Sharing Falsehoods in an Information-poor Environment: An Experiment with Adolescents in Rural India*

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Abstract

Misinformation can have severe consequences, especially among populations with low levels of digital literacy, education, and access to technology. A large body of literature looks at interventions to counter misinformation, but we know less about the message-level attributes that make particular pieces of information attractive. In this study, we field an in-person survey in Bihar, India, with a sample of over 6,000 adolescents to determine what factors influence the sharing of (mis)information. Using a conjoint design that randomizes a piece of information's topic, veracity, transmitter identity, original source, and social endorsement – each in an online or offline setting with an effective sample size of $\approx$ 36,000 profiles – our study reveals three key findings. First, respondents relied on source and social endorsement when deciding what information to share and shared true claims more than false claims. Second, results revealed a bias against Muslim transmitters of information, with (mis)information originating from Muslim transmitters being shared (by our majority Hindu sample) at significantly lower levels. Finally, while social endorsement plays a significant role in information sharing, its impact varies between online and offline settings, with controversial information being shared at higher rates and both mostly rejected and endorsed statements being shared at lower rates in-person compared to online. These results demonstrate that religious biases can extend to information processing and that whether information is received and shared in an online or offline context can significantly alter how information attributes affect sharing. Focusing on less privileged populations in terms of access to information and digital connectivity can reveal striking findings.

Keywords: Misinformation, Vignette Experiment, India, Sharing Behavior

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1 Introduction

Misinformation continues to be a critical threat to public health and democratic governance worldwide. Over the past decade, a large body of literature has accordingly investigated the psychological factors that drive individuals to share, believe, and accept misinformation (Pennycook and Rand, 2021; Ecker et al., 2022).

Yet, because this literature focuses almost exclusively on *Western* and *online* contexts, substantial gaps remain in our understanding of the message-level attributes that make particular pieces of misinformation more or less attractive. While there is a substantial literature on source credibility (Bauer and Clemm Von Hohenberg, 2021; Berinsky, 2023; Wittenberg et al., 2023), its focuses on Western contexts leads scholars to conceive of sources as news outlets and/or platforms, and highlights partisanship or ideology as a primary factor driving the assessment of misinformation. This may not be adequate in information-poor environment in which information sources are relatively unlikely to be news outlet, and in which partisanship plays a less central role. Moreover, existing research, when it does address the Global South, often skews towards the relatively affluent and connected segments of these societies, thereby overlooking the experiences of a vast majority whose access to information is more limited and representative of the median person in many parts of the world (Badrinathan and Chauchard, 2024; Blair et al., 2024).

Very little is in fact known about potential drivers of misinformation in such information-poor environments. As noted in Blair et al. (2023), perceived social norms, the identity of the individual from whom information is received (hereafter, the *transmitter*), as well as the forum in which this sharing takes place are all likely to influence sharing decisions in such contexts, and the importance of these contextual factors relative to that of content and source may be different from what is observed in the handful of countries in the Global North in which existing research has taken place. The weakness of misinformation research on the Global South additionally implies that little is known about *offline* (mis)information transmission, and that scholarship has not compared whether the determinants of (mis)information transmission differ across online and offline settings. As large populations of Global South users are increasingly and quickly transitioning from offline to online sources, comparing information transmission in offline and online settings, among users who switch between both - such as partly online adolescents - seems crucial.

We address these gaps through a vignette experiment in Bihar, India. We field an in-person survey in Bihar with a sample of $\approx$ 6,000 teenagers aged 13 to 18. Our sample is expansive; it is drawn from 583 villages across the state and constitutes a representative sample of the rural school-going adolescent population aged 13-18. By centering our analysis on teenagers, we not only capture a demographic that is more emblematic of the global median in terms of information access and digital connectivity but also reverse the trend of focusing on the most privileged.

To compare online and offline sharing decisions systematically, we use a vignette experiment that independently randomizes a piece of information's topic (politics, vaccines, health, science), veracity (true, false), transmitter identity (Hindu stranger, Muslim stranger, local doctor, community leader, relative), cited original medium (reputable newspaper, government, social media, no source cue), and perceived social endorsement based on others' reactions (endorsed, controversial, rejected). We implement a forced-choice outcome measure by asking respondents which piece of news they would be more inclined to share in hypothetical online or offline settings. In doing so we can causally estimate the marginal effect of each attribute level on sharing intentions, further comparing these marginal component effects (AMCEs) between the online versus offline settings.

We outline three key findings. First, respondents relied on source and social endorsement when deciding what information to share, and shared true claims more than false claims, with true statements being 9 percentage points more likely to be shared relative to false statements. Second, the results revealed a bias against minority (Muslim) transmitters of information but not majority (Hindu) transmitters: respondents were significantly less likely to share information coming from a Muslim source on average. However on interacting source with veracity, we find that Muslim sources are penalized more severely for disseminating false information, while Hindu sources are not. Finally, while social endorsement plays a significant role in information sharing, its impact varies between online and offline settings. Respondents share controversial statements more often and statements in which there is wide agreement or disagreement less often in-person compared to online.

This experiment is embedded in an in-person survey of $\approx$ 6,000 adolescents in Bihar, India. Leveraging the sample and context of this in-person sample provides several advantages. First, the very large sample size of 6,000 adolescents — each of which evaluates a total of 6 profiles, leading to an effective sample size of $\approx$ 36,000 profiles — allows for precise estimation of even small effect sizes, as well as leverage to investigate subgroup effects based on multiple, cross-cutting identities that respondents may have, such as religion, caste, gender, and partisan identity. Second, focusing on adolescents in a hard-to-reach, largely offline population with lower digital literacy provides an important yet understudied perspective, complementing prior work that has largely been conducted with Western adult samples in online settings. The scale and context provide a unique opportunity to rigorously investigate drivers of misinformation transmission among youth in a region grappling with significant misinformation challenges.

Our study yields several contributions. First, by pitching message-level drivers of virality against each other in the vignette experiment, we are able to study their comparative importance for influencing sharing behavior in the population of interest.[1] Second, much existing work relies on self-reported measures whereas our forced-choice design better recreates naturalistic sharing decisions involving tradeoffs. Third, rather than focusing exclusively on online transmission, we also study offline interpersonal sharing which remains the predominant transmission mode for rumor and misinformation in developing countries despite increasing technology penetration. Finally, the comparative online/offline approach allows testing theoretical perspectives on how contextual factors shape social transmission and persuasion processes. Our study contributes to and expands the body of work seeking to understand citizens' choices around misinformation spread and consumption outside of Western countries (Blair et al., 2024). Simultaneously it also speaks to research on news avoidance (Toff and Kalogeropoulos, 2020) and selective exposure (Eady et al., 2019) in American politics, while also contributing to the literature on the effect of coethnicity or religious ties in comparative politics (Habyarimana et al., 2009; Chauchard, 2016).

[1] We note a single exception in the literature: Mukerjee and Yang (2021) use a vignette design to look at the effects of different cues on information consumption. However, their paper focuses on the US context, online platforms, and manipulates only source, headline, and endorsement cues.

2 Theoretical Expectations

A large body of work focuses on why citizens consume and share misinformation online. This includes work trying to identify the volume of misinformation diffusion (Allcott, Gentzkow, and Yu, 2019) and the reasons for its spread. On the latter, results from studies across contexts and disciplines suggest that people share information to gain attention online (Agarwal et al., 2023) and tend to overlook its accuracy when doing so (Globig and Sharot, 2024). Certain populations — such as the elderly — may be vulnerable to sharing misinformation out of a need to mitigate loneliness or meet social goals (Brashier and Schacter, 2020). Further, cognitive biases such as confirmation bias and motivated reasoning may make identity-congruent information, regardless of its veracity, more attractive than the truth (Kahan et al., 2017). Thus, across a range of studies, there is some consensus that the structure of societal cleavages and social networks makes it easy for misinformation to spread.

However, much of this existing literature on misinformation and news choice focuses predominantly on developed contexts (Blair et al., 2024), and as such, on contexts in which exposure to misinformation is largely construed of as an online phenomenon. Further, and importantly, in identifying the causal effects of different variables on misinformation sharing, existing work has manipulated one or many variables in a factorial experimental design. For example, studies that seek to identify the effect of partisanship on misinformation sharing often experimentally vary the partisan slant of news headlines, and then measure as dependent variable a respondent's intention to share that headline (see for example Pennycook and Rand (2019)). In reality, however, citizens are taking into account a number of cues and attributes while choosing to share information - while partisan slant may be one of them, the source of the information, the environment they encounter it in, the level of social endorsement it has all likely play a role in decisions regarding sharing information. Manipulating only one or two of these variables means that we are ignoring a host of other factors that citizens taking into account; further, manipulating a few variables might mean that citizens are imputing information about missing variables.

To solve both these issues, we (1) undertake a vignette experiment that simultaneously manipulates a number of cues that are present while respondents make decisions about whether or not to share misinformation and (2) focus on the state of Bihar, India, highlighting responses from a largely rural and less privileged population. Developing countries possess distinct characteristics that influence information processing and consumption in ways that differ significantly from those in developed nations. First, low state capacity in these regions often hinders governments' ability to secure citizen compliance with official directives, such as vaccination campaigns (Lee, 2019). This also implies that official information sources may be unreliable or inconsistently accessible. For example, if information about vaccines is conveyed through government posters, individuals will only access this information if they happen to frequent areas where such posters are displayed. Second, this situation fosters a reliance on informal networks, including friends, family, and community-based sources, where information is disseminated through word of mouth, social cohesion, and rumors (Gadjanova, Lynch, and Saibu, 2022). Third, the platforms utilized in these regions differ considerably from those in developed countries. The absence of widely-used public platforms like Facebook and Twitter means that encrypted platforms are often the primary channels of information dissemination (Valeriani and Vaccari, 2018). Fourth, in some cases, the information ecosystems in developing countries are deteriorating. This is particularly evident in contexts like India, where media capture by authoritarian forces results in a scarcity of trustworthy official news sources, with most outlets aligned with the state (Aneez et al., 2019).

Given that most misinformation studies are centered on Western contexts, they often overlook these specific scope conditions that shape information processing in the rest of the world (Badrinathan and Chauchard, 2024). Therefore, in our research design, we prioritize factors that have been neglected in the literature thus far. Specifically, we examine not only the original source of information but also the transmitter, varying the transmitter to highlight differences in religion, ethnicity, local elites, and social distance. Additionally, we emphasize the role of social norms that may influence information sharing in more community-oriented or collectivistic cultures.

