Examining Source Effects on Perceptions of Fake News in Rural India

FARHANA SHAHID, Cornell University, United States
SHRIRANG MARE, Western Washington University, United States
ADITYA VASHISTHA, Cornell University, United States

This paper presents a between-subjects design experiment with 478 people in India to investigate how rural and urban social media users perceive credible and fake posts, and how different types of sources impact their perceptions of information credibility and sharing behaviors. Our findings reveal that: (1) rural social media users were less adept in differentiating between credible and fake posts than their urban counterparts, and (2) source effects on trust and sharing intent manifested differently for urban and rural users. For example, fake posts from family members garnered greater trust among urban users but were trusted the least by rural users. In case of sharing Facebook posts, urban users were more willing to share fake posts from family, whereas, rural users were more inclined to share fake posts from journalists. Drawing on these findings, we propose design interventions to counteract fake news in low-resource environments of the Global South.

CCS Concepts: • **Human-centered computing** → **Social media**.

Additional Key Words and Phrases: Fake News, Facebook, COVID-19, Global South, HCI4D

ACM Reference Format:
Farhana Shahid, Shrirang Mare, and Aditya Vashistha. 2022. Examining Source Effects on Perceptions of Fake News in Rural India. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW1, Article 89 (April 2022), 29 pages. https://doi.org/10.1145/3512936

1 INTRODUCTION

Fake news on social media has caused serious harm to communities worldwide. Take the case of coronavirus-related misinformation in India which led people to eat poisonous seeds to build immunity [90], villagers to jump into a river to avoid vaccination [59], and Muslim minorities to be brutally beaten [70]. The risks of fake news are particularly high for millions of new social media users in low-income communities in the Global South who are more likely to believe any information they see online and who may lack the awareness and skills to verify information [98]. In this environment, fake news has led to devastating events, including lynchings [108], civil unrest [91], and hundreds of deaths [51].

A large body of prior work has examined prevalence of fake news [44, 106], its diffusion [24, 38, 97, 109], and people's perceptions and interactions with it [40, 44, 114]. In particular, several scholars have identified the critical role that *source* (***who*** posted the content) plays in impacting people's perceptions of credibility and sharing behavior [37, 53, 102]. However, most research to date has focused on fake news in the West, leaving a paucity of research on the drivers of fake news

Authors' addresses: Farhana Shahid, Cornell University, United States, fs468@cornell.edu; Shrirang Mare, Western Washington University, United States, shri.mare@wwu.edu; Aditya Vashistha, Cornell University, United States, adityav@cornell.edu.

2573-0142/2022/4-ART89 $15.00
https://doi.org/10.1145/3512936

in the Global South, particularly neglecting the viewpoints of social media users in rural regions who lag behind their urban counterparts in digital skills, literacy, and social media adoption.

Our study focuses on examining source effects on perceptions of fake news in India, the fastest growing market for social media corporations with over 250 million Facebook users and 400 million WhatsApp users, many of those are new users in rural regions. We especially focus on examining *how* differently source effects manifest between urban social media users and their rural counterparts who are relatively new to murky online information environments, and often lag behind in social media adoption and digital skills [93]. In particular, we sought to answer the following research questions:

RQ1: Do social media users in rural and urban areas perceive credible and fake posts differently?
RQ2: How do source effects impact their trust in credible and fake posts?
RQ3: How do source effects impact their attitude towards sharing credible and fake posts?

To answer our research questions, we focused on fake news propagating in India during the COVID-19 pandemic. We conducted a between-subjects design experiment with 159 rural residents and 319 urban residents who were randomly assigned to one of the seven source conditions: *No source* (baseline), *Strangers*, *Friends*, *Family*, *Celebrity*, *Journalist*, and *News Media*. We selected COVID-related Facebook posts considering the timeliness and familiarity of the topic both in urban and rural areas. During the experiment, we showed our participants a set of credible and fake posts coming from the assigned source and asked them to indicate how much they trusted the content in the post, would they like to share the post on Facebook, and if so, with whom.

Our analysis revealed several important findings. In response to **RQ1**, we found that rural social media users were more susceptible to fake news than urban social media users. Rural participants could hardly discern fake posts from credible ones and wanted to share both types of posts equally. In contrast, urban participants trusted credible posts more and wanted to share them more frequently and more widely than the fake posts. In response to **RQ2**, we found that rural participants trusted fake posts the most when shared by *Journalists*, whereas, urban participants trusted fake posts the most when shared by their *Family*, suggesting that source effect on one's perceptions of trust manifests differently for urban and rural users. In response to **RQ3**, we found that rural participants were more willing to share fake posts from public sources, e.g., *Journalists* and *News Media*. In contrast, urban residents were more willing to share fake posts from *Family* and credible posts from public sources. Taken together, our findings indicate that the spread of credible and fake posts from different sources are likely to follow different trajectories in urban and rural areas.

We synthesize key takeaways for HCI and CSCW researchers interested in combating the spread of fake news within low-resource communities. Drawing on our findings, we discuss potential remedies to address people's gullibility to detect fake news as well as their varying susceptibility to source effects. In summary, our contributions include:

(1) The **first** study that systematically examines how rural social media users in India perceive and interact with fake news, revealing key differences between them and urban users.
(2) A **quantitative** examination of source effects on how urban and rural social media users trust and share social media posts, showing that fake news from different sources propagate differently within urban and rural areas.

2 BACKGROUND AND RELATED WORK

The widespread prevalence of fake news has led to an explosion of research from HCI and CSCW scholars who have examined people's motivations to share fake news [25, 26, 112] along with its prevalence and diffusion patterns [24, 44, 106]. A large body of scholarly work has examined the role socio-psychological factors [58, 62, 83], sociocular beliefs [86], and personality traits [25] play in shaping people's perceptions of information credibility. For example, scholars have found that social media routinely exposes people to posts that align with their beliefs, resulting in filter bubbles and echo chambers [9, 80]. Users thus often share content based on homogeneity that reinforces confirmation bias, segregation, and polarization [30]. In addition, post content along with perceived reliability of information source as well as sender's profile and follower-base have been shown to influence how people engage with online news [22, 28, 37, 40, 102]. Scholars have shown that interpersonal trust in other users often makes people accept low-credibility posts at face value without any investigation [40]. In addition, affective and motivational factors as well as personality [25] and demographic traits (e.g., age [44]) have been shown to influence the engagement with fake news.

Despite these rich research advances, much remains unknown about the factors that impact information credibility and sharing behaviors of emerging social media users in the Global South. This is because most of the work to date focuses on social media users and fake news in the West (particularly the US and Europe). Drawing on prior work in HCI that advocates cross-validating principles and measures with different populations [105], our work contributes to the nascent, but growing body of research that examines the perceptions and dynamics of fake news in the Global South, which we discuss next.

2.1 Fake News in the Global South

Several HCI and CSCW scholars have examined the prevalence, nature, and diffusion of fake news in the Global South [10, 57], particularly focusing on political misinformation propagating during elections [35, 69, 88]. For example, Garimella and Eckles [39] studied a large collection of politically-oriented WhatsApp groups in India and found that images were either photoshopped or used out of context to spread fake news during the election. Scholars have also examined the challenges to counteract fake news in the Global South. Haque et al. [46] found that most social media users in Bangladesh expected news media agencies to assess the credibility of the news. However, journalists often skirted away from fact-checking online information and voluntary fact-checkers lacked sufficient infrastructural support. Similarly, Lu et al. [66] found that most social media users in China were less aware of the current fact-checking features and failed to distinguish astroturfers from ordinary users.

A growing body of work is focusing on the nature and consequences of health-related fake news in the Global South. For example, Chen et al. [24] examined the nature and diffusion of gynecologic cancer-related fake news on Weibo and observed that prevention-related fake news diffused more widely and rapidly than credible information in China. Besides, Leong et al. [63] found that YouTube videos containing fake information related to diabetes were very popular among the masses in India. Such widespread acceptance of fake news among the masses often result in dire consequences. For example, Vinck et al. [110] found that low institutional trust and high belief in fake news increased the chances of people declining vaccines during the Ebola outbreak in Congo. Similarly, Bahk et al. [8] observed that anti-vaccine conversations around Polio persisted longer than pro-vaccine reactions in Pakistan. During the COVID-19 pandemic, proliferation of misleading information and fake news has led to an infodemic of unprecedented scale [92]. Lu et al. [67] observed that Chinese WeChat users prioritized valence over veracity while seeking COVID-19 related information. Apart from various rumors on prevention and treatment of COVID-19 [36] and anti-vaccine propaganda [89], fake news also ignited racial hatred [68] and communal prejudices [6, 13].

Dynamics and ramifications of fake news manifest *differently* for rural social media users who lag behind their urban counterparts in literacy and digital skills [12, 29, 96]. Fake news has led to devastating consequences in rural areas, in the form of targeted physical violence and mob lynchings causing the loss of lives of hundreds of people [43, 77]. However, all the research advances described thus far either solely focuses on social media users in urban locations [110] or doesn't investigate the differences between rural and urban social media users in how they perceive and propagate fake news. To the best of our knowledge, ours is the first study that fills this urgent gap by examining: (1) how rural users perceive credible and fake news compared to urban users in India, and (2) how source effects impact the perceptions of information credibility and sharing behavior of rural and urban residents. We now situate our research in the body of related work examining source effects in online news evaluation.

2.2 Source Effects in News Evaluation

Many HCI and CSCW scholars have noted the importance of information source in shaping people's perceptions of information credibility [37, 102], which is defined as the extent to which users perceive information to be believable [73]. Perceived credibility also affects the engagement and amount of attention that a post receives [75, 103].

Scholars have investigated people's perceptions of trust in online news source. For example, Flintham et al. [37] and Sterrett et al. [102] found that people perceived the posts as credible when shared by trusted news media. In contrast, Messing and Westwood found that people trusted the person, who either posted or shared an article, more than the news media source of the article. In line with these findings, some studies report that authority of the news sources hardly matters when it comes to sharing the news [17, 27]. For example, Jakesch et al. [53] and Spezzano et al. [100] found weak effects of news media source on political news evaluation. Instead, they observed significant effect of political alignment on how people perceived political news on social media.

Scholars have also examined the impact of sender of the post on perceptions of information credibility. For example, Stewart [104] and Wagner et al. [111] found that people relied on their friends and personal contacts on social media to assess information credibility. Besides, Buchanan and Benson [18] observed that people perceived a post as more credible when it came from a trustworthy friend. Even seeing more friends on social media sharing a news increased people's trust in the content [33]. Given the influence one's inner circles and peers exert on their perception of online contents, it is concerning that people often take their trusted poster's content at face value and do not even try to assess the credibility of the content [40].

All of the work described thus far examines source effects in Western settings. By comparison, only a small number of studies have investigated source effects on social media news credibility in the Global South. For example, Lu et al. [65] found that people in China considered health professionals, academic institutions, and government agencies as trusted information sources and were willing to share posts on the COVID-19 pandemic from these sources to raise awareness and promote disease prevention. Besides, Ejaz and Ittefaq [34] explored how Pakistani millennials responded to COVID-19 related information and found that they trusted information from scientists the most and the least when it came from politicians. In addition, Bowles et al. [16] studied public responses to COVID-19 information in Zimbabwe and found that exposure to credible messages from the WhatsApp accounts of trusted organizations increased knowledge and reduced potentially harmful behavior. On the contrary, a digital literacy program arranged by FactShala in India reported that people usually relied on the content aligning with their beliefs and personal biases to decide whether to trust a post instead of questioning source credibility or authority [50].

Not only prior work is divided in how source effects manifest in online news evaluation, but also lacks the granularity about how the effect of different sources might vary. Furthermore, none of the prior work has yet analyzed : (1) how source effects manifest for rural social media users and, (2) whether the effects vary between urban users and their rural counterparts who lag behind in social media adoption, digital skills, and literacy. Acting on the call of cross-validating principles and measures with different populations [105] to design for socially and culturally diverse user populations [19, 64], we conduct controlled field experiments with urban and rural social media users in India to examine how different sources might influence the perceptions of fake news differently. In doing so, we make important contributions to HCI and CSCW scholarship on misinformation by showing that: (1) rural and urban users differ in their attitudes towards fake news and (2) source effects manifest differently among rural and urban users in how they perceive and share content on social media. To the best of our knowledge, this is the first study to explore the varying effects of different sources both within rural and urban populations.

3 METHODS

We conducted a between-subjects design experiment with urban and rural social media users in India to answer our three research questions.

