A survey of fake news: Fundamental theories, detection methods, and opportunities," ACM Comput. Surv., vol. 53, no. 5, art. 109, 2020, doi: 10.1145/3395046.