In sum, our experiment relies on a vignette design, where we separately randomize four classes of attributes — topic, veracity, source attributes, and perceived social norms – that we theorize work in conjunction to shape selection and sharing misinformation. The following sections elaborate on each of these attributes in detail.

2.1 Source credibility

First we vary information about the **source attributes** of each story. This includes both the original source of information as well as the transmitter sharing this content. Existing work on misinformation sharing largely conceptualizes of sources as creators of information, focusing on platforms or news outlets as supply-side producers of content. Consequently, this work has neglected transmitters of misinformation. We conceive of transmitters as not those who create information but those who pass it on and aid in its spread. Focusing on transmitters is especially crucial in developing country contexts that rely on platforms like WhatsApp where it is close to impossible to trace the original creator of a message (Badrinathan, 2021). Further, in contexts like India, where collectivistic cultures prevail and significant value is placed on relationships with family, kin, and neighbors (Singh, 2005), it becomes crucial to differentiate between the original source of a message (such as a TV channel) and the sender (such as a relative). The same message may be trusted and disseminated in markedly different ways depending on whether it is received from a stranger or a family member.

In addition, when the transmitter is a stranger, we anticipate that the demographic identity of that stranger plays a significant role. In contexts like India, religious identity often forms the foundation of social life, political mobilization, and community dynamics (Chhibber and Verma, 2018a; Brass, 2005). Villages and communities, particularly in rural areas like our study context, are frequently organized along religious lines. Religion has long served as a cleavage in the country, contributing to division, polarization, and even violence (Chandra, 2004; Jaffrelot, 2021). Therefore, understanding whether religious coethnicity influences the sharing of misinformation is crucial for our analysis.

We expect that the credibility of sources matters in determining whether or not to share information. In line with previous literature (Bauer and Clemm Von Hohenberg, 2021; Berinsky, 2023; Traberg and Van Der Linden, 2022; Wittenberg et al., 2023), we hypothesize that credible sources are perceived as more trustworthy, thereby affecting whether information is believed and shared. In our conjoint, this attribute has two levels that indicate sources with higher credibility (government agencies and a credible daily newspaper, the Times of India) and two levels that indicate low credibility (social media, and not having any information about the source).

Accordingly, we hypothesize:

Hypothesis 1 *Information attributed to high-credibility sources (quality newspapers and government agencies) is more likely to be shared than information from low credibility sources (social media or no cited source).*

Similar to source credibility, we also expect that the transmitter via whom respondents receive information matters for decisions about sharing. This attribute has 5 levels intended to signify different levels of social distance and trustworthiness, including two trusted community transmitters (local doctors, or community leaders), a relative or family member, and strangers. Further, when the transmitter is a stranger, we also vary whether they are Hindu or Muslim by varying their name as a signal.

We purposely opted not to vary the partisan identity of either the transmitter or the source of news for two main reasons. First, our respondents are aged 13-18, so they are unlikely to have adopted fully formed partisan identities that could act as a potential source cue. Furthermore, in the Indian context, evidence on the role of partisanship as a pivotal identity is mixed. India's party system is not historically viewed as ideologically structured: parties are not institutionalized (Chhibber, Jensenius, and Suryanarayan, 2014), elections are highly volatile (Heath, 2005), and the party system itself is not ideological (Chandra, 2007; Kitschelt and Wilkinson, 2007). On the other hand, India is a country where religion has long been the basis for political mobilization and the formation of political parties (Chhibber and Verma, 2018b; Brass, 2005). More recently, religious cleavages have resulted in riots as well as vigilante violence in the country, often fueled by misperceptions and rumors (Wilkinson, 2006; Banaji et al., 2019). Hence we opted to focus on religion as the main identity cleavage of interest. Accordingly, we hypothesize:

Hypothesis 2a *Information transmitted by trusted authorities (local doctors, community leaders) is more likely to be shared than information transmitted by strangers.*

Hypothesis 2b *Information transmitted by in-group strangers is more likely to be shared than information transmitted by out-group strangers.*

2.2 Social norms

Next we randomize the perception of social norms. Our goal with this attribute was to vary levels of social endorsement or controversy attached to a news story, thereby highlighting important bandwagon dynamics that might affect the spread of misinformation (Roozenbeek et al., 2020). Specifically, we indicate whether "most people agreed", "most disagreed" or "some agreed, some disagreed" with the statements, reflecting consensus or lack thereof. We hope to understand by varying this attribute how the "common knowledge" aspect of misinformation – that they might derive power from social circulation – affects sharing. The literature and social norms predicts that information that is perceived to be widely believed will be more likely to be shared Tankard and Paluck (2016). Beyond attributes of information itself, perceptions that ideas are socially endorsed provide a descriptive norm that signals validity through consensus. Thus, we hypothesize:

Hypothesis 3 *Information that is perceived to be widely endorsed is shared at higher rates than information that is perceived to be controversial or widely rejected.*

2.3 Veracity

Next, the veracity of a piece of information itself can affect sharing intentions. We included a total of 16 statements in our study, balanced on veracity. We made sure to include statements that were equally salient across a range of topics, and chose false statements with expert consensus that they were factually incorrect.

On one hand, some research shows that false information often spreads farther than true information. For instance, Vosoughi, Roy, and Aral (2018a, p. 1146) analyze tweets by more than 3 million people to find that "[f]alsehood diffused significantly farther, faster, deeper, and more broadly than the truth in all categories of information." On the other hand, Cinelli et al. (2020) find that information from reliable and unreliable sources is not shared at different rates. Guess, Nagler, and Tucker (2019) find that sharing misinformation during the 2016 U.S. presidential campaign was a relatively rare activity. They also find a strong age effect, with those over 65 sharing about 7 times as many fake news articles than the youngest age group, which is relevant for this study since our target population is comprised of adolescents in a low-information environment. Since most existing research finds mixed evidence for the independent effect of veracity on sharing behavior, and since this existing research primarily centers around online sharing behavior in Western contexts, we do not have clear theoretical expectations about the direction of the effect of veracity on sharing intentions. Therefore, we hypothesize:

Hypothesis 4 *All else equal, veracity affects sharing behavior.*

2.4 Topic of story

Finally, we vary the **topic** of each story. We select four different topics designed to cover a range of news stories; these include politics, vaccine safety debates, health and medicine, and science communication (Baumann et al., 2020; Tucker et al., 2018). While we do not hypothesize about the independent effects of each topic, previous work does show that topic characteristics like emotionality and arousal value can increase sharing (Berger and Milkman, 2012). Furthermore, sensitive topics dealing with moral values are more likely to spread in homophilous networks (Litt, 2012).

2.5 Online vs. Offline Sharing

Beyond specific attributes inherent to messages, the context within which information is encountered represents an additional layer influencing information processing and sharing (Hansen et al., 2011; Lazer et al., 2018). Existing research concerning the consumption and propagation of misinformation commonly assumes the context as a static backdrop, presuming that information exchange and processing primarily occur in online domains. Consequently, there exists an underestimation of the significance of non-online dialogues and spaces. Moreover, in developing countries, existing scholarship underscores the primacy of offline spheres (Oh, Agrawal, and Rao, 2013; Scott, Stuart, and Barber, 2022). This predominance is likely attributable to the communal and collectivist cultures characterizing these settings, compounded by often densely populated neighborhoods and towns. Offline contexts, characterized by interpersonal discussions with acquaintances and communal gatherings, including information consumption venues such as marketplaces and village hubs, assume paramount importance in such contexts. Such settings might provide a richer capacity to gauge validity of information, through nonverbal signals unavailable online potentially discouraging transmission of false rumors compared to cycles of automatic re-sharing on social media (Kahai and Cooper, 2003; Vosoughi, Roy, and Aral, 2018a). Meanwhile, when bandwagon pressures strongly endorse certain ideas offline, individuals conform through descriptive norms exceeding polarized attitudes amplified online instead (Centola, 2018). Hence, contextual attributes pose tradeoffs interacting with message and source-characteristics (Southwell, 2013).

Furthermore, for India specifically, citizens still rely on traditional media platforms such as television and newspapers to a larger extent as opposed to social media channels. For instance, in Bihar, statistical data from the Telecom Regulatory Authority of India (TRAI) reveals that merely one-third of households possess internet connectivity, and internet access for teens is expected to be even lower as households often share one phone that is mostly operated by the head of the household. Consequently, the exploration of offline communication channels emerges as a pivotal and indispensable endeavor. Absent such investigation, a fundamental variable of information processing within developing contexts would remain unexplored and inadequately understood. Our vignette design orthogonally randomizes attributes across priming online and offline settings, thereby shedding light on these dynamics.

3 Research Design

To answer our research question, we field an in-person conjoint experiment in Bihar, India (analyses pre-registered at OSF). Data collection for the study took place in two rounds. First, a recruitment and baseline survey was conducted in September-October 2023. This survey collected data on students from nearly 600 villages across 32 districts of the state of Bihar, India's third most populous state, with over 127 million inhabitants. Consequently, we are able to sample a primarily rural population, where dynamics of information sharing are understudied. Within each village, we targeted about 20 to 24 households, requiring that each household have a school-going child between the ages of 13 and 18. Ultimately, this allowed us to sample nearly 14,000 adolescents across the state. Enumerators re-visited baseline households in March-April 2024 to field the vignette experiment to a random half of the initial sampled households, meaning that 5977 respondents were a part of the current study, accounting for some attrition. The study took place face-to-face and the entire experiment was conducted in Hindi. Sampling strategy and household selection is detailed in Appendix A[2]. The composition of the final sample is detailed in Table 2.