3.1 Experimental Setup

We launched the experiment as an online survey on Qualtrics with 319 urban residents and 159 rural residents. Participants were randomly assigned to one of the **seven** source conditions: *No source* (baseline), *Strangers*, *Friends*, *Family*, *Celebrity*, *Journalist*, and *News Media*. In each experimental arm, participants were asked to review a set of Facebook posts shared by other users in the past six months (e.g., from friends, celebrities, or news media) based on the assigned source condition. In reality, these posts were chosen from a list of COVID-related credible and fake Facebook posts curated by us (more details in Section 3.2). The seven source conditions were as follows:

- ***No source***: In our baseline condition, we displayed Facebook posts with redacted username and profile photo. Participants could only see the posts without any indication of who posted them.
- ***Stranger***: We created six fake Facebook profiles, representing three male and three female users, by using random stock profile pictures of Indians and names of Indian origin. We showed the contents to be posted by three of these six Facebook profiles selected at random.
- ***Friends***: We asked participants to provide Facebook profile links of their three friends. Using a JavaScript program, we retrieved the publicly available names and profile picture URLs from the links in real-time. We then added profile picture and name to the post content to make participants believe that the content was posted by their friends.
- ***Family***: Similar to the *Friends* condition, we asked participants to provide Facebook profile links of their three family members. Using the same JavaScript program, we retrieved the publicly available profile name and profile picture URL from these links. We then displayed the posts as if they were posted from the Facebook accounts of their family members.
- ***Celebrity***: We curated a list of top 20 Indian celebrities based on their number of followers on Facebook [99]. We included celebrities from different fields, e.g., actors, musicians, authors, and athletes to cover diverse interests of the participants. Even though politicians and religious *gurus* in India have large follower base on social media, we excluded them because prior work has shown extreme biases towards specific political parties or ideologies [101], especially in the context of fake news [6]. We asked our participants to select three celebrities they either like or follow from our given list. We then presented the posts as if they were posted from the Facebook profiles of the selected celebrities.
- ***Journalist***: We curated a list of eight popular Indian journalists based on their follower base on Facebook and asked the participants to choose three journalists they either know or follow. Then we showed them the posts as if they came from the Facebook profiles of their selected journalists.
- ***News Media***: We curated a list of 19 Indian news media outlets based on their readership, TRP [11], and follower base on Facebook. We asked the participants to choose three news media

Fig. 1. A post displayed to participants in *Celebrity* (left) and *News Media* (right) source conditions based on the celebrities and news media they like or follow respectively. Priyanka Chopra is a popular Indian actor with over 50 million Facebook followers. Times Now is India's leading English news channel with over six million Facebook followers.

they follow from the list. We then presented the posts as if they were posted from the Facebook pages of their chosen news media. Appendix A provides the lists of celebrities, journalists, and media outlets used in the study.

At the beginning of the survey, we informed our participants that they would review screenshots of recent Facebook posts on the COVID-19 pandemic. We took several measures, like using the same font and formatting to mimic the layout of Facebook posts. Participants in all conditions saw the same fake and credible posts, albeit in a random order and shown to be posted by a different source. For example, Figure 1 shows how the same post was presented to be coming from different sources: from Priyanka Chopra to a participant in *Celebrity* source condition and from Times Now to another participant in *News Media* source condition. For each post, participants answered three questions:

- How much do they trust the post on a five-point Likert scale: from "Not at all" to "Entirely"?
- Would they like to share the post on Facebook: "Yes" or "No"?
  - If they chose "Yes" to previous question, we asked with whom they would like to share the post? For this, we used four Facebook privacy settings: *Public*, *Friends*, *Friends except...*, and *Specific friends*.
  - If they chose "No", we asked whether they would like to share the post on other social media platforms.

Once participants reviewed all posts, we asked them a set of demographic questions, like age, location, gender identity, years of formal education, among others. All participants received a compensation of USD 1.50 for participating in our study.

3.2 Selecting Credible and Fake Facebook Posts

We curated a list of credible and fake Facebook posts on COVID-19 pandemic in India. To select fake posts, the authors together reviewed 110 posts from a public database [107] containing verified fake posts from IFCN-certified fact-checkers like Alt.News and BOOM [84]. We discarded 80 posts that were either not related to the COVID-19 pandemic or were deemed inappropriate, for example, for being too graphic, too lengthy, or hurting religious sentiments. We also curated a list of ten posts from the Facebook pages of trusted Indian news media and independently verified them to be credible. Our initial set thus had 30 fake posts and ten credible posts.

We then conducted a pre-test with 40 MTurk workers and asked them to rate the credibility of ten posts selected randomly from our initial set (30 fake and 10 credible). On average, each post was rated by ten MTurk workers. For the final experiment, we selected six credible posts that received greater trust rating from the majority of the respondents and three fake posts whose credibility the majority of the respondents felt unsure about. Table 1 lists the six credible and three fake posts that we used in our main experiment.

3.3 Data Collection and Analysis

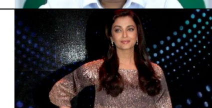
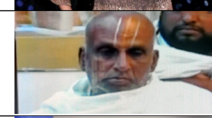
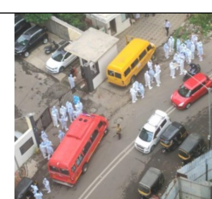
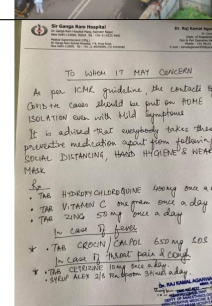
Experiment with Urban Residents. In order to recruit urban residents from different geographic locations in India, we conducted our experiment with MTurk workers who were social media users living in urban regions. We collected location metadata (e.g., longitude and latitude) from Qualtrics to verify the locations reported by MTurk participants. We conducted the survey from August to September 2020 when COVID-19 infections were rapidly increasing in India. Urban participants reviewed nine posts in English in randomized order along with an attention check question at the end. Since MTurk workers are geographically spread across India, we opted to use English, the language of MTurk website, instead of Hindi because only 26% of Indians are reported to be native Hindi speaker [47]. For each post, we gave participants 90 seconds to answer three questions, so that they don't get enough time to verify the posts online. We also disabled right click, text selection, image download, and copy functions for the same reason.

In total, 461 participants completed the study. We discarded the data from 142 participants who either were not from an urban region, failed the attention check, or provided the same Facebook profile links for multiple Facebook connections in *Friends* or *Family* source conditions. Our final set contained data from 319 urban participants.

Experiment with Rural Residents. Our field experiment took place from August to October 2020 in partnership with Nehru Yuva Sangthan-Tisi [94], a grassroots organization focusing on rural development, community health, and primary education. As part of these programs, they frequently work with rural communities in different villages in Uttar Pradesh, India. To recruit participants, an organization staff member reached out to their primary contacts in the villages and through snowball sampling recruited more rural residents, many of whom never worked with the organization in the past. Our field coordinator explained them the purpose of the study (i.e., requesting feedback on Facebook posts), and then gave us the contact information of those who were willing to participate. With the help of the staff member, we sent an online survey to interested people. All our interactions and communications with the field coordinator and rural residents took place online, primarily via phone calls or WhatsApp to comply with social distancing and ensure other health related safeguards due to the pandemic.

Before launching the survey, we requested NYST staff members to provide feedback, based on which we made minor changes. First, we transcribed the posts and survey prompts in Hindi given low English literacy rates in rural regions. Second, we added more news media outlets in *News Media* source condition that cater to Hindi-speaking audience. Third, we removed three posts (C3, C6, and F2 in Table 1) because they were deemed insensitive or irrelevant for rural residents in our study region. For example, C3 reports the death of a priest and our partner organization was worried that it might cause religious tension between Hindus and Muslims [95]. Similarly, C6 mentions Donald Trump and the organization felt that most people in rural areas would not know him. For F2, it was difficult to recreate the image of hand-written English prescription in Hindi. In total, 159 rural participants completed the study.

Table 1. Set of credible (C1–C6) and fake posts (F1–F3).

ID	Text Content	Accompanied Image
C1	Delhi Chief Minister Arvind Kejriwal has said that the number of coronavirus-related deaths has declined.	
C2	Actor Aishwarya Rai Bachchan, earlier in home quarantine for coronavirus, admitted to Mumbai hospital.	
C3	Former chief priest of the Tirumala Tirupati Balaji temple in Andhra Pradesh died this morning due to coronavirus-related complications.	
C4	Singapore scientists develop coronavirus testing that yields results in 36 minutes.	
C5	Global death count from the coronavirus pandemic passed 650,000 on Monday.	
C6	President Donald Trump's administration is urging an investigation into the origins of the coronavirus pandemic, saying it doesn't rule out that it came from a laboratory researching bats in Wuhan, China.	
F1	Omkar Alta Monte building in Malad, on Western Express Highway discovered 169 positive cases yesterday.	
F2	A guideline for General people by Ganga Ram Hospital..	Sir Ganga Ram Hospital Dr. Raj Kamal Agarwal TO WHOM IT MAY CONCERN As per ICMR guideline, the contacts of COVID +ve cases should be put on HOME ISOLATION even with Mild Symptoms It is advised that everybody takes these preventive medication apart from following SOCIAL DISTANCING, HAND HYGIENE & WEARING MASK Rx • TAB HYDROXYCHLOROQUINE 400mg once a week • TAB VITAMIN C one gram once a day • TAB ZING 50 mg once a day In case of fever * • TAB CROCIN/CALPOL 650 mg SOS In case of throat pain & cough * • TAB CETRIZINE 10mg once a day. • SYRUP ALEX 2/3 Tea spoon 3 times a day. DR. RAJ KAMAL AGARWAL DEPTT. OF ANAESTHESIOLOGY PERIOPERATIVE MEDICINE & PAIN SIR GANGARAM HOSPITAL Residence :
F3	Just In | Congress MP Rahul Gandhi talks to Nobel laureate Professor Abhijit Banerjee about the #economic impact of #COVID19. The real problem in the short run is that the weak UPA policies were embraced by the current govt: Professor Abhijit Banerjee.	

Analysis. Since urban and rural participants rated nine and six posts, respectively, we removed urban participants' responses to posts C3, C6, and F2 to be consistent with rural participants. We

Table 2. Demographics of the participants.

Participants	Gender			Age (years)			Education (%)					
	Male	Female	Other	Range	Mean	SD	No	Primary school	Middle school	High school	Bachelors	Masters
Urban	224	94	1	19-62	30.4	6	-	-	0.6	3.5	71	25
Rural	109	48	2	18-60	34.6	10.4	3	6	14	14	42	21

performed different statistical analyses on our collected data and performed non-parametric tests as our data did not follow normal distribution. To control false discovery rate for multiple hypothesis testing, we applied Benjamini-Hochberg error correction [72] on all results.

3.4 Demographics

Urban participants came from 51 cities in 11 states in India. About 98% of them were from cities with population over 100,000 and 75% were from cities with over one million population. In contrast, rural participants came from 41 small, hard-to-reach villages in Uttar Pradesh, India with the average population of around 2,500. Table 2 shows the demographics of the participants who chose to answer the optional demographic questions. We did not find significant differences in the age and gender distribution of both groups of participants. However, a Chi-square test revealed significant differences between educational background of rural and urban participants ($\chi^2(5, N = 471) = 96.08, p < 0.0001$) as well as years of social media use. For instance, 96% of urban residents at least earned their bachelor's degree compared to 64% of rural residents. Nearly 30% of rural residents had less than ten years of formal education in contrast to 0.6% of urban residents. Similarly, urban participants used social media platforms significantly longer than rural participants. We conducted a regression analysis to see whether participants' demographics have any impact on their trust and sharing tendency of Facebook posts apart from the sources. However, we did not find a significant effect of the demographic factors on participants' perceived trust rating and sharing attitude. We also did not find any significant interaction effect between participants' demographic and the sources of the posts.

3.5 Ethical and Privacy Considerations

Our study protocol was approved by Institutional Review Board at the principal investigator's institution. We took several additional measures to conduct our experiment ethically and responsibly. For example, after participants finished the study, we debriefed them that the motivation of the study was to examine how source effects impact participants' perceptions and interactions with credible and fake Facebook posts. We also disclosed that some posts they reviewed during the experiment were fake and none of them were posted by the Facebook profiles they saw during the experiment.

We also made several adjustments in our study protocol to conduct research responsibly during the COVID-19 pandemic. For example, our initial plan was to conduct in-person surveys in rural areas along with follow-up interviews. However, for ours and our participants' safety, we decided to conduct our study virtually, which added layers of challenges in recruiting and supporting rural participants, most of whom were living in hard-to-reach areas and were participating in a research study for the first time. Moreover, we avoided adding descriptive questions in our survey as our partner organization reported that the rural residents would find it difficult to write descriptive responses on their mobile devices.

Finally, we were also respectful of our participants' privacy. For example, in *Friends* and *Family* source conditions, we only collected publicly accessible profile names and profile picture URLs of

Table 3. Average responses of the participants.

Participants	Median trust rating	Sharing tendency	Sharing audience			
			Public	Friends	Friends except	Specific friends
Rural	3	35%	7%	25%	1%	0.7%
Urban	4	64%	32%	18%	3%	2%

participants' friends and family members. We did not collect any personally identifiable information, e.g., Facebook profile links of the participants, limiting our ability to verify whether the Facebook profile links they shared of their friends and family members were indeed accurate. This was also done in part to comply with MTurk's policy that prevents collection of any personally identifiable information of workers.

4 FINDINGS

In the study, 478 participants (159 rural, 319 urban) responded to 1,912 instances of credible and 956 instances of fake posts. Through an in-depth analysis of participants' responses to these posts, we answer our research questions. We begin by examining the differences in how participants in rural and urban India perceive credible and fake posts (Section 4.1). Next, we investigate how source effects impact their trust in credible and fake posts (Section 4.2). Finally, we analyze how source effects impact their willingness to share credible and fake posts (Section 4.3).

4.1 Differences in Perceptions of Credible and Fake Posts (RQ1)

As a first step in our analysis, we explored the differences in perceptions of credible and fake posts among rural and urban participants. Specifically, we wanted to know if participants in rural and urban areas can differentiate between credible and fake posts? Which posts they want to share and with whom? We examined participants' responses to credible and fake posts along three dimensions: **belief** (reported trust rating), **sharing tendency** (willingness to share), and **sharing audience** (with whom they want to share).

Table 3 gives an overview of the responses from rural and urban participants. Each participant responded to six posts (four credible and two fake posts); a participant who correctly identified the credible and fake posts would have a median trust rating of four or higher. On average, urban participants rated posts with a median trust rating of four, they were willing to share 64% posts, and their sharing audience was largely public (32%), followed by friends (18%). In contrast, rural participants reported uncertainty in believing posts (median trust rating of three out of five), they were willing to share fewer posts (35%), and their sharing audience was largely friends (25%). These indicate that rural and urban participants differ in their responses to Facebook posts. We further analyze these differences below.

Trust Ratings. The median trust ratings of all the posts from urban and rural residents were four and three, respectively. A Mann-Whitney's U test revealed small effect of participant's group on the trust ratings of all the posts ($U = 29673$, $Z = -3.2592$, $p < 0.01$, $r = 0.15$). To determine how well urban and rural participants could distinguish between credible posts and fake posts, we compared their trust ratings for both types of posts separately.

Figure 2a shows the distribution of trust ratings from urban and rural participants. The median trust rating for fake posts from both group of participants is three, suggesting that neither group successfully identified fake posts. Instead, they reported a neutral score (three out of five) indicating doubt in discrediting a fake post. For credible posts, we observed similar uncertainty among rural participants, which suggests that they could not distinguish between credible and fake posts. In contrast, urban participants rated credible posts significantly higher on the trust scale than the

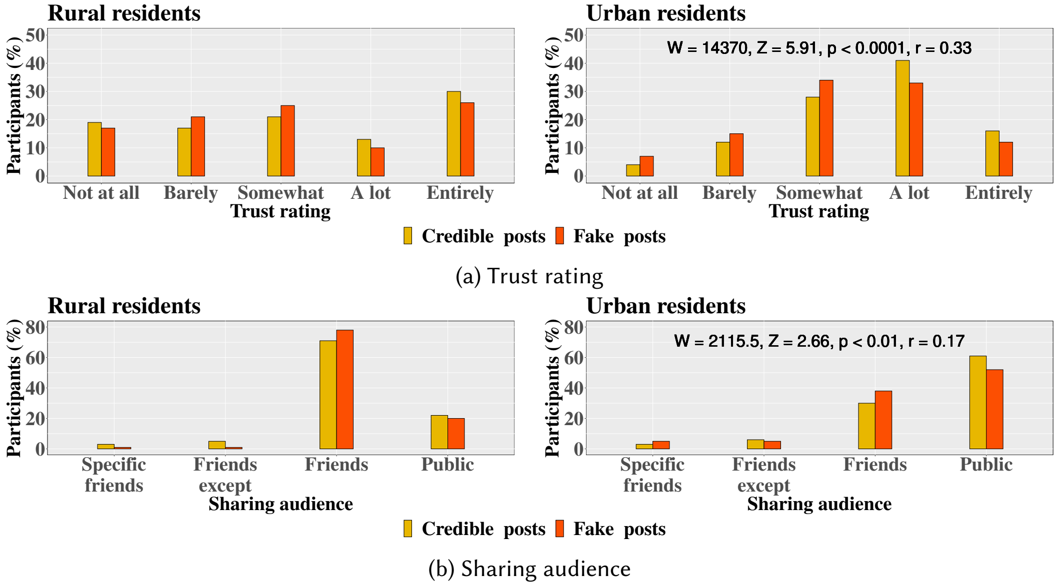


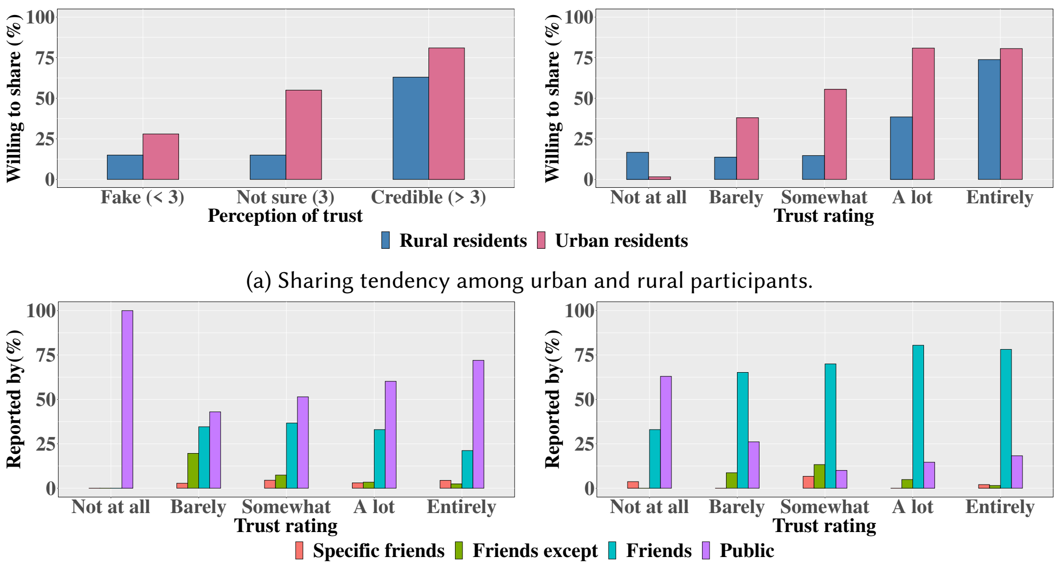
Fig. 2. Differences in participants' responses to actual credible and fake posts. Grouped bar charts show distribution of participants' responses both for credible and fake posts.

fake posts. A Wilcoxon signed-rank test indicated significant difference between the trust ratings of credible posts and fake posts from urban participants ($W = 14370, Z = 5.91, p < 0.0001, r = 0.33$). This indicates that, compared to rural participants, urban participants responded to credible posts more favorably than to the fake ones. This suggests that urban participants were better equipped than their rural counterparts in distinguishing between credible and fake posts.

Sharing Tendency. Do people only share posts they believe to be credible? Can we use sharing tendency as a proxy for belief in posts, as it has been done in prior HCI studies (e.g., [114])? We examined the relationship between participants' belief in a post (i.e., their perceived trust rating) and their sharing tendency (i.e., willingness to share). For both groups of participants, we observed significant medium size correlations (Kendall rank correlation coefficient, $\tau = 0.33 - 0.42, p < 0.001$) between their trust ratings and sharing tendencies for both credible and fake posts. This implies that participants were willing to share any post that they perceived as trustworthy. From Figure 3a, we can see that both urban (81%) and rural participants (63%) were more willing to share the posts they perceived as credible, i.e., rated higher (> 3) on the trust scale compared to the ones they perceived as fake (< 3).

However, we also found that even when participants did *not* find a post trustworthy, they expressed some willingness to share it (see Figure 3a). Some urban participants reported they "Barely" (38%) or "Somewhat" (55.5%) trusted certain posts, but they still wanted to share those posts on Facebook. Some rural participants expressed similar sharing tendency, and more so for posts they reported as "Not at all" trustworthy (16.7%). This indicates that even though willingness to share might correlate with perceived trust rating, sharing does not necessarily imply one's trust in the post. This echoes prior work where participants reported that they *knowingly* shared fake posts to obtain other's opinions as well as to express their opinions [25].

We also found that the willingness to share posts across different trust ratings significantly differed by participants' demographic group ($\chi^2(4, N = 2016) = 443.73, p < 0.0001$). For instance,



(a) Sharing tendency among urban and rural participants.

(b) Sharing audience reported by urban (left) and rural participants (right).

Fig. 3. Participants' sharing behavior for posts with different *perceived* trust ratings. Figure (a) shows the percentage of participants who opted to share the posts for varying levels of perceived credibility. Figure (b) shows with whom these participants wanted to share the posts.

urban participants were more enthusiastic than the rural people to share any post irrespective of the trust rating they attributed to it (except for "Not at all") (see Figure 3a).

Sharing Audience. Misinformation spreads when people share fake posts. To understand sharing behavior, it is important to examine not only whether participants want to share posts but also with whom, i.e., their sharing audience. We found significant small size correlations (Kendall rank correlation coefficient, $\tau = 0.12 - 0.16, p < 0.01$) between urban participants' trust ratings and sharing audiences for both credible and fake posts. Urban participants were willing to share posts that they found *trustworthy* with a broader audience (see Figure 3b). Besides, their sharing audiences for credible and fake posts differed significantly (see Figure 2b). However, no such correlation or difference was observed for the rural participants. In fact, we found significant differences ($\chi^2(3, N = 1755) = 183.2, p < 0.0001$) while comparing sharing audiences of rural and urban participants for all posts. Urban participants were more willing to share posts *publicly* irrespective of their trust in the post, whereas, rural participants opted to share posts with their Facebook *friends* (see Figure 3b). This tendency to keep accounts private among rural social media users was also observed in a prior study [42].

To sum up, our findings indicate that rural and urban participants differ in how they perceive credible and fake posts, and in their sharing tendency and sharing audiences as well. Unlike urban participants, rural participants could not discern between credible and fake posts, which makes them more susceptible to the risks and harms of fake news. But rural participants expressed a lower tendency to share and also with a smaller audience, which suggests that they would contribute less to the propagation of fake news compared to their fellow urban social media users.

4.2 Source Effect on the Perceptions of Trust in Credible and Fake Posts (RQ2)

In the previous section, we showed how urban participants performed better in differentiating between credible and fake posts compared to rural participants. Here, we ask: "Does a participant's ability to differentiate between credible and fake posts depend on the source of the post, i.e., 'who' posted it on Facebook? We analyze the effect of source on participants' perceived trust ratings for credible and fake posts through two conditions: same-source and same-post. In the same-source condition, we compared between participants' responses to credible and fake posts from the same source, whereas, in the same-post condition, we compared among participants' responses to the same post (either credible or fake) from different sources.

Differences in Perceptions of Trust for *Same-Source* Conditions. We found that urban participants' ability to distinguish between credible and fake posts varied by source. In the baseline condition (i.e., *No source*), they rated credible posts significantly higher on the trust scale compared to the fake posts, i.e., they were good at differentiating credible posts from fake ones. However, for other sources, the difference in the trust ratings of credible and fake posts decreased (in descending order of effect): *News Media*, *Celebrity*, *Friends*, and *Journalists*. For *Stranger* and *Family*, urban participants did not do well in differentiating between credible and fake posts. Table 7 in Appendix B reports significant results from Wilcoxon signed-rank test for various source conditions.

As shown in Figure 4, majority of the urban participants rated both credible and fake posts from *Strangers* as somewhat trustworthy (median trust rating three), suggesting that they were reluctant to trust any post from strangers. For posts shared by *Family*, even though urban participants showed a small-significant difference in their trust ratings of credible and fake posts ($W = 277.5, Z = 1.20, p < 0.05, r = 0.17$), their median trust rating for both types of posts was four. This indicates that urban participants – who, on average, performed well in distinguishing between credible and fake posts – did poorly when the fake posts came from the Facebook profiles of their family. Even we observed that they trusted fake posts from *Family* (median trust rating of four) more than that coming from any other source (median trust rating of three for fake posts from all other sources). This is inline with some prior studies that reported social media users often accept trusted posters' content at face value without probing further [40].