3.1 Vignette Experiment

To estimate the causal effects of characteristics of hypothetical pieces of information on sharing intentions and to test whether key attributes have differential marginal effects in online versus offline settings, we utilize a forced-choice vignette experiment. To compare the determinants of online and offline sharing, we first randomize respondents into one of two conditions:

1. **Offline Sharing**: Before viewing the conjoint tasks, respondents will be primed to think about which of the two pieces of information they would rather share in an *offline* setting by prompting them to talk about an in-person meeting with people they know well.[3] Then, for each profile pair, respondents were asked *"Imagine you're meeting in person with people you know well. [. . .] Which of these two pieces of information are you more likely to share with the people you're meeting with?"*
2. **Online Sharing**: Respondents will be primed to think about sharing in online settings.[4] For each information profile pair, they will be asked to choose which piece of information they would rather share in a WhatsApp group chat: *"Imagine you're in a WhatsApp group chat with people you know well. [. . .] Which of these two pieces of information are you more likely to share with the people in the WhatsApp group chat?"*

Once respondents are randomized into the online versus offline sharing condition, we presented them with hypothetical information scenarios in a vignette setup. Within this setup, we randomize the following attributes and levels. Across four topic areas (politics, vaccines, health, and science), we vary (1) the veracity, (2) the transmitter, (3) the original source, and (4) the perceived social norms. Below we list the various attributes and their respective levels:

We randomize which of these features are associated with a given claim and measure using a forced-choice task whether propensity to share misinformation changes as a function

[2] We note here that this experiment is embedded in the endline survey of a large-scale media literacy RCT. Consequently, sampling strategy for the study was also determined by the sample for the RCT. Crucially, we underscore that our randomization for the experiment is independent of the RCT treatment assignment. We describe sampling more closely in Appendix A.

[3] The exact wording for the priming question is: "Imagine you're meeting in person with people you know well, for example at a family gathering or a meeting with friends after school. In your experience, what kinds of things do people talk about in such situations?"

[4] The exact priming question wording is: "Imagine you are in an online group chat, for example on WhatsApp. In your experience, what kinds of things do people share in such group chats?"

Table 1: Attributes and their corresponding levels.

Attribute	Levels
Topic	Politics, Vaccines, Health, Science
Veracity	True, False
Original source	Credible daily newspaper, Government agency, Social media, No source cue
Transmitter	Hindu stranger, Muslim stranger, Local doctor, Community leader, Relative
Perceived social norms	Endorsed by most peers, Rejected by most peers, Mixed social acceptance

of the characteristics of a given claim. Instead of presenting the claims in a standard conjoint table, we present respondents with vignette scenarios to increase realism. As an example, a true statement about politics, shared from a Hindu stranger, seen in a credible newspaper and endorsed by many in the *offline* condition reads (randomized attributes in **bold**):

> ***Someone named Rajesh*** *told you in person that* ***the voting age in India is 18****. They saw this news in* ***The Times of India****.* ***Among those who were around when he said this news****,* ***most people agreed*** *with Rajesh.*

An example of a false statement about vaccines, shared by a relative, seen on social media and rejected by most in the *online* condition reads:

> ***A respected village elder*** *posted a link on WhatsApp* ***to a YouTube video*** *saying that* ***vaccines can lead to childhood asthma****.* ***Among those in the group chat****,* ***most people disagreed*** *with the village elder.*

After being randomized into either the online or offline condition, each respondent is asked to choose which pieces of information they would be more likely to share for three sets of profile pairs. True and false statements across the four issue domains were selected to be relevant to the context and in consultation with our local implementation partners. A full list is included in Appendix B. It should be noted that we tried to ensure that all statements were comparable in their relevance and in the language they used.

Table 2: Sample Descriptives

Variable	**Level**	**Samples** **Offline Condition**	 **Online Condition**	 **Full Sample**
Total (n)		3023	2954	5977
Class	(mean)	9.57 (1.27)	9.63 (1.28)	9.6 (1.28)
Religion	Hindu	2747 (90.9%)	2670 (90.4%)	5417 (90.6%)
	Muslim	264 (8.7%)	275 (9.3%)	539 (9%)
Gender	Male	1222 (40.4%)	1210 (41%)	2432 (40.7%)
	Female	1801 (59.6%)	1744 (59%)	3545 (59.3%)
Caste	GEN	234 (7.7%)	233 (7.9%)	467 (7.8%)
	OBC/EBC	2084 (68.9%)	2028 (68.7%)	4112 (68.8%)
	SC	589 (19.5%)	586 (19.8%)	1175 (19.7%)
	ST	66 (2.2%)	61 (2.1%)	127 (2.1%)
School	Government	2909 (96.2%)	2857 (96.7%)	5766 (96.5%)
	Private	112 (3.7%)	89 (3%)	201 (3.4%)
	Other	1 (0%)	8 (0.3%)	9 (0.2%)

Given the unique context of sampling adolescents in a developing context who predominantly lack access to phones, the design choices we made were carefully crafted to ensure the accessibility of our research to this population. First, our experiment was administered entirely offline and in face-to-face settings. This approach necessitated innovation in how we presented the attributes. Instead of the standard conjoint format, where attributes are listed individually, we developed short vignette scenarios that incorporated randomized attribute levels, designed to be read as cohesive paragraphs of information, resembling story narration. Enumerators read these vignettes aloud to the students, making a significant portion of our fieldwork focused on training the enumerators. The training emphasized reading in a manner that was both comprehensible and balanced, avoiding any undue emphasis on specific content. Finally, another innovative aspect of our approach was to prime participants with both online and offline scenarios at the outset, enhancing the contextual relevance of the study.

4 Results

To measure the overall effect of different attribute levels on sharing intentions, the main estimand of interest is the average marginal component effect (AMCE) of a change in the value of one of the attributes, relative to the reference category, on the probability that the information profile is preferred. The key outcome measure for each information profile is a binary indicator that measures whether the information was selected for sharing by the individual. To estimate the AMCE, we use ordinary least squares (OLS) regression with standard errors clustered at the level of the respondent and regress the dependent variable on factor variables that indicate the different levels for each attribute, with standard errors clustered at the respondent level. Results from our the baseline specification are presented in Figure 1.[5]

We first look at the veracity of statements, i.e., how likely respondents were to focus on accuracy when deciding what information to share. We find that respondents are significantly more likely to share true statements than false ones. Specifically, true statements are shared 9 percentage points more often than false statements, and this difference is larger for respondents

[5]Marginal means shown in Appendix C.

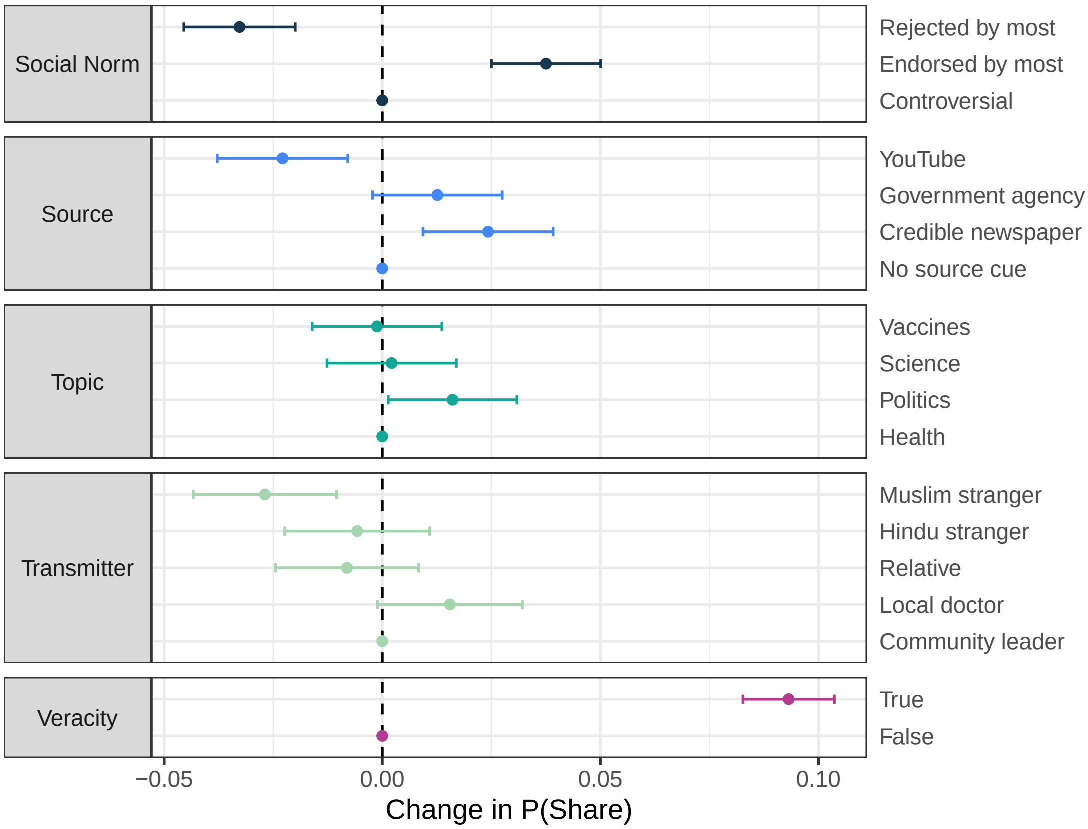

Figure 1: Main Effects of Different Attributes on Sharing

whose pre-treatment ability to discern true from false information is above the sample median (11.5 points) and smaller for those performing below (7.1 points), as Figure 6 in Appendix C shows. This finding is important for several reasons. While we cannot exclude more nuanced explanations,[6] this suggests that, across various topics, sources, and message characteristics, respondents in our sample distinguished between true and false messages and subsequently expressed a lower likelihood of sharing information that they assessed as false. A substantial body of literature on misinformation suggests that personal biases, such as motivated reasoning and identity-protective cognition, can impair judgment, leading individuals to prioritize messages that align with their prior beliefs over those that are accurate (Taber and Lodge, 2006; Kahan

[6]False headlines may for instance have differed from true ones on a dimension other than veracity, for instance potential for entertainment.

et al., 2017). Additionally, other research has indicated that false messages tend to spread more rapidly than true ones (Vosoughi, Roy, and Aral, 2018b). However, our findings reveal that in a context where respondents must consider not only accuracy but also other factors, they still exhibit a preference for sharing true messages over false ones.

Importantly, we did not intervene to enhance their ability to identify or share true messages—for example, by emphasizing accuracy or providing fact checks for these stories (Pennycook and Rand, 2019; Porter and Wood, 2019). Moreover, the use of multiple attributes in a vignette design effectively obscures researcher intentions, reducing the likelihood that respondents reported a preference for true statements due to social desirability bias. To investigate under which circumstances misinformation will be shared over true information, we subset our sample to choice-pairs in which (1) one piece of information was true and the other false, and (2) the latter was chosen over the former. Figure 7 in Appendix C plots the marginal means or the $\mathbb{P}(\text{False}|\text{False chosen over True})$ among this subset of the data. When false information was chosen over true, the false piece of information was significantly more likely to display positive non-veracity reliability cues — such as positive social norms, credible sources, or credible transmitters — and less likely to display negative reliability cues, such as negative social norms or negative source cues. This suggests a substitution effect: falsehoods may be shared over true information when the false information is nested in positive non-veracity reliability cues.

Finally, we examine interaction effects between veracity and other attributes: source credibility, transmitter identity, and social norms. The average marginal interaction effects are precisely estimated as null in all cases. This suggests that the perceived veracity of the information is a significant determinant of sharing behavior, regardless of other factors that might typically influence perceptions of trustworthiness (see Appendix C).

By contrast, we find that the topic of news stories does not significantly influence sharing intentions. Compared to the reference group (health), statements about politics are shared more frequently, but the effect size is small. This finding aligns with some existing research that suggests political news or more controversial topics are more likely to be shared.

Next, we find that respondents place significant value on social norms related to information sharing, particularly norms of endorsement—whether information is widely believed or rejected by peers. Respondents exhibit preferences accordingly: they are less likely to share information that is rejected by a majority and more likely to share information that is endorsed by a majority, compared to information that lacks consensus. This finding aligns with existing research on group norms and the perceived validity of information, showing that sharing misinformation can derive from what others think is acceptable and valid in a given context (Tankard and Paluck, 2016; Chauchard and Badrinathan, 2024). In previous work, social endorsement is shown to not only be a significant determinant of news choice, but that it can be strong enough to offset the effect of potential partisan cues (Messing and Westwood, 2014; Anspach, 2017).

Next, we observe that both the source and the transmitter of information do indeed condition and influence intentions to share. As hypothesized, less credible sources, such as YouTube, are less likely to be shared. Conversely, more credible sources, such as news from a government agency or a reputable newspaper, are more likely to be shared compared to situations where no source cues are provided. Interestingly, our findings indicate that respondents consider not only the source but also the transmitter of the information. For example, statements from local doctors are shared significantly more often than those from the reference category (community leader). While we do not detect significant effects based on the social distance from or familiarity with the sender (e.g., a relative is no more likely to prompt sharing than a stranger), we do find that the identity of the stranger matters.

In particular, we find that overall, respondents penalize information coming from Muslim strangers – when the transmitter has a Muslim name, respondents are significantly less likely to share the information. It is important to note that our sample consists of over 90% Hindus and only 9% Muslims, reflecting the demographics of the state of Bihar. Thus for the majority of respondents, a Muslim name signifies the outgroup, while a Hindu name represents the ingroup. Breaking down the sample by ethnicity, we see that among Hindu respondents, statements transmitted by Muslim strangers are shared significantly less often, while among Muslim respondents, statements by Muslims are shared significantly *more* often. Statements by a Hindu stranger are no more or less likely to be shared among both subgroups (Figure 9 in Appendix D). Interestingly, the overall sharing penalty for outgroup transmitters only persists among members of the majority Hindu population; Muslim respondents are no less likely to share statements transmitted by Hindu strangers. This result is crucial because it highlights that religious biases, which are pervasive in India across various domains – manifesting in discrimination, extrajudicial violence, and the stereotyping of the Muslim community (Jaffrelot, 2021) – also extend to information processing. Particularly striking is the fact that even our sample of adolescents exhibit these biases, indicating that these prejudices emerge early in the life cycle and may be resistant to change.

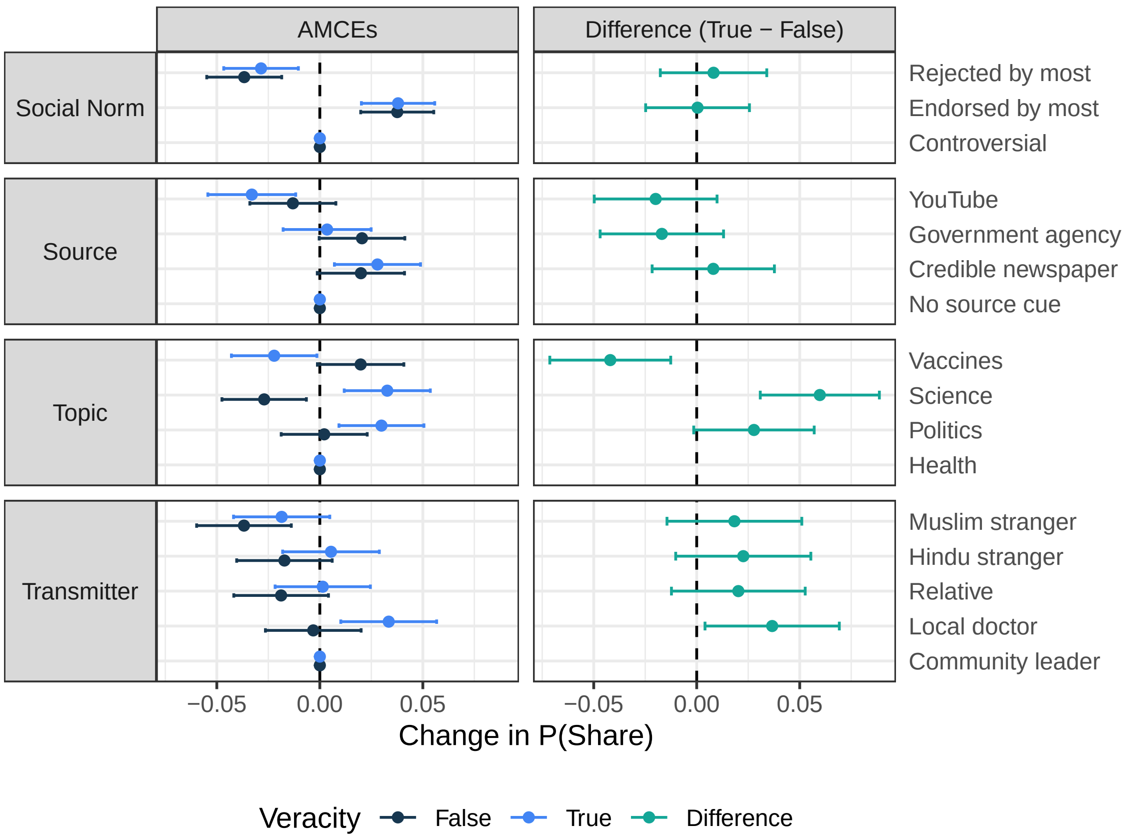

Figure 2: AMCE by Veracity

Interventions aimed at countering misinformation should therefore consider not only the veracity and accuracy of information but also the identity of the sender and the alignment of identities between the sender and receiver, especially in contexts where identities are polarized (Gottlieb, Adida, and Moussa, 2022). In our study, we did not vary the topics of the stories to include discussions of specific political or religious groups; while the stories were political, they did not favor any particular party. Yet, respondents were still less likely to share these stories when they were transmitted by members of the outgroup. This suggests that information from news elites, media, or politicians, even if credible, will be valued less if the identities of the sender and receiver are unaligned. To investigate this further, we examine the AMCE broken down by statement veracity to determine if true versus false statements are shared at different rates depending on the identity of the transmitter (Figure 2). We find that the sharing penalty for transmitters with a Muslim name is significant only for false statements, although the coefficient remains negative for true statements as well. The difference between true and false statements is not however statistically significant.

This finding demonstrates that respondents consider both the veracity of the statements and the identity of the transmitters when deciding whether to share information. However, when transmitters with Muslim names share false content, they are penalized, but this penalty does not apply when they share true content. On the other hand, when transmitters with non-Muslim names (in this case, those with Hindu names) share false content, they do not face a similar penalty, suggesting that respondents overlook veracity when the sender has a favorable co-ethnic identity.

Next, we examine whether the medium through which information is received – online or offline – affects sharing behavior. To assess this, we first trained random forest models on our data and extracted the importance of each attribute in affecting sharing behavior. Figure 3 displays estimates of variable importance[7] from our random forest model, including bootstrapped standard errors. Across both conditions, we find that veracity is the most important predictor for whether a piece of information is shared or not. However, veracity is significantly more important when sharing information online. We corroborate this finding using another commonly used estimate of attribute importance in conjoints: the maximum absolute difference between the attribute level with the lowest and highest marginal means within a certain attribute. In Figure 4, we show that on average, false information is shared at a lower rate and true information at a higher rate in the online compared to the offline condition. Conversely, both the transmitter and source of a piece of information seem to matter more offline than they do online, suggesting that offline information sharing might be less affected by veracity and more by contextual cues,

[7]IncNodePurity (*Increase in Node Purity*) refers to a measure of variable importance in random forest models. It quantifies the improvement or 'purity' increase in the decision nodes for each split that a particular variable contributes to within the forest.

such as identity of the transmitter and the perceived credibility of the source. Furthermore, in online environments, where information is more readily accessible and sharable, respondents might place a higher emphasis on the veracity of information, possibly due to the public nature of online sharing and the potential for wider scrutiny.