On the contrary, we found no significant difference between the rural participants' trust ratings of credible and fake posts for any source condition, as shown in Figure 5. This implies that they could not differentiate between credible and fake posts irrespective of the source of the post. On average, rural participants rated most of the posts with a median trust score of three (out of five) across different source conditions. However, as shown in Figure 5, their responses to posts from *Family*, *Friends*, and *Journalists* are worth noting. For posts from *Family*, rural participants showed a greater trust for credible posts (median trust rating of four) than the fake posts (median rating of three), but the difference was not significant. For posts from *Friends*, rural participants seemed skeptical to trust any posts (reflected in the greater distribution of both credible and fake posts that were *somewhat* trusted compared to posts from other sources). And finally, for posts from *Journalists*, their median trust ratings for both credible and fake posts are on par and high (median trust rating of four) implying that they trusted content from journalists irrespective of the actual credibility of the shared content.

Differences in Perceptions of Trust for *Same-Post* Conditions. For each type of post in our study, we investigated how rural and urban participants' perceived trust in that post varied by source. Do participants trust a post (irrespective of whether it is credible or fake) if it is posted by, for example, their family member, friends, or a journalist? By understanding how different sources might potentially impact perceived trust in a post, we can design interventions that might help people reconsider their perception of a post.

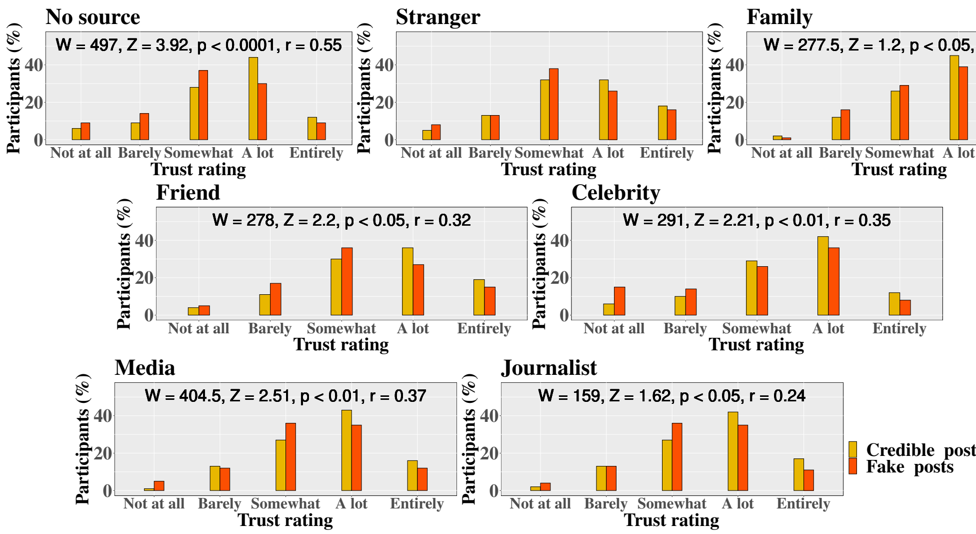


Fig. 4. Differences in urban participants' perceived trust ratings for actual credible and fake posts by source.

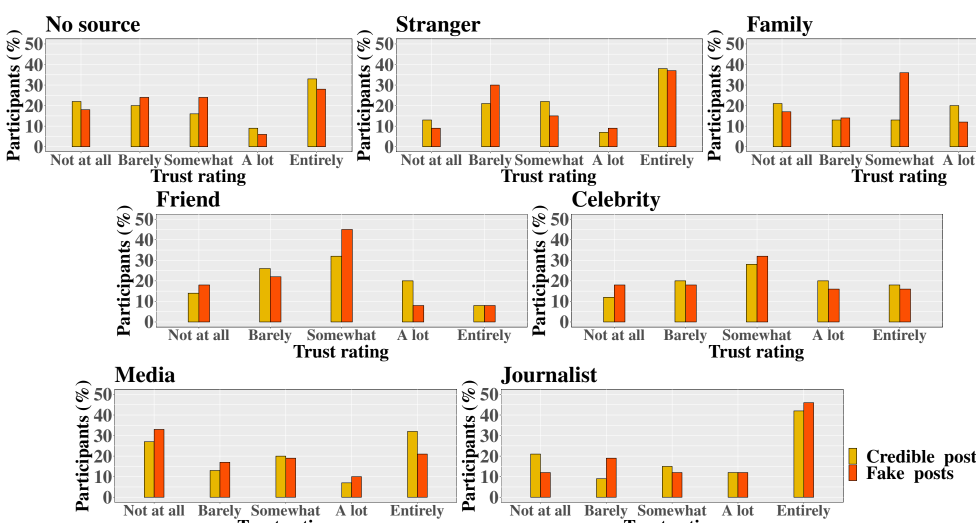


Fig. 5. Differences in rural participants' perceived trust ratings for actual credible and fake posts by source.

For each credible post, we compared among participants' trust rating for all seven sources. We did not find any significant difference in their trust ratings for different sources. Urban participants rated credible posts from all source conditions (except *Stranger*) with a median trust rating of four. Rural participants gave a median trust rating of four to credible posts from *Journalists* and *Family*, and a median trust rating of three to posts from other sources, but these differences were not statistically significant.

Even for fake posts, we did not observe any significant difference among their trust ratings for different sources. Urban participants rated fake posts from all source conditions (except *Family*)

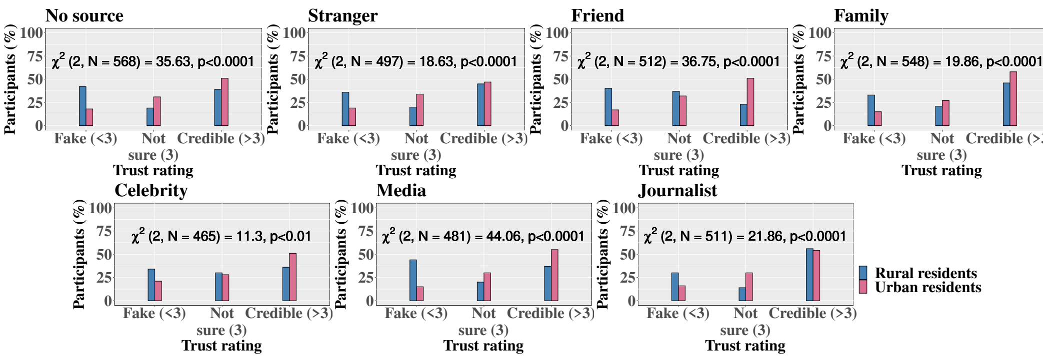
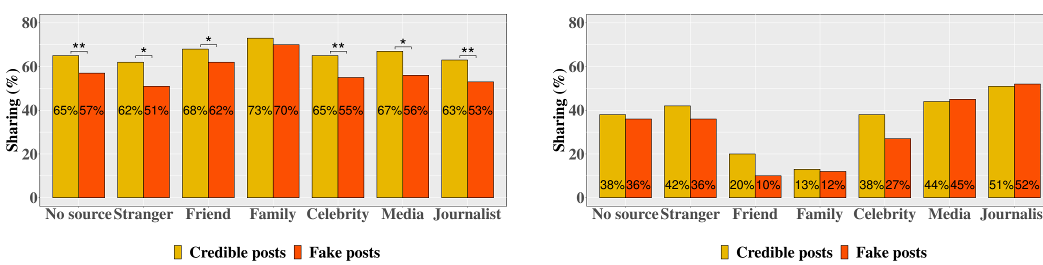


Fig. 6. Differences between rural and urban participants' perceived trust ratings in each source condition, suggesting that source differently impacts how rural and urban participants perceive credibility of posts.



(a) Urban participants. (b) Rural participants.

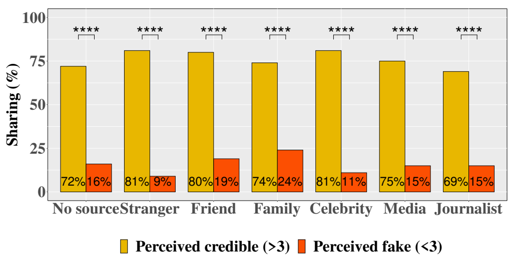
Fig. 7. Differences between the sharing tendency for *actual* credible and fake posts among our participants in different source conditions. Statistically significant differences are reported at $p < 0.01(**)$ and $p < 0.05(*)$.

with a median trust rating of three. Similarly, rural residents rated fake posts from all source conditions (except *Journalists*) with a median trust rating of three. Our findings about source effects on perceptions of trust surface three key takeaways.

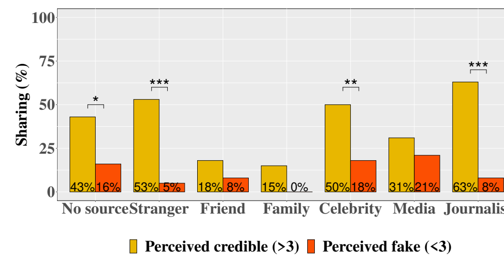
(1) Within *same-source* conditions, urban participants trusted credible and fake posts differently, suggesting that the source shaped their perceptions of credibility. We found significant differences for urban participants, but not for rural participants.
(2) For both groups of participants, we did not find any significant difference in their trust ratings among different source conditions. However, we observed some interesting trend emerging. For example, while urban participants trusted fake posts from family members more than other sources, rural participants trusted fake posts from journalists the most.
(3) Finally, rural and urban participants significantly differed from each other in terms of what posts they perceived to be credible or fake for each source condition (see Figure 6), suggesting that source effect manifests differently in rural and urban areas.

4.3 Source Effects on Sharing Behavior of Credible and Fake Posts

Sharing behaviors impact the diffusion and propagation of fake news. In this section, we examine the effects of source on participants' willingness to share a post as well as their sharing audience (e.g., *Public*, *Friends*). Similar to the analysis in Section 4.2, we examine participants sharing behavior for two conditions: same-source and same-post.



(a) Urban participants.



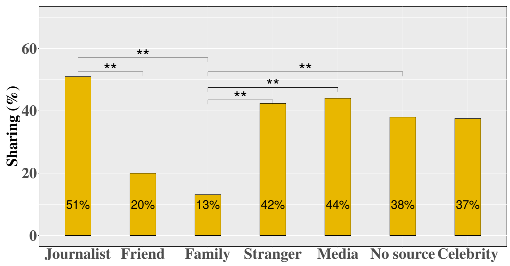
(b) Rural participants.

Fig. 8. Differences between the sharing tendency for *perceived* credible and fake posts among participants in different source conditions. Statistically significant differences are reported at $p < 0.0001$ (****), $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

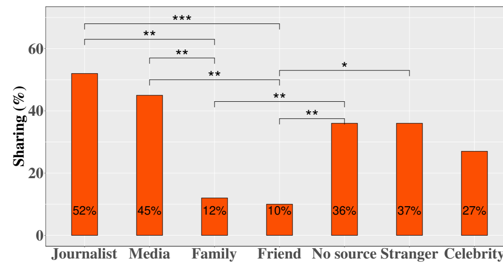
Differences in Willingness to Share for *Same-Source* Conditions. Figure 7 and 8 show participants' willingness to share *actual* and *perceived* credible and fake posts respectively for different source conditions. One thing worth noticing here is that irrespective of source, urban participants' willingness to share actual credible and fake posts are very high (at least $> 50\%$). However, when we considered *perceived* credible and fake posts, we found that urban participants were very willing ($> 68\%$ cases) to share *perceived* credible posts and much less willing ($< 25\%$ cases) to share the posts they perceived as fake. Significant differences emerged between the sharing tendency of perceived credible and fake posts when the posts came from (in decreasing order of effect): *Celebrity*, *Stranger*, *Friend*, *News Media*, *No source*, *Family*, *Journalist*; see Table 8 in Appendix B for significant test results. We can see that most urban participants were willing to share fake posts when it was posted by their *Family* (70% for actual fake and 24% for perceived fake), suggesting their susceptibility to fake posts when shared by family members (see Figure 7a and 8a). On the contrary, they were the least willing to share fake posts when it came from the Facebook profiles of *Strangers* (51% for actual fake and 9% for perceived fake) – again confirming urban participants' reluctance to engage with the Facebook posts from *Strangers*. These findings show that source effect prevails and significantly shapes urban participants' willingness to share credible and fake posts.

On the other hand, rural participants were overall less willing to share posts, as shown in Figure 7b and 8b. We did not observe any significant difference between their sharing tendency of actual credible and fake posts (see Figure 7b). Compared to urban participants, they were less willing to share posts from their *Family*. This might be because a majority (54%) of them did not perceive those posts as credible (see Figure 6). Instead, they were significantly more willing to share the posts they perceived as credible compared to the ones they considered fake, when the posts came from (in decreasing order of effect): *Journalist*, *Stranger*, *Celebrity*, and *No source* (see Table 8). A majority of them (52%) also opted to share actual fake posts from *Journalists* followed by that of *News Media* (see Figure 7b). About 20% of them were willing to share posts they perceived as fake, particularly when the posts came from *News Media* and *Celebrity* (see Figure 8b). These findings indicate that even though rural participants were less inclined to share posts at large, they shared fake posts originating from public sources, such as *Journalists*, *News Media*, and *Celebrities*, even when they perceived the posts to contain fake information.