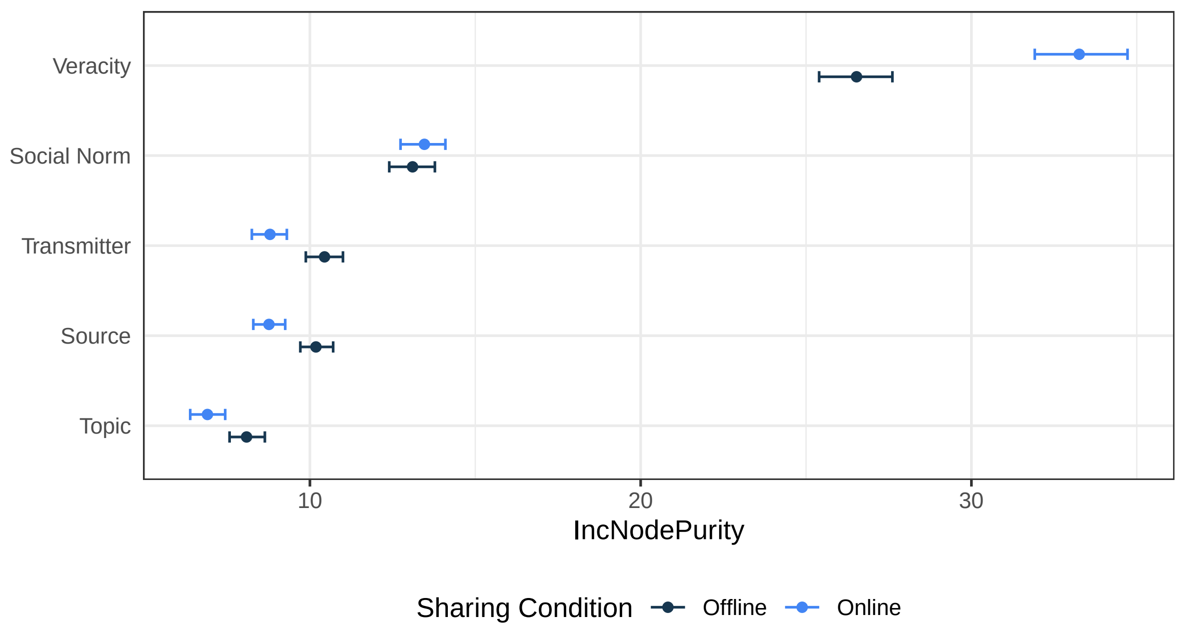

Figure 3: Attribute Importance across Sharing Conditions

Across both conditions, we find that perceived social norms are the second most important determinant of sharing behavior. However, Figure 4 suggests that social norms matter in different ways online than they do offline. Positive social norm cues (indicating that a message is endorsed by most) increased the probability of sharing across both conditions, although more so online than offline. Conversely, negative social norm cues (indicating that a message is rejected by most) decrease sharing probability but more so offline compared to online. Social norms cues that suggest a piece of information is controversial (having mixed but polarizing opinions) lead to drastically different sharing behavior online versus offline: online, controversial statements are shared at significantly lower rates, while online, the opposite is true, providing an important point of contrast to other studies that find that the anonymity and distance afforded by online platforms may allow individuals to share unpopular or widely rejected information with less concern for their reputation (Gurgun et al., 2023; Asenbaum, 2018). In online spaces, sharing controversial content can lead to public backlash or social penalties, as online platforms often involve interactions with a mix of ingroup and outgroup members. The fear of sparking debates or attracting negative attention may deter individuals from sharing controversial statements online. This aversion to controversy might explain why controversial statements are shared at significantly lower rates online. Offline, however, the opposite may be true. In more private settings, people feel more comfortable engaging in discussions around controversial topics, particularly if they are within a trusted group of friends or acquaintances. In these settings, controversial content can be shared more freely as it can spark interesting discussions or debates without the same level of public scrutiny or fear of social sanctions.

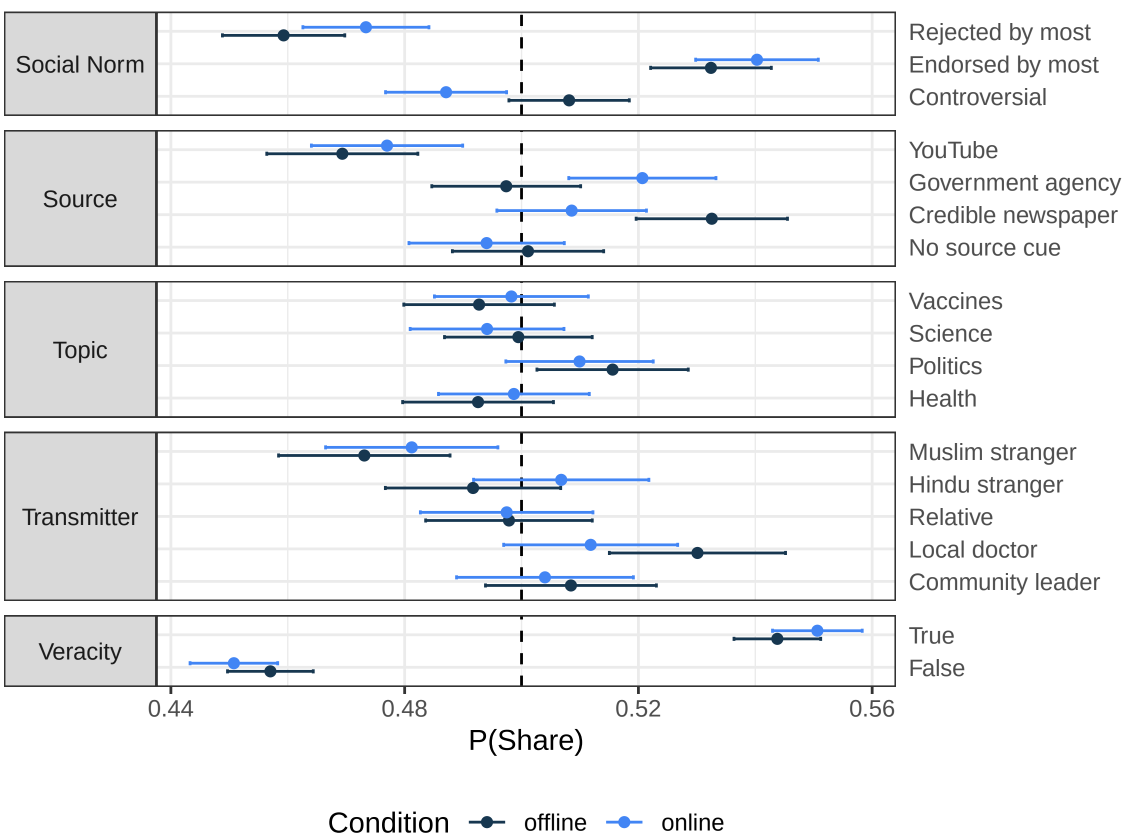

Figure 4: MMs by Online and Offline Sharing Condition

In sum, in the online environment, respondents place considerable emphasis on whether a message is widely endorsed, which is consistent with findings from other studies in the field (Messing and Westwood, 2014). However, in offline settings, respondents place greater importance on whether a message is widely rejected, a factor that seems to be less influential in online contexts. This difference likely stems from the anonymity and distance afforded by online platforms, which may allow individuals to share unpopular or widely rejected information with less concern for their reputation (Asenbaum, 2018). In contrast, in offline settings — where social interactions are more personal and reputations are more at stake — sharing unpopular information could negatively impact one's standing within the community. These results underscore the importance of considering the context or platform through which information is shared. They also highlight that in close-knit communities like those we study, factors beyond veracity or source play a crucial role in determining whether rumors spread through word of mouth.

Finally, we also find that the effect of non-credible sources is significantly reduced when the information is perceived to be widely socially endorsed. Similarly, the impact of source credibility diminishes when the statement is broadly rejected by most. This suggests that social norms may play a more critical role in influencing sharing behavior than source credibility; it is only when social norms are ambiguous or inconclusive that source credibility begins to exert a stronger influence on whether information is shared (see Appendix D).

5 Discussion and Conclusion

In this paper, we conducted an in-person study with over 6,000 adolescents in rural areas of Bihar, India, to investigate the factors that influence individuals' decisions regarding which information to share and under what circumstances they disseminate false news. To achieve this, we employed a vignette experiment that emphasized attributes not commonly discussed in the existing literature, such as the identity of the transmitter, the online versus offline context of information sharing, alongside other factors like social endorsement, topic of the story, and source. Utilizing a forced-choice design, where respondents were presented with vignettes depicting potential news stories, we highlight three key findings. First, respondents relied on source, social endorsement, and veracity cues when deciding what information to share, with a pronounced emphasis on veracity and accuracy. Second, the results revealed a bias against Muslim transmitters of information, but not Hindu transmitters, with Muslim sources being penalized more severely for disseminating false information. Finally, while social endorsement plays a significant role in information sharing, its impact varies between online and offline settings, with controversial information being shared at higher rates and both mostly rejected and endorsed statements being shared at lower rates in-person compared to online.

These findings hold significant implications for several reasons. Theoretically, this study innovates by being, to the best of our knowledge, the first to examine news sharing within a predominantly rural population and among respondents who are not adults. This required us to consider not only different platforms but also the fact that news is primarily shared offline in this context (Gadjanova, Lynch, and Saibu, 2022), where misinformation spreads through rumors and word of mouth. Additionally, we contribute to the literature by distinguishing between the primary source of information and the transmitter through which that information is received—an aspect often conflated in previous studies, which typically treat them as the same. Practically, our findings suggest that while social norms are indeed influential (Messing and Westwood, 2014), their significance is highly context-dependent—a factor that has been largely overlooked in prior research on this topic. Moreover, our results support the widely held view that while the accuracy of information is crucial in shaping people's news-sharing choices (Pennycook and Rand, 2019), individuals also rely heavily on cues derived from the identity of the transmitters. This indicates that misinformation countermeasures should not only focus on enhancing accuracy but also incorporate strategies that address the influence of identity in the dissemination of information.

A key innovation of this work was its focus on adolescents. We pursued this sample for several reasons. First, while a significant portion of our sample currently lacks internet access, as internet connectivity expands in rural regions of India, adolescents are likely to be among the first to encounter new technologies. Thus, we aimed to capture their attitudes at this early stage of exposure. Second, existing research suggests that adolescence is a period when individuals' attitudes are particularly malleable (Jennings and Niemi, 1968). Therefore, our findings could serve as a foundation for future interventions targeting this age group. Despite prior research indicating that adolescent attitudes are less formed (Margolis, 2018), our study reveals the presence of religious bias within our sample. Although India has a long history of bias against Muslims, the fact that such attitudes are already evident among adolescents highlights how deeply entrenched these biases are. This underscores our broader argument that misinformation can arise not only from trusting inaccurate news but also from distrust of certain individuals or communities.

Despite these significant findings, we acknowledge several limitations of this study. First, because we conducted the survey in an in-person setting where enumerators interacted directly with respondents, we were unable to fully manipulate the online versus offline contexts. Ideally, participants in the online condition would have received information through online platforms, but due to logistical and safety constraints, this was not feasible. Instead, we primed participants for online and offline settings by instructing them to imagine being in a WhatsApp group or to picture an in-person interaction with acquaintances. Future research should aim to fully manipulate—rather than prime—these contexts to better assess their impact on news choices. Additionally, while we differentiated original sources in terms of social media and credible newspapers, we did not distinguish between specific types of platforms or newspapers. This decision was informed by previous research indicating that most television channels and newspapers in the region are not markedly different in their partisan orientation (Aneez et al., 2019). However, this approach may have neutralized some potential source effects (Prior, 2007), and future work should consider exploring these distinctions more thoroughly to uncover any nuanced influences on information-sharing behavior.

Despite these limitations, our findings hold significant value for research aimed at understanding when and why individuals choose to share or withhold pieces of information. They offer insights from contexts that are often understudied in political science and communication, thereby enriching our understanding of misinformation in regions beyond a small set of wealthy countries. As an extension of this work, if we can identify that effects are influenced by religious identity, it is plausible that similar effects might be observed with other intersecting identities, such as language background and caste. Through this research, we aim not only to contribute to the study of misinformation and news sharing but also to advance our understanding of the effects of coethnicity across diverse settings. Finally, our methods and design choices, which were specifically intended to reach populations that consume misinformation offline and may not have access to phones, offer a template for researchers seeking to adapt conjoint designs to offline settings. By emphasizing story narration and vignettes to randomize vignette attributes, our approach provides a flexible and effective model for conducting similar studies in contexts where digital access is limited.

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A Sampling

This vignette experiment was embedded in the endline survey of a concurrent RCT project. The sampling strategy for this study is determined by the sampling strategy of the RCT. For the RCT the unit of randomization to treatment or control was the village. Villages were selected based on their proximity to 99 library locations involved in the intervention. We describe this process below.

A.1 Village selection

To sample villages, we proceeded as follows. We first identified all villages within a radius of 3 kilometers of a library location. We restrict attention to villages in close proximity to libraries. We then selected 6 villages around each library. To do so, we proceeded in several steps:

1. **First round**: in the first round, we selected one village from each gram panchayat (GP) – the administrative unit governing villages (a gram panchayat counts several villages on average) – that lies within a 3 kilometer radius around each library. In each case, within each gram panchayat, we selected the largest village, and excluded villages with < 100 households. Depending on the number of GPs within this radius, this procedure allowed us to select 1-6 villages around a library.

2. **Second round**: in the second round, we select additional villages when the first round led to the selection of < 6 villages (this was almost always the case). In this round, we tried to minimize the number of GPs we draw the rest of the villages to be selected from (ideally selecting them from a single GP). To do so, we select the remaining villages to be selected (1-5) from as few different GPs as possible, and ideally from a single GP. Our intuition in doing so in the second round is to preserve as many of the villages we sampled in the first round - by definition, only one village per GP - from potential spillovers. As we select villages for the second round, we first target the GP that counts the largest number of selectable villages (within the 3km radius, > 100 households) after the first round, and select within it villages by population size (starting with the largest). If this does not allow us to complete our sampling of 6 villages around each library, we target the second GP that

counts the largest number of selectable villages after the first round, and so on.

If there were several GPs which have the same number of villages, we randomly selected one of these GPs. If there were two villages with the same total number of households within the GP we have selected, we randomly select one of them. In case there are fewer than 6 villages with these ”selectable” characteristics around a library, we select however many we can. Proceeding in this manner, we were ultimately able to select 583 villages around 99 libraries.

A.2 Sampling households

Within each of the 583 selected villages, we then relied on a local government representative to provide a list of students eligible for the study, based on existing household list data that the government has from voter rolls and enrolment in government programs. Initial criteria for eligibility in the study included households with children enrolled in government schools in grades 8 to 12. Once a long list of such households was generated, a representative from the study visited these households to (a) confirm that an age-eligible and school-going child was indeed present, and (b) if so, to ask whether the student as well as a parent or guardian present were interested in the study. Once students and parents agreed after this initial pitch, a shorter list (of 20 to 24) eligible and interested students was generated within each selected village.

Next, our survey team visited eligible and interested students to conduct the baseline survey, including demographic and household characteristics. Enumerators visited each house in person for the baseline survey, which included additional eligibility criteria. First, enumerators obtained official oral consent from both children as well as one parent or guardian present to conduct the baseline as well as return for an endline survey. Second, we included a one-item measure of students’ basic (second-grade) reading comprehension in Hindi. If students failed or performed badly on this item, the household in question was replaced in our sampling frame.

After students and their parents opted in, the baseline survey was completed and the final sample was generated. Ultimately, this allowed us to sample nearly 14,000 adolescents across the state. Enumerators re-visited baseline households in March-April 2024 to field the vignette experiment to a random half of the initial sampled households, meaning that approximately 6,000 respondents were a part of the current study, accounting for some attrition. The study took place face-to-face and the entire experiment was conducted in Hindi. Crucially, we underscore that our randomization for the conjoint is independent of the RCT treatment assignment.

A.3 Power analysis

Assuming an effective sample size of 36000 profiles, we are powered to detect AMCEs of 0.05 with 85% power (Schuessler and Freitag, 2020).

B Statements

Table 3: Statements categorized by topic and veracity.

Topic (veracity)	**Statement**
Politics (true)	The voting age in India is 18
Politics (true)	There are two houses of parliament (Lok Sabha and Rajya Sabha) in India
Politics (false)	The Indian President can serve an unlimited number of terms
Politics (false)	High school students have to pass a political knowledge test before graduating
Vaccines (true)	The national immunization schedule for children includes a chickenpox vaccine
Vaccines (true)	Children are recommended to receive two doses of the measles vaccine
Vaccines (false)	Vaccines can lead to childhood asthma
Vaccines (false)	The government has approved a new vaccine that makes people immune to all types of flu viruses
Health (true)	Doctors recommend regular hand washing to prevent the flu
Health (true)	Boiling water can help prevent waterborne diseases such as cholera
Health (false)	Eating spicy food can cure viral infections like the common cold
Health (false)	Standing barefoot on grass can cure diabetes
Science (true)	The earth revolves around the Sun
Science (true)	Photosynthesis in plants typically occurs during daylight hours
Science (false)	Indians invented planes 7000 years before the Wright brothers
Science (false)	Plants grow faster when they are exposed to classical music