To summarize, our findings show that sources significantly influence the sharing tendency of credible and fake posts both among urban and rural residents. Besides, Chi-square tests with Yates' continuity correction revealed that the willingness to share posts significantly differed between rural



(a) Sharing tendency for credible posts.



(b) Sharing tendency for fake posts.

Fig. 9. Differences in rural participants' sharing tendency of same types of post (either credible or fake). Statistically significant differences are reported at $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*).

and urban participants for all source conditions, except for *Journalists* (see Table 9 in Appendix B). Both groups were equally willing to share posts from *Journalists*, implying the broader impact and reach of Facebook posts from journalistic sources in both rural and urban regions.

Differences in Willingness to Share for *Same-Post* Conditions. Next, we examined if sources can influence one's tendency towards sharing a particular type of post, be it credible or fake.

For urban participants, we did not observe any significant difference in their sharing tendency of posts (either credible or fake) across all source conditions, likely because irrespective of source they were overall more willing to share posts. However, we did observe significant differences among rural participants' sharing tendencies. Rural participants were more willing to share credible posts from (in decreasing order of effect) *Journalists*, *Stranger*, *News Media*, and *No source* compared to posts from *Family* (see Figure 9a and Table 10). They were also significantly more willing to share credible posts from *Journalists* than from *Friends*. We also observed significant differences for fake posts: rural participants were significantly more willing to share fake posts from *Journalists*, *News Media*, and *No source* than that from *Family* and *Friends* (see Figure 9b and Table 10 in Appendix B).

Taken together, these findings indicate that rural participants were more willing to share a post if it was from a journalist or a news channel than a friend or a family. This might be tied to their skepticism for posts from *Friend* and *Family*. Around 77% and 54% rural participants reported posts from friends and family, respectively, as non-credible (see Figure 6). However, their inclination to share posts (even fake posts) from journalists and news media puts greater responsibility on these sources to share authentic information on social media and reduce biased reporting.

Sharing Audience for *Same-Source* and *Same-Post* Conditions. Next, we examined source effect on participants' choice of sharing audience – Facebook group (*Public*, *Friends*, *Friends except*, or *Specific Friends*) with whom they wanted to share posts. We investigated if sources might introduce differences in the sharing audiences of credible and fake posts to understand the reach of such content when shared from a particular source. In the same-source conditions, we did not observe any significant difference between the sharing audiences for credible and fake posts among the rural participants. On average, irrespective of source, they were more willing to share posts with their Facebook friends, implying that they might not feel comfortable sharing posts publicly.

On the other hand, urban participants were willing to share credible posts with a significantly broader audience compared to fake posts when the posts came from *Celebrity* ($W = 87, Z = 3.09, p < 0.01, r = 0.55$), *Friend* ($W = 161.5, Z = 2.67, p < 0.01, r = 0.43$), *Journalist* ($W = 63, Z = 2.32, p < 0.01, r = 0.43$), and *News Media* ($W = 108.5, Z = 1.81, p < 0.05, r = 0.34$) (see Figure 10). Aside from source effects, there may be other factors that contribute to this sharing behavior. For example,

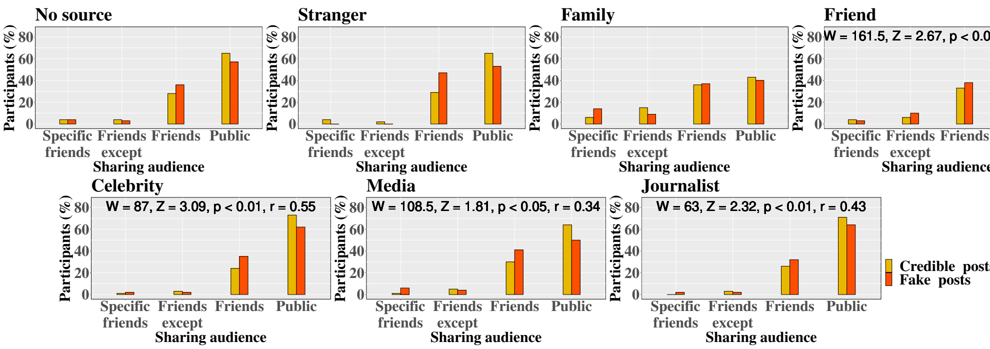


Fig. 10. Differences between the sharing audiences for actual credible and fake posts among urban participants in different source conditions.

individual privacy preferences (if participants are more open in their privacy management [14] they may share widely) or the visibility of posts when they are shared (if posts are already public participants may choose to post them publicly). Besides, in case of same-post condition, urban participants shared credible posts from *Celebrity* with a broader audience compared to credible posts from *Family* ($U = 824, Z = 2.89, p < 0.01, r = 0.35$), perhaps because they felt more comfortable in sharing posts publicly from public figures instead of the posts from their family members.

5 DISCUSSION

Our work systematically examines how belief (i.e., perception of trust) and sharing behavior (i.e., willingness to share and sharing audience) towards credible and fake posts vary among social media users in rural and urban India. Our findings show that rural residents struggled to distinguish between credible and fake posts, had similar sharing preferences for both types of posts, and wanted to share posts mostly with their inner circles. On the contrary, urban participants could distinguish between credible and fake posts, and they shared credible posts more often and more widely than the fake posts. These results demonstrate that rural residents engage with credible and fake posts on social media *differently* than urban residents, suggesting the need to go beyond "one-size-fits-all" approaches to combat fake news on social media.

Our analysis revealed how different sources influence one's perception of and engagement with credible and fake posts. We found that responses for posts from one's close social network (*Family* and *Friends*) manifest differently both in urban and rural areas. For example, urban participants trusted fake posts from their *Family* and were willing to share these posts the most but not with a broader audience (e.g., publicly). In contrast, rural participants were skeptical of the credibility of posts shared by *Friends* and *Family*, and were the least willing to share these posts.

Patterns also emerged for public sources (*Journalists*, *News Media*, and *Celebrity*). Overall, urban participants were willing to share *credible* posts from these sources *publicly*. On the other hand, many rural participants were willing to share fake posts from *Journalists* and *News Media*, even when they doubted the credibility of the posts. Thus, we show that sources influence people's attitude towards credible and fake posts along three dimensions (i.e., trust, sharing tendency, and sharing audience), suggesting that there might not be a single uniform measure to reliably counteract the diverse effects of sources on one's attitude towards fake news. Based on our findings, we now discuss design implications to combat fake news in rural areas along with measures to mitigate source effects in social media news evaluation.

5.1 Design Interventions to Combat Fake News in Rural Areas

Our findings on how social media users from rural India perceive and respond to fake news are alarming. The observed differences between urban and rural residents might have emerged due to their potential differences in technological know-how, educational background, digital literacy [56], usage and access to smartphone devices [85].

So, how can designers and builders enable new social media users in rural communities to discover and verify fake posts? What tools and approaches can be used to prevent rural users from the emerging risks and threats of fake news? One approach could be to rely on automated tools to detect fake news along with credibility indicators on trending posts that might help them navigate social media platforms safely and reliably. Since fact-checking by human moderators often lag behind the rapidly propagating fake news [115], many researchers have developed computational models to detect fake news using linguistic features and various metadata from posts and users' interaction [41, 45, 55]. Taking advantage of advances in AI, several AI-driven fact-checking organizations have also emerged in India recently [7, 20]. However, there are several practical barriers in fully realizing automated methods to detect and combat fake news in low-resource environments. As an example, most of India's 122 major languages are unsupported by advancements in natural language processing, making it very difficult to automate the analysis of social media posts that are often multilingual, code-mixed, and multimodal. Instead, a semi-automated, crowd-powered approach to fact-checking by trained locals has more promise. However, prior research [15] shows that crowd demographic and political leaning influence their fact-checking performance. For this approach to be viable, demographic filtering and training both are required to facilitate high-quality, large-scale credibility assessment [15].

With the growth of automated and semi-automated AI tools that attempt to predict credibility of posts [21, 48, 87], it is important to examine ways to explain the underlying features that guide AI to make predictions [76]. This is particularly important for new users of technology who often have inaccurate mental models of digital threats [23] and lack knowledge of AI, often placing more trust in its capabilities and believing it to be more knowledgeable than them [79]. For new social media users, developing and operating on incorrect mental models about how AI predictions work under the hood could have serious implications, e.g., if they propagate fake news that AI incorrectly predicts as credible. Thus, it is critical that designers and builders of AI-based fake news prediction tools make the AI explainable and its decisions interpretable, so that users are more informed especially when the decisions by AI are in contrast with their political and religious biases. Prior work in HCI [114] shows that among different types of credibility indicators, AI-based indicators are the least effective in deterring users from sharing fake news. However, adding human-style explanations [60, 74] to AI-based credibility indicators that fill causal gaps in users' mental models [32] might make them more impactful in reducing the spread of fake news. Future work should explore ways to design such AI-based credibility indicators that are trustworthy, transparent, and explainable to new social media users with limited digital skills and low literacy.

Another promising approach could be to build capacity of new social media users to discover and verify fake news. Recently Google, FactShala, and Alt.News have organized training programs for journalists, fact-checkers, and social media users in India [4, 49, 50]. With the support of grassroots organizations with stronghold in rural communities, such initiatives could be extended to rural regions to equip new social media users with necessary skills to assess news credibility. However, more work is needed to examine ways to make training programs accessible to users with limited technology skills and literacy, and to appropriate current fact-checking tools and techniques to meet rural needs. Even despite training, users will fact-check posts only when they are aware of emergent risks. Thus, it would be also critical to explore ways to form accurate mental models around threats of misinformation that nudges users to interact with information on social media cautiously.

5.2 Design Interventions to Address Source Effects in News Evaluation

Apart from rural residents' poor capability to discern between credible and fake posts, they were inclined to trust and share fake posts from *Journalists*. Even though overall rural residents preferred to share less, their tendency to share fake contents from public sources, such as *Journalists* and *News Media*, might at best, contribute more to the spread of fake news and, at worst, cause serious harm to people in their communities. In fact, several scholarly and media reports describe the damaging consequences of fake news in rural areas [61], including mob and sectarian violence resulting in hundreds of deaths and displacement of thousands of people [43, 81]. Although urban users trusted credible posts more than fake posts, even they opted to share posts from these public sources with a broader audience (i.e., publicly). Hence, social media platforms should carefully design interventions considering the broader impact of public sources both in urban and rural areas. For example, social media platforms could remind people to cautiously approach posts from verified accounts. Another approach is to remind people that the shared content might represent the views of the post creators (e.g., journalists and celebrities) and might be tied to their political and religious leanings. Fact-checking organizations may prioritize posts from social media profiles of hyper-partisan news media and journalists, considering that many Indian news media agencies and journalists have been reported not only to be politically or religiously biased but have also been accused of purposefully misreporting news [31].

In addition, rural residents tended to perceive majority of the posts (44%) from News Media as fake, but they were still willing (22% cases) to share these *perceived* fake posts the most. Social media platforms are taking several steps to deter people from sharing misinformation, for example, by decreasing the visibility of their posts, suspending them, and removing fake accounts [1–3]. Law enforcement agencies in many countries—including India, Indonesia, and Bangladesh—have also arrested people for propagating fake news [5]. Despite the enforcement of such penalties and harsh measures, misinformation continues to spread wildly. Future work should explore a range of light-weight penalties and harsh measures that social media platforms can enforce on users who *knowingly* share fake news, e.g., even when the post is accompanied by a label describing that it is fake, misleading, or partly false.

In our study, posts from people's inner circle (i.e., family and friends) inspired different reactions both among urban and rural participants. Even though prior studies point that people relied on their personal contacts to consider the veracity of social media posts [104, 111], in our study, only urban participants exhibited the behavior. In contrast, rural participants were reluctant to trust and share posts from their personal contacts. What is more concerning is that urban participants tended to trust and share fake posts from their family members the most. To address such biases, social media platforms could also nudge people with questions about their trust in posts, asking them to tag or provide reasons behind their perceived trust or distrust in a post when they try to interact with contents from their social networks. Prior work from Jahanbakhsh et al. [52] show that such lightweight interventions reduce the sharing of fake news and make people reconsider their decision as they often tend to take posts from their personal contacts at face value [40]. Another approach to reduce source bias could be to add additional valid sources for the content in the post; for example, if an individual is posting news that was first reported by a journalist, the platform could append the journalist's name to the post. Given how prevalent sharing was among urban participants and how number of shares on posts have been shown to influence perceptions of credibility [54], social media platforms could also remind users, for viral fake news, that number of shares are a bad predictor of post's credibility.