C Additional Results on Veracity

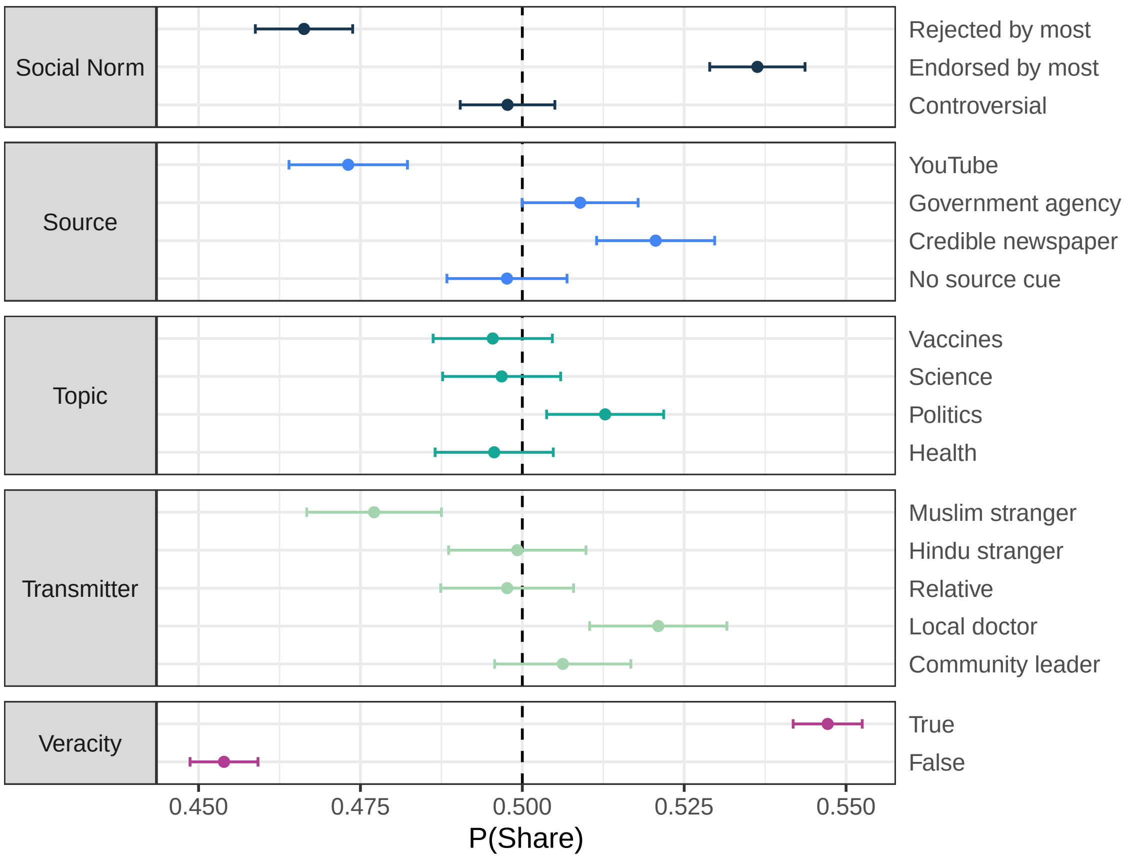

Figure 5: Main Effects Marginal Means

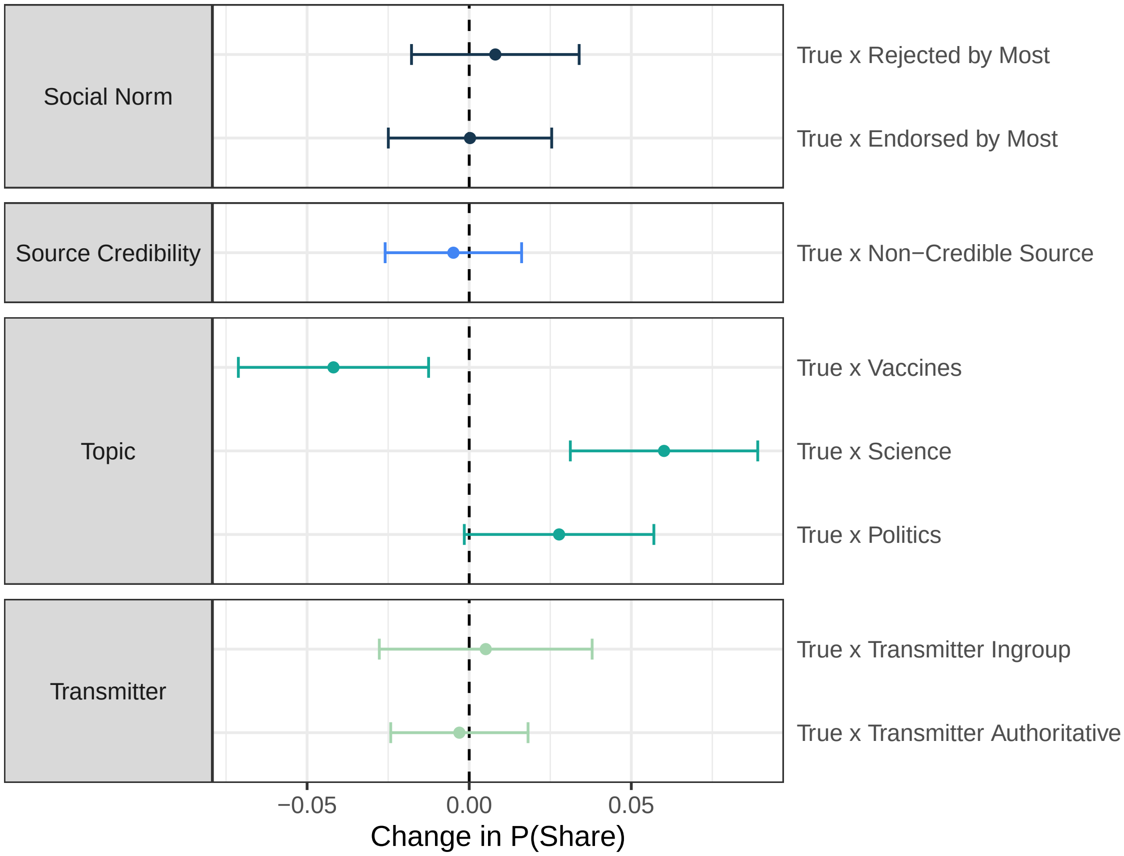

Figure 6: Conditional Effects of Veracity

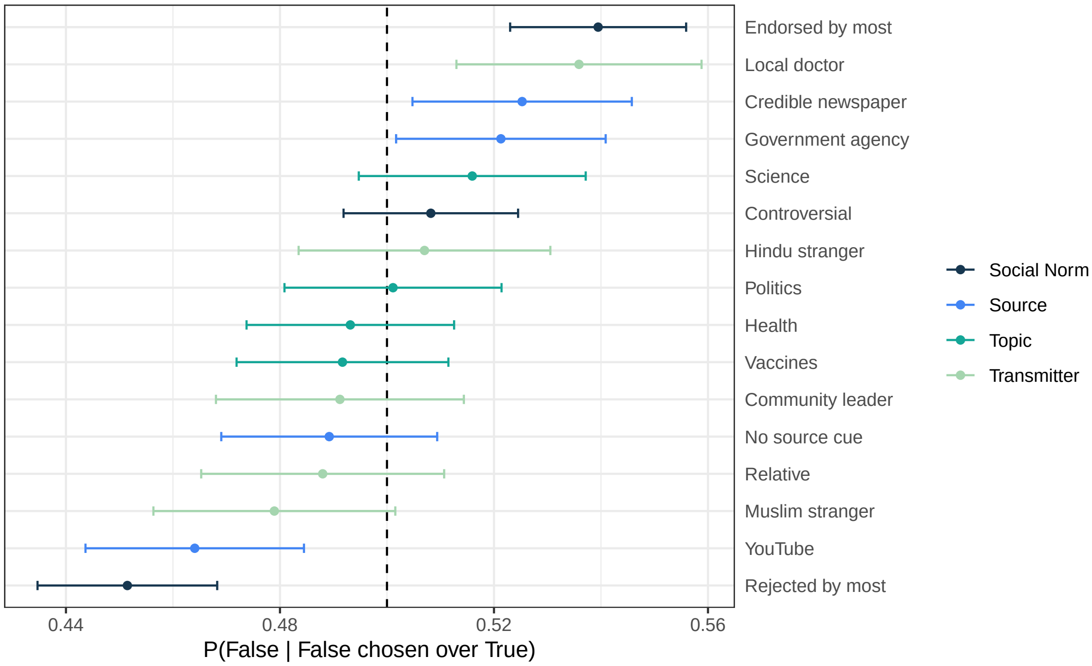

Figure 7: MMs among False Information that was Shared over True Information

D Source Credibility Conditional Effects

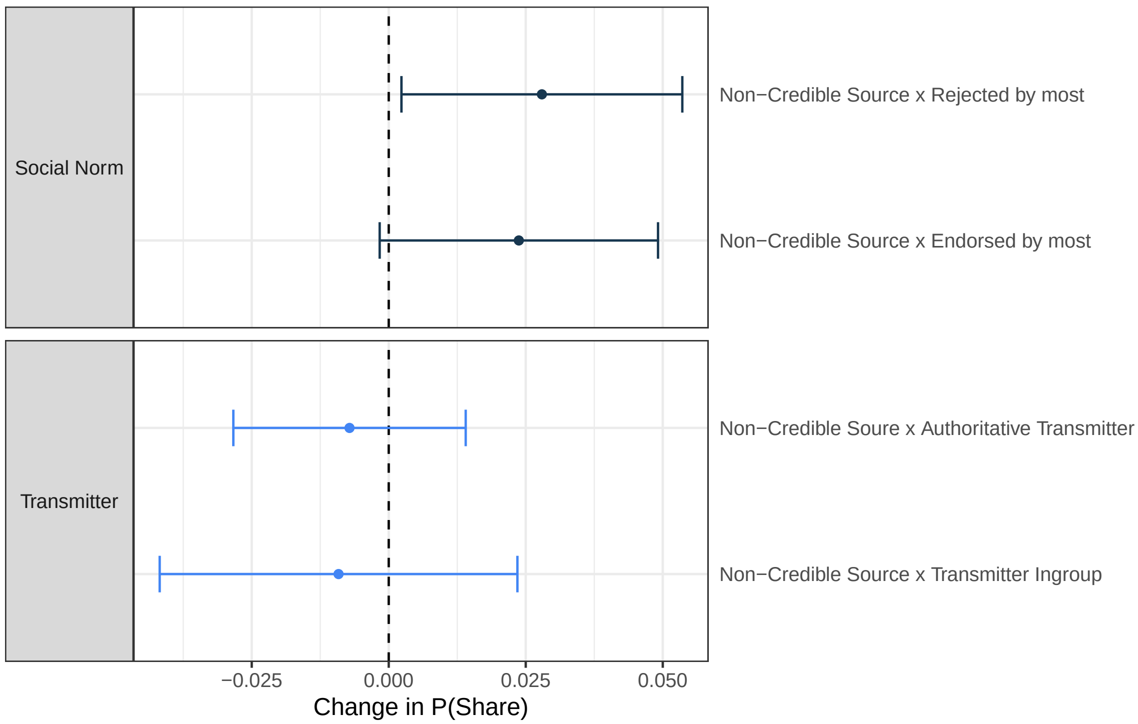

Figure 8: Conditional Effects of Sources

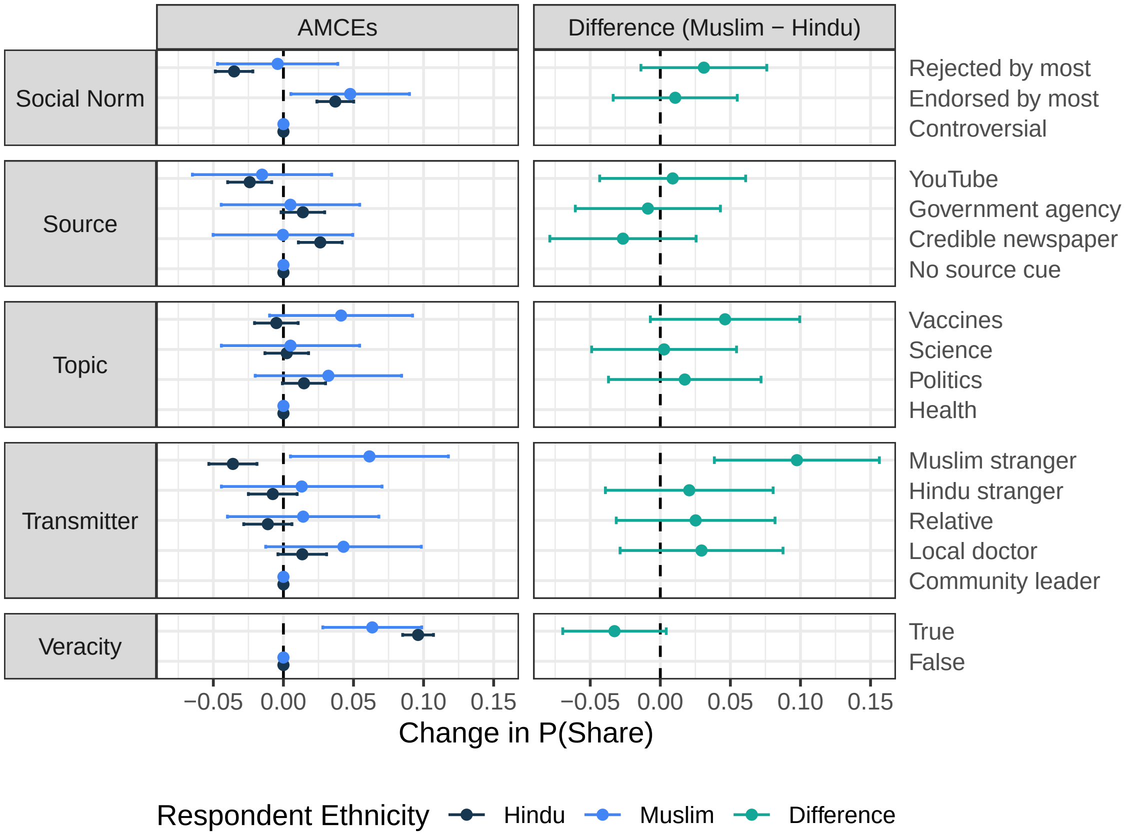

Figure 9: AMCEs by Respondent Ethnicity

E Tabulated Results

Table 4: AMCEs

Feature	Level	Estimate	SE	lower	upper
Topic	Health	0.000	NA	NA	NA
Topic	Politics	0.016	0.008	0.001	0.031
Topic	Science	0.002	0.008	-0.013	0.017
Topic	Vaccines	-0.001	0.008	-0.016	0.014
Veracity	False	0.000	NA	NA	NA
Veracity	True	0.093	0.005	0.083	0.104
Transmitter	Community leader	0.000	NA	NA	NA
Transmitter	Local doctor	0.015	0.008	-0.001	0.032
Transmitter	Relative	-0.008	0.008	-0.024	0.008
Transmitter	Hindu stranger	-0.006	0.008	-0.022	0.011
Transmitter	Muslim stranger	-0.027	0.008	-0.043	-0.010
Source	No source cue	0.000	NA	NA	NA
Source	Credible newspaper	0.024	0.008	0.009	0.039
Source	Government agency	0.013	0.008	-0.002	0.027
Source	YouTube	-0.023	0.008	-0.038	-0.008
Social Norm	Controversial	0.000	NA	NA	NA
Social Norm	Endorsed by most	0.038	0.006	0.025	0.050
Social Norm	Rejected by most	-0.033	0.007	-0.045	-0.020

[a] Statistic: AMCEs. Models based on OLS with SEs clustered at respondent level.