Several scholars have examined how various types of credibility indicators impact perceptions and diffusion of fake posts differently [78, 82, 113, 114]. However, a detailed understanding of the effectiveness of different credibility indicators on various demographic groups is still missing and more so in the context of the Global South. Our findings on source effect reveal that rural people tended to trust posts from Journalists the most (56%) among all other source conditions. Hence, rural residents might find credibility indicators citing journalistic sources more reliable. On the other hand, urban residents exhibited more trust in their personal contacts. Therefore, this group might benefit more from community-sourced approaches to predict post credibility, like Twitter's Birdwatch, that mention how many of their personal contacts identified the post as credible or fake along with notes that provide informative context.

6 LIMITATIONS AND FUTURE WORK

Our work has a few limitations. The between-subjects design experiment revealed *how* different sources influenced participants' trust and sharing behavior, but it lacks descriptive insights on *why* participants perceived posts differently. Although we planned to conduct follow-up interviews to qualitatively examine the factors that influence participants' perceptions of and interactions with fake posts, we had to alter these plans for participants' safety during the COVID-19 pandemic. Future research should provide qualitative insight into participants' mental models around how they choose to respond to online news coming from different sources and what factors shape how they perceive and interact with posts from varying sources.

Our study focused only on mainstream news instead of local or regional news for which source effects might manifest differently in rural communities. Future work should explore how different sources mediate people's perceptions of mainstream as well as local news. Our study focused on health information in the context of the COVID-19 pandemic. Even though some posts featured politicians (C1 and C6), celebrity (C2), and religious personality (C3), future work should systematically explore if source effect manifests differently for religious, political, or other kinds of misinformation. In addition, expertise of sources on the presented information could also influence people's perceptions about the information. For example, people might trust political news from the politicians more than other sources. Moreover, individual beliefs along with religious and political alignments [71] and prior exposure [83] might influence one's perceptions of online news. Future work should tease apart several of these factors to examine how source effects impact new social media users in diverse geographies and cultures in the Global South.

7 CONCLUSION

We conducted a between-subjects design experiment to quantitatively examine how rural and urban social media users in India perceive credible and fake posts on social media and how different sources impact their perceptions of trust and sharing behavior. Our analysis revealed key findings, that paints a concerning picture of how the dynamics and diffusion of fake news vary among rural and urban populations. We found that rural users struggled to distinguish credible posts from fake ones compared to their urban counterparts. They trusted and expressed willingness to propagate fake posts from *Journalists* in contrast to urban users who trusted fake posts from *Family* and were eager to share them the most. Drawing on our findings on how source effects vary across urban and rural users, we synthesized key takeaways for HCI and CSCW researchers focusing on examining drivers of fake news and made design recommendations to enable new social media users to contend with the risks and harms of fake news. This work fills a critical gap in research on fake news that has so far neglected the experiences and viewpoints of rural communities in developing regions.

REFERENCES

[1] 2021. Combatting Misinformation on Instagram | Instagram. https://about.instagram.com/blog/announcements/combatting-misinformation-on-instagram.

[2] 2021. COVID-19 misleading information policy. https://help.twitter.com/en/rules-and-policies/medical-misinformation-policy.

[3] 2021. Fact-Checking on Facebook. https://www.facebook.com/business/help/2593586717571940.

[4] 2021. FactEd by Alt News - YouTube. https://www.youtube.com/channel/UCIyajsbcEWqEQlFzJPntldQ.

[5] 2021. A guide to anti-misinformation actions around the world. https://www.poynter.org/ifcn/anti-misinformation-actions/.

[6] Syeda Zainab Akbar, Anmol Panda, Divyanshu Kukreti, Azhagu Meena, and Joyojeet Pal. 2021. Misinformation as a Window into Prejudice: COVID-19 and the Information Environment in India. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW3, Article 249 (2021), 28 pages.

[7] Shrabonti Bagchi and Nitin Sreedhar. 2018. Can algorithms solve the fake news problem in India? Retrieved January 8, 2021 from https://www.livemint.com/Leisure/57YAqVjoTqFo0M6Lcc4NOI/Can-algorithms-solve-the-fake-news-problem-in-India.html

[8] Chi Y. Bahk, Melissa Cumming, Louisa Paushter, Lawrence C. Madoff, Angus Thomson, and John S. Brownstein. 2016. Publicly Available Online Tool Facilitates Real-Time Monitoring Of Vaccine Conversations And Sentiments. *Health Affairs* 35, 2 (2016), 341–347.

[9] Eytan Bakshy, Solomon Messing, and Lada A. Adamic. 2015. Exposure to ideologically diverse news and opinion on Facebook. *Science* 348, 6239 (2015), 1130–1132.

[10] Amila Banerjee and Mehrazun Haque. 2018. Is Fake News Real in India? *Journal of Content, Community and Communication* 4 (12 2018), 46–49.

[11] BARC. 2020. What India Watches: Data Insights. Retrieved July 24, 2020 from https://www.barcindia.co.in/statistic.aspx

[12] BBC. 2018. What we've learnt about fake news in Africa. Retrieved July 13, 2021 from https://www.bbc.com/news/world-africa-46138284

[13] BBC. 2020. COVID-19 sparks online Islamophobia as fake news and racist memes are shared online, new research finds. Retrieved July 11, 2021 from https://www.bcu.ac.uk/about-us/coronavirus-information/news/covid-19-sparks-online-islamophobia-as-fake-news-and-racist-memes-are-shared-online-new-research-finds

[14] Michael A Beam, Jeffrey T Child, Myiah J Hutchens, and Jay D Hmielowski. 2018. Context collapse and privacy management: Diversity in Facebook friends increases online news reading and sharing. *New Media & Society* 20, 7 (2018), 2296–2314.

[15] Md Momen Bhuiyan, Amy X. Zhang, Connie Moon Sehat, and Tanushree Mitra. 2020. Investigating Differences in Crowdsourced News Credibility Assessment: Raters, Tasks, and Expert Criteria. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2, Article 93 (2020), 26 pages.

[16] Jeremy Bowles, Horacio Larreguy, and Shelley Liu. 2020. Countering misinformation via WhatsApp: Preliminary evidence from the COVID-19 pandemic in Zimbabwe. *PLOS ONE* 15, 10 (2020), 1–11.

[17] Tom Buchanan. 2020. Why do people spread false information online? The effects of message and viewer characteristics on self-reported likelihood of sharing social media disinformation. *PLOS ONE* 15, 10 (2020), 1–33.

[18] Tom Buchanan and Vladlena Benson. 2019. Spreading Disinformation on Facebook: Do Trust in Message Source, Risk Propensity, or Personality Affect the Organic Reach of "Fake News"? *Social Media + Society* 5, 4 (2019), 2056305119888654.

[19] Jenna Burrell and Kentaro Toyama. 2009. What Constitutes Good ICTD Research? *Information Technologies & International Development* 5, 3 (Oct. 2009), pp. 82–94. https://itidjournal.org/index.php/itid/article/view/382 Number: 3.

[20] Puja Changoiwala. 2019. Can an AI Fact-Checker Solve India's Fake News Problem? Retrieved January 15, 2021 from https://www.fastcompany.com/90445139/this-startup-is-fighting-indias-fake-news-problem-on-whatsapp

[21] Puja Changoiwala. 2019. Can an AI Fact-Checker Solve India's Fake News Problem? Retrieved July 15, 2021 from https://undark.org/2019/12/18/ai-fact-checker-india/

[22] Apoorva Chauhan and Amanda Lee Hughes. 2020. Trustworthiness Perceptions of Social Media Resources Named after a Crisis Event. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW1, Article 044 (2020), 23 pages.

[23] Jay Chen, Michael Paik, and Kelly McCabe. 2014. Exploring Internet Security Perceptions and Practices in Urban Ghana. In *10th Symposium On Usable Privacy and Security (SOUPS 2014)*. USENIX Association, Menlo Park, CA, 129–142.

[24] Liang Chen, Xiaohui Wang, and Tai-Quan Peng. 2018. Nature and Diffusion of Gynecologic Cancer–Related Misinformation on Social Media: Analysis of Tweets. *Journal of Medical Internet Research* 20, 10 (2018), e11515.

[25] Xinran Chen and Sei-Ching Joanna Sin. 2013. 'Misinformation? what of it?': motivations and individual differences in misinformation sharing on social media. In *Proceedings of the 76th ASIS&T Annual Meeting: Beyond the Cloud: Rethinking Information Boundaries (ASIST '13)*. American Society for Information Science, USA, 1–4.

[26] Xinran Chen, Sei-Ching Joanna Sin, Yin-Leng Theng, and Chei Sian Lee. 2015. Why Do Social Media Users Share Misinformation?. In *Proceedings of the 15th ACM/IEEE-CS Joint Conference on Digital Libraries (JCDL '15)*. Association for Computing Machinery, New York, NY, USA, 111–114.

[27] Xinran Chen, Sei-Ching Joanna Sin, Yin-Leng Theng, and Chei Sian Lee. 2015. Why Students Share Misinformation on Social Media: Motivation, Gender, and Study-level Differences. *The Journal of Academic Librarianship* 41, 5 (2015), 583–592.

[28] Alton Y. K. Chua, Cheng-Ying Tee, Augustine Pang, and Ee-Peng Lim. 2016. The Retransmission of Rumor-Related Tweets: Characteristics of Source and Message. In *Proceedings of the 7th 2016 International Conference on Social Media & Society* (London, United Kingdom) *(SMSociety '16)*. Association for Computing Machinery, New York, NY, USA, Article 22, 10 pages.

[29] Mark Coddington and Seth Lewis. 2021. New research shows how journalists are responding and adapting to "fake news" rhetoric. Retrieved July 13, 2021 from https://www.niemanlab.org/2021/02/new-research-shows-how-journalists-are-responding-and-adapting-to-fake-news-rhetoric/

[30] Michela Del Vicario, Alessandro Bessi, Fabiana Zollo, Fabio Petroni, Antonio Scala, Guido Caldarelli, H. Eugene Stanley, and Walter Quattrociocchi. 2016. The spreading of misinformation online. *Proceedings of the National Academy of Sciences* 113, 3 (2016), 554–559.

[31] Priyanka Deo. 2020. Biased Mainstream Media Carries Grave Consequences for Indian Democracy. Retrieved January 14, 2021 from https://www.news18.com/news/opinion/biased-mainstream-media-carries-grave-consequences-for-indian-democracy-2541333.html

[32] Ullrich K. H. Ecker. 2017. Why rebuttals may not work: the psychology of misinformation. *Media Asia* 44, 2 (April 2017), 79–87. https://doi.org/10.1080/01296612.2017.1384145 Publisher: Routledge _eprint: https://doi.org/10.1080/01296612.2017.1384145.

[33] Jr Edson C Tandoc, Richard Ling, Oscar Westlund, Andrew Duffy, Debbie Goh, and Lim Zheng Wei. 2018. Audiences' acts of authentication in the age of fake news: A conceptual framework. *New Media & Society* 20, 8 (2018), 2745–2763.

[34] Waqas Ejaz and Muhammad Ittefaq. 2020. Data for understanding trust in varied information sources, use of news media, and perception of misinformation regarding COVID-19 in Pakistan. *Data in Brief* 32 (2020), 106091.

[35] Gowhar Farooq. 2018. Politics of Fake News: How WhatsApp Became a Potent Propaganda Tool in India. *Media Watch* 9, 1 (2018), 106–117.

[36] Nic Fleming. 2020. Coronavirus misinformation, and how scientists can help to fight it. Retrieved July 11, 2021 from https://www.nature.com/articles/d41586-020-01834-3

[37] Martin Flintham, Christian Karner, Khaled Bachour, Helen Creswick, Neha Gupta, and Stuart Moran. 2018. Falling for Fake News: Investigating the Consumption of News via Social Media. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–10.

[38] Adam Fourney, Miklos Z. Racz, Gireeja Ranade, Markus Mobius, and Eric Horvitz. 2017. Geographic and Temporal Trends in Fake News Consumption During the 2016 US Presidential Election. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management (CIKM '17)*. Association for Computing Machinery, New York, NY, USA, 2071–2074.

[39] Kiran Garimella and Dean Eckles. 2020. Images and Misinformation in Political Groups: Evidence from WhatsApp in India. arXiv:2005.09784 [cs.SI]

[40] Christine Geeng, Savanna Yee, and Franziska Roesner. 2020. Fake News on Facebook and Twitter: Investigating How People (Don't) Investigate. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–14.

[41] Amira Ghenai and Yelena Mejova. 2018. Fake Cures: User-Centric Modeling of Health Misinformation in Social Media. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 58 (2018), 20 pages.

[42] Eric Gilbert, Karrie Karahalios, and Christian Sandvig. 2008. The Network in the Garden: An Empirical Analysis of Social Media in Rural Life. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Florence, Italy) *(CHI '08)*. Association for Computing Machinery, New York, NY, USA, 1603–1612.

[43] Vindu Goel, Suhasini Raj, and Priyadarshini Ravichandran. 2018. How WhatsApp Leads Mobs to Murder in India. Retrieved January 7, 2021 from https://www.nytimes.com/interactive/2018/07/18/technology/whatsapp-india-killings.html,https://www.nytimes.com/interactive/2018/07/18/technology/whatsapp-india-killings.html

[44] Andrew Guess, Jonathan Nagler, and Joshua Tucker. 2019. Less than you think: Prevalence and predictors of fake news dissemination on Facebook. *Science Advances* 5, 1 (Jan. 2019), eaau4586. Publisher: American Association for the Advancement of Science Section: Research Article.

[45] Aditi Gupta, Ponnurangam Kumaraguru, Carlos Castillo, and Patrick Meier. 2014. *TweetCred: Real-Time Credibility Assessment of Content on Twitter.* Springer International Publishing, Cham, 228–243.

[46] Md Mahfuzul Haque, Mohammad Yousuf, Ahmed Shatil Alam, Pratyasha Saha, Syed Ishtiaque Ahmed, and Naeemul Hassan. 2020. Combating Misinformation in Bangladesh: Roles and Responsibilities as Perceived by Journalists, Fact-Checkers, and Users. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2, Article 130 (Oct. 2020), 32 pages.

[47] The Hindu. 2019. Just 26% of Indians speak Hindi as mother tongue. Retrieved 2021-07-07 from https://www.thehindu.com/data/just-26-percent-of-indians-speak-hindi-as-mother-tongue/article29439701.ece

[48] Benjamin D. Horne, Dorit Nevo, Sibel Adali, Lydia Manikonda, and Clare Arrington. 2020. Tailoring heuristics and timing AI interventions for supporting news veracity assessments. *Computers in Human Behavior Reports* 2 (Aug. 2020), 100043.

[49] Internews. 2019. One Year On: Combating Misinformation in India. Retrieved January 14, 2021 from https://internews.org/story/one-year-combating-misinformation-india

[50] Internews. 2020. Why do people believe fake news? Retrieved July 12, 2021 from https://internews.org/story/why-do-people-believe-fake-news/

[51] Md Saiful Islam, Tonmoy Sarkar, Sazzad Hossain Khan, Abu-Hena Mostofa Kamal, S. M. Murshid Hasan, Alamgir Kabir, Dalia Yeasmin, Mohammad Ariful Islam, Kamal Ibne Amin Chowdhury, Kazi Selim Anwar, Abrar Ahmad Chughtai, and Holly Seale. 2020. COVID-19–Related Infodemic and Its Impact on Public Health: A Global Social Media Analysis. *The American Journal of Tropical Medicine and Hygiene* 103, 4 (2020), 1621–1629. https://doi.org/10.4269/ajtmh.20-0812

[52] Farnaz Jahanbakhsh, Amy X. Zhang, Adam J. Berinsky, Gordon Pennycook, David G. Rand, and David R. Karger. 2021. Exploring Lightweight Interventions at Posting Time to Reduce the Sharing of Misinformation on Social Media. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 18 (April 2021), 42 pages.

[53] Maurice Jakesch, Moran Koren, Anna Evtushenko, and Mor Naaman. 2018. The Role of Source, Headline and Expressive Responding in Political News Evaluation. *SSRN Electronic Journal* 1, 1 (2018), 5 pages.

[54] Eva L Jenkins, Jasmina Ilicic, Amy M Barklamb, and Tracy A McCaffrey. 2020. Assessing the Credibility and Authenticity of Social Media Content for Applications in Health Communication: Scoping Review. *J Med Internet Res* 22, 7 (2020), e17296.

[55] Shan Jiang and Christo Wilson. 2018. Linguistic Signals under Misinformation and Fact-Checking: Evidence from User Comments on Social Media. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 82 (2018), 23 pages.

[56] Shemin Joy. 2020. Digital literacy for rural population hasn't met half of the target. Retrieved January 14, 2021 from https://www.deccanherald.com/national/digital-literacy-for-rural-population-hasnt-met-half-of-the-target-813995.html

[57] Masato Kajimoto, Yenni Kwok, Yvonne Chua, and Ma Labiste. 2018. Information Disorder in Asia and the Pacific: Overview of Misinformation Ecosystem in Australia, India, Indonesia, Japan, the Philippines, Singapore, South Korea, Taiwan, and Vietnam. *SSRN Electronic Journal* 1, 1 (2018), 70.

[58] Alireza Karduni. 2019. Human-Misinformation interaction: Understanding the interdisciplinary approach needed to computationally combat false information. *CoRR* abs/1903.07136, 1 (2019), 1–21.

[59] Arshad Afzaal Khan. 2021. Villagers jump into river to evade Covid vaccine shots. Retrieved 2021-11-01 from https://timesofindia.indiatimes.com/india/villagers-jump-into-river-to-evade-covid-vaccine-shots/articleshow/82927966.cms

[60] Jan Kirchner and Christian Reuter. 2020. Countering Fake News: A Comparison of Possible Solutions Regarding User Acceptance and Effectiveness. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2, Article 140 (2020), 27 pages.

[61] Khabar Lahariya. 2019. "They pluck out hearts of children"—how fake news is crippling Indian villages with anxiety. Retrieved January 15, 2021 from https://qz.com/india/1710209/rural-india-in-turmoil-over-whatsapp-kidnapping-fake-news/

[62] David M. J. Lazer, Matthew A. Baum, Yochai Benkler, Adam J. Berinsky, Kelly M. Greenhill, Filippo Menczer, Miriam J. Metzger, Brendan Nyhan, Gordon Pennycook, David Rothschild, Michael Schudson, Steven A. Sloman, Cass R. Sunstein, Emily A. Thorson, Duncan J. Watts, and Jonathan L. Zittrain. 2018. The science of fake news. *Science* 359, 6380 (2018), 1094–1096.

[63] Amanda Y. Leong, Ravina Sanghera, Jaspreet Jhajj, Nandini Desai, Bikramjit Singh Jammu, and Mark J. Makowsky. 2018. Is YouTube Useful as a Source of Health Information for Adults With Type 2 Diabetes? A South Asian Perspective. *Canadian Journal of Diabetes* 42, 4 (2018), 395 – 403.e4.

[64] Sebastian Linxen, Christian Sturm, Florian Brühlmann, Vincent Cassau, Klaus Opwis, and Katharina Reinecke. 2021. How WEIRD is CHI?. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, Article 143, 14 pages.

[65] Linqi Lu, Jiawei Liu, Y. Connie Yuan, Kelli S. Burns, Enze Lu, and Dongxiao Li. 2020. Source Trust and COVID-19 Information Sharing: The Mediating Roles of Emotions and Beliefs About Sharing. *Health Education & Behavior* 0, 0 (2020), 1–8.

[66] Zhicong Lu, Yue Jiang, Cheng Lu, Mor Naaman, and Daniel Wigdor. 2020. The Government's Dividend: Complex Perceptions of Social Media Misinformation in China. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, USA, 1–12.
[67] Zhicong Lu, Yue Jiang, Chenxinran Shen, Margaret C. Jack, Daniel Wigdor, and Mor Naaman. 2021. "Positive Energy": Perceptions and Attitudes Towards COVID-19 Information on Social Media in China. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 177 (2021), 25 pages.
[68] Eoghan Macguire. 2020. Anti-Asian hate continues to spread online amid COVID-19 pandemic. Retrieved July 11, 2021 from https://www.aljazeera.com/news/2020/4/5/anti-asian-hate-continues-to-spread-online-amid-covid-19-pandemic
[69] Caio Machado, Beatriz Kira, Vidya Narayanan, Bence Kollanyi, and Philip Howard. 2019. A Study of Misinformation in WhatsApp Groups with a Focus on the Brazilian Presidential Elections.. In *Companion Proceedings of The 2019 World Wide Web Conference* (San Francisco, USA) *(WWW '19)*. Association for Computing Machinery, New York, NY, USA, 1013–1019.
[70] Gayathri Mani. 2020. Muslim man brutally thrashed on suspicion of spreading coronavirus. Retrieved January 7, 2021 from https://www.newindianexpress.com/nation/2020/apr/09/muslim-man-brutally-thrashed-on-suspicion-of-spreding-coronavirus-2127927.html
[71] Alice E. Marwick. 2018. Why Do People Share Fake News? A Sociotechnical Model of Media Effects. *Georgetown Law Technology Review* 2, 2 (2018), 474–512.
[72] John H. McDonald. 2014. *Handbook of Biological Statistic* (3 ed.). Sparky House Publishing, Baltimore, Maryland.
[73] D. Harrison McKnight and Charles J. Kacmar. 2007. Factors and effects of information credibility. In *Proceedings of the ninth international conference on Electronic commerce (ICEC '07)*. Association for Computing Machinery, New York, NY, USA, 423–432.
[74] Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence* 267 (Feb. 2019), 1–38. https://doi.org/10.1016/j.artint.2018.07.007
[75] Tanushree Mitra, Graham Wright, and Eric Gilbert. 2017. Credibility and the Dynamics of Collective Attention. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW, Article 80 (2017), 17 pages.
[76] Sina Mohseni, Fan Yang, Shiva K. Pentyala, Mengnan Du, Yi Liu, Nic Lupfer, Xia Hu, Shuiwang Ji, and Eric D. Ragan. 2020. Machine Learning Explanations to Prevent Overtrust in Fake News Detection. *CoRR* abs/2007.12358 (2020).
[77] BBC News. 2018. How WhatsApp helped turn an Indian village into a lynch mob. Retrieved January 7, 2021 from https://www.bbc.com/news/world-asia-india-44856910
[78] Brendan Nyhan, Ethan Porter, Jason Reifler, and Thomas J. Wood. 2020. Taking Fact-Checks Literally But Not Seriously? The Effects of Journalistic Fact-Checking on Factual Beliefs and Candidate Favorability. *Political Behavior* 42, 3 (Sept. 2020), 939–960.
[79] Chinasa T. Okolo, Srujana Kamath, Nicola Dell, and Aditya Vashistha. 2021. "It cannot do all of my work": Community Health Worker Perceptions of AI-Enabled Mobile Health Applications in Rural India. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–20. https://doi.org/10.1145/3411764.3445420
[80] Eli Pariser. 2011. *The Filter Bubble: What The Internet Is Hiding From You* (1 ed.). Penguin Books Limited, London, UK.
[81] Samir Patil. 2019. Opinion | India Has a Public Health Crisis. It's Called Fake News. Retrieved 2021-01-16 from https://www.nytimes.com/2019/04/29/opinion/india-elections-disinformation.html
[82] Gordon Pennycook, Adam Bear, Evan Collins, and David G. Rand. 2019. *The Implied Truth Effect: Attaching Warnings to a Subset of Fake News Headlines Increases Perceived Accuracy of Headlines Without Warnings*. SSRN Scholarly Paper ID 3035384. Social Science Research Network, Rochester, NY. https://papers.ssrn.com/abstract=3035384
[83] Gordon Pennycook, Tyrone Cannon, and David G. Rand. 2018. Prior Exposure Increases Perceived Accuracy of Fake News. *Journal of Experimental Psychology: General* 147, 12 (2018), 1865–1880.
[84] Poynter. 2021. International Fact-Checking Network. Retrieved January 13, 2021 from https://www.poynter.org/ifcn/
[85] Adharsh Raj and Manash Goswami. 2020. Is fake news spreading more rapidly than COVID-19 in India? A representative study of people's perspective on controlling the spread of fake news on social media. *Journal of Content, Community and Communication* 11 (06 2020), 208–220.
[86] Giselle Rampersad and Turki Althiyabi. 2020. Fake news: Acceptance by demographics and culture on social media. *Journal of Information Technology & Politics* 17, 1 (Jan. 2020), 1–11. https://doi.org/10.1080/19331681.2019.1686676 Publisher: Routledge _eprint: https://doi.org/10.1080/19331681.2019.1686676.
[87] Julio C. S. Reis, André Correia, Fabrício Murai, Adriano Veloso, and Fabrício Benevenuto. 2019. Explainable Machine Learning for Fake News Detection. In *Proceedings of the 10th ACM Conference on Web Science* (Boston, Massachusetts, USA) *(WebSci '19)*. Association for Computing Machinery, New York, NY, USA, 17–26.
[88] Julio C. S. Reis, Philipe Melo, Kiran Garimella, Jussara M. Almeida, Dean Eckles, and Fabrício Benevenuto. 2020. A Dataset of Fact-Checked Images Shared on WhatsApp During the Brazilian and Indian Elections. *Proceedings of the*

International AAAI Conference on Web and Social Media 14, 1 (2020), 903–908.
[89] Dorit Rubinstein Reiss. 2021. COVID-19 Vaccine Misinformation and the Anti-Vaccine Movement. Retrieved July 11, 2021 from https://blog.petrieflom.law.harvard.edu/2021/01/20/covid-19-vaccine-misinformation-anti-vaccine-movement/
[90] The Hindu Reporter, Staff. 2020. Twelve taken ill after consuming 'coronavirus shaped' datura seeds. Retrieved January 7, 2021 from https://www.thehindu.com/news/national/andhra-pradesh/twelve-taken-ill-after-consuming-coronavirus-shaped-datura-seeds/article31282688.ece
[91] Gustavo Resende, Philipe Melo, Hugo Sousa, Johnnatan Messias, Marisa Vasconcelos, Jussara Almeida, and Fabrício Benevenuto. 2019. (Mis)Information Dissemination in WhatsApp: Gathering, Analyzing and Countermeasures. In *The World Wide Web Conference* (San Francisco, CA, USA) *(WWW '19)*. Association for Computing Machinery, New York, NY, USA, 818–828.
[92] Usha M Rodrigues and Jian Xu. 2020. Regulation of COVID-19 fake news infodemic in China and India. *Media International Australia* 177, 1 (2020), 125–131.
[93] Luke Runyon. 2017. Rural Areas Still Lag Behind In Digital Technology Adoption. Retrieved 2021-11-01 from https://indianapublicmedia.org/eartheats/rural-areas-lag-digital-technology-adoption.php
[94] Nehru Yuva Sangathan-Tisi. 2020. Nehru Yuva Sangathan-Tisi. Retrieved 2021-07-07 from https://www.nystindia.org/
[95] Sonia Sarkar. 2020. Religious discrimination is hindering the covid-19 response. Retrieved January 11, 2021 from https://www.bmj.com/content/369/bmj.m2280
[96] Akanksha Saxena. 2021. India fake news problem fueled by digital illiteracy. Retrieved July 13, 2021 from https://p.dw.com/p/3q6Qa
[97] Jieun Shin, Lian Jian, Kevin Driscoll, and François Bar. 2018. The diffusion of misinformation on social media: Temporal pattern, message, and source. *Computers in Human Behavior* 83 (June 2018), 278–287.
[98] Manish Singh. 2019. Reliance Jio partners with Facebook to launch literacy program for first time internet users in India. Retrieved January 7, 2021 from https://social.techcrunch.com/2019/07/03/reliance-jio-facebook-digital-literacy-udaan-india/
[99] socialbaker. 2020. Facebook stats of popular Celebrities pages in India. Retrieved July 24, 2020 from https://www.socialbakers.com/statistics/facebook/pages/total/india/celebrities
[100] Francesca Spezzano, Anu Shrestha, Jerry Alan Fails, and Brian W. Stone. 2021. That's Fake News! Reliability of News When Provided Title, Image, Source Bias, and Full Article. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 109 (2021), 19 pages.
[101] Dominic Spohr. 2017. Fake news and ideological polarization: Filter bubbles and selective exposure on social media. *Business Information Review* 34, 3 (2017), 150–160.
[102] David Sterrett, Dan Malato, Jennifer Benz, Liz Kantor, Trevor Tompson, Tom Rosenstiel, Jeff Sonderman, and Kevin Loker. 2019. Who Shared It?: Deciding What News to Trust on Social Media. *Digital Journalism* 7, 6 (July 2019), 783–801.
[103] David Sterrett, Dan Malato, Jennifer Benz, Liz Kantor, Trevor Tompson, Tom Rosenstiel, Jeff Sonderman, and Kevin Loker. 2019. Who Shared It?: Deciding What News to Trust on Social Media. *Digital Journalism* 7, 6 (2019), 783–801.
[104] Kamari Stewart. 2019. *Do You Trust Me(dia)?: How Students Perceive and Identify Fake News.* Master's thesis. Pace University.
[105] Stanley Sue. 2000. Science, ethnicity, and bias - Where have we gone wrong? *The American psychologist* 54 (01 2000), 1070–7. https://doi.org/10.1037/0003-066X.54.12.1070
[106] Briony Swire-Thompson, Ullrich K. H. Ecker, Stephan Lewandowsky, and Adam J. Berinsky. 2020. They Might Be a Liar But They're My Liar: Source Evaluation and the Prevalence of Misinformation. *Political Psychology* 41, 1 (2020), 21–34.
[107] Tattle. 2021. Tattle Civic Techologies International Fact-Checking Network. Retrieved January 13, 2021 from https://tattle.co.in/
[108] Feeza Vasudeva and Nicholas Barkdull. 2020. WhatsApp in India? A case study of social media related lynchings. *Social Identities* 26, 5 (2020), 574–589.
[109] Michela Del Vicario, Alessandro Bessi, Fabiana Zollo, Fabio Petroni, Antonio Scala, Guido Caldarelli, H. Eugene Stanley, and Walter Quattrociocchi. 2016. The spreading of misinformation online. *Proceedings of the National Academy of Sciences* 113, 3 (Jan. 2016), 554–559. Publisher: National Academy of Sciences Section: Physical Sciences.
[110] Patrick Vinck, Phuong N Pham, Kenedy K Bindu, Juliet Bedford, and Eric J Nilles. 2019. Institutional trust and misinformation in the response to the 2018–19 Ebola outbreak in North Kivu, DR Congo: a population-based survey. *The Lancet Infectious Diseases* 19, 5 (2019), 529 – 536.
[111] María Celeste Wagner and Pablo J. Boczkowski. 2019. The Reception of Fake News: The Interpretations and Practices That Shape the Consumption of Perceived Misinformation. *Digital Journalism* 7, 7 (2019), 870–885.

[112] Luping Wang and Susan R. Fussell. 2020. More Than a Click: Exploring College Students' Decision-Making Processes in Online News Sharing. *Proc. ACM Hum.-Comput. Interact.* 4, GROUP, Article 09 (2020), 20 pages.
[113] Thomas Wood and Ethan Porter. 2019. The Elusive Backfire Effect: Mass Attitudes' Steadfast Factual Adherence. *Political Behavior* 41, 1 (March 2019), 135–163.
[114] Waheeb Yaqub, Otari Kakhidze, Morgan L. Brockman, Nasir Memon, and Sameer Patil. 2020. Effects of Credibility Indicators on Social Media News Sharing Intent. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–14.
[115] Arkaitz Zubiaga, Maria Liakata, Rob Procter, Geraldine Wong Sak Hoi, and Peter Tolmie. 2016. Analysing How People Orient to and Spread Rumours in Social Media by Looking at Conversational Threads. *PLOS ONE* 11, 3 (2016), 1–29.

A LIST OF CELEBRITIES, NEWS MEDIA, AND JOURNALISTS

Table 4. List of 20 Indian celebrities.

Actors	Sportsmen	Musicians	Authors
Priyanka Chopra	Virat Kohli	Shreya Ghoshal	Arundhati Roy
Salman Khan	Sachin Tendulkar	A. R. Rahman	Chetan Bhagat
Deepika Padukone	MS Dhoni	Sonu Nigam	Salman Rushdie
Amitabh Bachchan	Yuvraj Singh	Arijit Singh	Jhumpa Lahiri
Shah Rukh Khan	Virender Sehwag	Sunidhi Chauhan	Amish Tripathi

Table 5. List of 19 Indian news media.

Zee News	Aaj Tak	India Today	The Times of India	Navbharat Times
Republic	NDTV	Indian Express	Hindustan Times	Punjab Kesari
TIMES NOW	News 18	The Hindu	The Wire Hindi	Divya Himachal
Jagaran	Dainik Bhaskar	Patrika	Amar Ujala	

For the celebrity source condition, we curated a list of 20 Indian celebrities (Table 4) based on their follower base on Facebook. For urban participants, we compiled a list of top 19 Indian news media based on their TRP and number of followers (Table 5) in their official Facebook page. For rural participants, we added Hindi TV news channels and popular Hindi dailies selected based on their readership. For the Journalist source condition, we curated a list of eight popular Indian journalists based on their follower base on Facebook (Table 6).

Table 6. List of 8 Indian journalists.

Sudhir Chaudhary	Ravish Kumar	Rajdeep Sardesai	Harsha Bhogle
Rajat Sharma	Arnab Goswami	Barkha Dutt	Sagarika Ghose

B STATISTICALLY SIGNIFICANT TEST RESULTS REPORTED IN FINDINGS

Received January 2021; revised July 2021; accepted November 2021

Table 7. Wilcoxon signed-rank test results (Benjamini-Hochberg corrected) for differences between urban participants' responses to credible and fake posts for same-source conditions.

Source	Perceived trust	Willingness to share (for actual credible and fake posts)
No source	$W = 497, Z = 3.92, p < 0.0001, r = 0.55$	$W = 231, Z = 1.66, p < 0.05, r = 0.23$
Stranger	-	$W = 321, Z = 2.22, p < 0.05, r = 0.33$
Friend	$W = 278, Z = 2.20, p < 0.05, r = 0.32$	$W = 224.5, Z = 1.63, p < 0.05, r = 0.24$
Family	$W = 277.5, Z = 1.20, p < 0.05, r = 0.17$	-
Celebrity	$W = 291, Z = 2.21, p < 0.01, r = 0.35$	$W = 215.5, Z = 1.92, p < 0.01, r = 0.30$
Journalist	$W = 159, Z = 1.62, p < 0.05, r = 0.24$	$W = 294.5, Z = 2.75, p < 0.01, r = 0.41$
Media	$W = 404.5, Z = 2.51, p < 0.01, r = 0.37$	$W = 263.5, Z = 2.38, p < 0.05, r = 0.35$

Table 8. Wilcoxon signed-rank test results (Benjamini-Hochberg corrected) for differences between the sharing tendency of *perceived* credible and fake posts of the participants.

Source	Urban participants	Rural participants
No source	$W = 649.5, Z = 5.33, p < 0.0001, r = 0.75$	$W = 76, Z = 2.09, p < 0.05, r = 0.42$
Stranger	$W = 739.5, Z = 5.66, p < 0.0001, r = 0.85$	$W = 78, Z = 3.42, p < 0.001, r = 0.71$
Friend	$W = 606, Z = 5.28, p < 0.0001, r = 0.78$	-
Family	$W = 581, Z = 4.94, p < 0.0001, r = 0.70$	-
Celebrity	$W = 561, Z = 5.44, p < 0.0001, r = 0.86$	$W = 44, Z = 2.46, p < 0.01, r = 0.53$
Journalist	$W = 661, Z = 4.50, p < 0.0001, r = 0.68$	$W = 120, Z = 3.84, p < 0.001, r = 0.75$
Media	$W = 604, Z = 5.20, p < 0.0001, r = 0.78$	-

Table 9. Chi-square test results for differences between rural and urban participants' sharing tendency of posts.

Source	Sharing tendency
No source	$\chi^2(1, N = 568) = 28.32, p < 0.0001$
Stranger	$\chi^2(1, N = 497) = 11.76, p < 0.001$
Friend	$\chi^2(1, N = 512) = 86.50, p < 0.0001$
Family	$\chi^2(1, N = 548) = 140.79, p < 0.0001$
Celebrity	$\chi^2(1, N = 464) = 31.28, p < 0.0001$
Journalist	-
Media	$\chi^2(1, N = 481) = 14.68, p < 0.001$

Table 10. Mann-Whitney's U test results (Benjamini-Hochberg corrected) for inter-source differences in rural participants' willingness to share posts.

Post	Source conditions	Willingness to share
Credible	Journalist > Family	$U = 396, Z = 2.95, p < 0.01, r = 0.43$
Credible	Stranger > Family	$U = 343, Z = 2.68, p < 0.01, r = 0.40$
Credible	News Media > Family	$U = 307.5, Z = 2.51, p < 0.01, r = 0.39$
Credible	No Source > Family	$U = 359, Z = 2.42, p < 0.01, r = 0.36$
Credible	Journalist > Friend	$U = 358, Z = 2.40, p < 0.01, r = 0.35$
Fake	Journalist > Family	$U = 394.5, Z = 3.01, p < 0.01, r = 0.44$
Fake	News Media > Family	$U = 313.5, Z = 2.74, p < 0.01, r = 0.42$
Fake	No Source > Family	$U = 356, Z = 2.43, p < 0.01, r = 0.36$
Fake	Journalist > Friend	$U = 381, Z = 3.14, p < 0.001, r = 0.46$
Fake	News Media > Friend	$U = 304, Z = 2.91, p < 0.01, r = 0.45$
Fake	No source > Friend	$U = 347, Z = 2.64, p < 0.01, r = 0.39$
Fake	Strangers > Friend	$U = 304, Z = 2.28, p < 0.05, r = 0.35$