Table 5: Marginal Means

Feature	Level	Estimate	SE	lower	upper
Topic	Health	0.496	0.005	0.487	0.505
Topic	Politics	0.513	0.005	0.504	0.522
Topic	Science	0.497	0.005	0.488	0.506
Topic	Vaccines	0.495	0.005	0.486	0.505
Veracity	False	0.454	0.003	0.449	0.459
Veracity	True	0.547	0.003	0.542	0.552
Transmitter	Community leader	0.506	0.005	0.496	0.517
Transmitter	Local doctor	0.521	0.005	0.510	0.532
Transmitter	Relative	0.498	0.005	0.487	0.508
Transmitter	Hindu stranger	0.499	0.005	0.489	0.510
Transmitter	Muslim stranger	0.477	0.005	0.467	0.488
Source	No source cue	0.498	0.005	0.488	0.507
Source	Credible newspaper	0.521	0.005	0.511	0.530
Source	Government agency	0.509	0.005	0.500	0.518
Source	YouTube	0.473	0.005	0.464	0.482
Social Norm	Controversial	0.498	0.004	0.490	0.505
Social Norm	Endorsed by most	0.536	0.004	0.529	0.544
Social Norm	Rejected by most	0.466	0.004	0.459	0.474

[a] Statistic: MMs.

Table 6: AMCEs by Veracity

Feature	Level	Subgroup	Estimate	SE	lower	upper
Topic	Health	False	0.000	NA	NA	NA
Topic	Politics	False	0.002	0.011	-0.019	0.023
Topic	Science	False	-0.027	0.010	-0.048	-0.007
Topic	Vaccines	False	0.020	0.011	-0.001	0.041
Transmitter	Community leader	False	0.000	NA	NA	NA
Transmitter	Local doctor	False	-0.003	0.012	-0.026	0.020
Transmitter	Relative	False	-0.019	0.012	-0.042	0.004
Transmitter	Hindu stranger	False	-0.017	0.012	-0.040	0.006
Transmitter	Muslim stranger	False	-0.037	0.012	-0.060	-0.014
Source	No source cue	False	0.000	NA	NA	NA
Source	Credible newspaper	False	0.020	0.011	-0.001	0.041
Source	Government agency	False	0.020	0.011	0.000	0.041
Source	YouTube	False	-0.013	0.011	-0.034	0.008
Social_Norm	Controversial	False	0.000	NA	NA	NA
Social_Norm	Endorsed by most	False	0.038	0.009	0.020	0.055
Social_Norm	Rejected by most	False	-0.037	0.009	-0.055	-0.019
Topic	Health	True	0.000	NA	NA	NA
Topic	Politics	True	0.030	0.011	0.009	0.051
Topic	Science	True	0.033	0.011	0.012	0.054
Topic	Vaccines	True	-0.022	0.011	-0.043	-0.001
Transmitter	Community leader	True	0.000	NA	NA	NA
Transmitter	Local doctor	True	0.033	0.012	0.010	0.057
Transmitter	Relative	True	0.001	0.012	-0.022	0.025
Transmitter	Hindu stranger	True	0.005	0.012	-0.018	0.029
Transmitter	Muslim stranger	True	-0.019	0.012	-0.042	0.005
Source	No source cue	True	0.000	NA	NA	NA
Source	Credible newspaper	True	0.028	0.011	0.007	0.049
Source	Government agency	True	0.004	0.011	-0.018	0.025
Source	YouTube	True	-0.033	0.011	-0.054	-0.012
Social_Norm	Controversial	True	0.000	NA	NA	NA
Social_Norm	Endorsed by most	True	0.038	0.009	0.020	0.056
Social_Norm	Rejected by most	True	-0.029	0.009	-0.047	-0.010

[a] Statistic: Subgroup AMCEs. Models based on OLS with SEs clustered at respondent level.

Table 7: MMs by Veracity

Feature	Level	Subgroup	Estimate	SE	lower	upper
Topic	Health	False	0.456	0.007	0.442	0.469
Topic	Politics	False	0.458	0.007	0.444	0.472
Topic	Science	False	0.428	0.007	0.415	0.442
Topic	Vaccines	False	0.475	0.007	0.461	0.490
Transmitter	Community leader	False	0.470	0.008	0.454	0.485
Transmitter	Local doctor	False	0.466	0.008	0.450	0.482
Transmitter	Relative	False	0.451	0.008	0.436	0.467
Transmitter	Hindu stranger	False	0.451	0.008	0.435	0.467
Transmitter	Muslim stranger	False	0.433	0.008	0.418	0.448
Source	No source cue	False	0.447	0.007	0.433	0.461
Source	Credible newspaper	False	0.467	0.007	0.453	0.481
Source	Government agency	False	0.468	0.007	0.454	0.481
Source	YouTube	False	0.433	0.007	0.419	0.447
Social Norm	Controversial	False	0.453	0.006	0.442	0.465
Social Norm	Endorsed by most	False	0.491	0.006	0.480	0.503
Social Norm	Rejected by most	False	0.417	0.006	0.405	0.428
Topic	Health	True	0.537	0.007	0.523	0.550
Topic	Politics	True	0.566	0.007	0.553	0.580
Topic	Science	True	0.570	0.007	0.556	0.584
Topic	Vaccines	True	0.515	0.007	0.502	0.529
Transmitter	Community leader	True	0.542	0.008	0.526	0.558
Transmitter	Local doctor	True	0.577	0.008	0.561	0.592
Transmitter	Relative	True	0.544	0.008	0.529	0.560
Transmitter	Hindu stranger	True	0.549	0.008	0.533	0.565
Transmitter	Muslim stranger	True	0.524	0.008	0.508	0.540
Source	No source cue	True	0.548	0.007	0.534	0.562
Source	Credible newspaper	True	0.575	0.007	0.561	0.588
Source	Government agency	True	0.551	0.007	0.537	0.565
Source	YouTube	True	0.514	0.007	0.500	0.528
Social Norm	Controversial	True	0.544	0.006	0.532	0.556
Social Norm	Endorsed by most	True	0.582	0.006	0.570	0.593
Social Norm	Rejected by most	True	0.516	0.006	0.504	0.527

[a] Statistic: Subgroup MMs.

Table 8: AMCEs by Sharing Condition

Feature	Level	Subgroup	Estimate	SE	lower	upper
Topic	Health	offline	0.000	NA	NA	NA
Topic	Politics	offline	0.023	0.011	0.002	0.043
Topic	Science	offline	0.008	0.010	-0.012	0.029
Topic	Vaccines	offline	-0.001	0.011	-0.022	0.020
Transmitter	Community leader	offline	0.000	NA	NA	NA
Transmitter	Local doctor	offline	0.022	0.012	-0.002	0.045
Transmitter	Relative	offline	-0.010	0.012	-0.033	0.012
Transmitter	Hindu stranger	offline	-0.016	0.012	-0.039	0.007
Transmitter	Muslim stranger	offline	-0.034	0.012	-0.057	-0.011
Veracity	False	offline	0.000	NA	NA	NA
Veracity	True	offline	0.087	0.007	0.072	0.102
Source	No source cue	offline	0.000	NA	NA	NA
Source	Credible newspaper	offline	0.033	0.011	0.012	0.054
Source	Government agency	offline	-0.002	0.011	-0.023	0.019
Source	YouTube	offline	-0.030	0.011	-0.051	-0.008
Social_Norm	Controversial	offline	0.000	NA	NA	NA
Social_Norm	Endorsed by most	offline	0.022	0.009	0.005	0.040
Social_Norm	Rejected by most	offline	-0.051	0.009	-0.069	-0.034
Topic	Health	online	0.000	NA	NA	NA
Topic	Politics	online	0.010	0.011	-0.011	0.031
Topic	Science	online	-0.003	0.011	-0.025	0.018
Topic	Vaccines	online	-0.001	0.011	-0.022	0.020
Transmitter	Community leader	online	0.000	NA	NA	NA
Transmitter	Local doctor	online	0.009	0.012	-0.014	0.033
Transmitter	Relative	online	-0.005	0.012	-0.029	0.018
Transmitter	Hindu stranger	online	0.005	0.012	-0.019	0.028
Transmitter	Muslim stranger	online	-0.019	0.012	-0.042	0.005
Veracity	False	online	0.000	NA	NA	NA
Veracity	True	online	0.100	0.008	0.085	0.115
Source	No source cue	online	0.000	NA	NA	NA
Source	Credible newspaper	online	0.015	0.011	-0.006	0.036
Source	Government agency	online	0.028	0.011	0.007	0.049
Source	YouTube	online	-0.016	0.011	-0.037	0.005
Social_Norm	Controversial	online	0.000	NA	NA	NA
Social_Norm	Endorsed by most	online	0.053	0.009	0.035	0.071
Social_Norm	Rejected by most	online	-0.014	0.009	-0.032	0.005

[a] Statistic: Subgroup AMCEs. Models based on OLS with SEs clustered at respondent level.

Table 9: MMs by Sharing Condition

Feature	Level	Subgroup	Estimate	SE	lower	upper
Topic	Health	offline	0.493	0.007	0.480	0.505
Topic	Politics	offline	0.516	0.007	0.503	0.529
Topic	Science	offline	0.499	0.006	0.487	0.512
Topic	Vaccines	offline	0.493	0.007	0.480	0.506
Veracity	False	offline	0.457	0.004	0.450	0.464
Veracity	True	offline	0.544	0.004	0.536	0.551
Transmitter	Community leader	offline	0.508	0.007	0.494	0.523
Transmitter	Local doctor	offline	0.530	0.008	0.515	0.545
Transmitter	Relative	offline	0.498	0.007	0.484	0.512
Transmitter	Hindu stranger	offline	0.492	0.008	0.477	0.507
Transmitter	Muslim stranger	offline	0.473	0.007	0.458	0.488
Source	No source cue	offline	0.501	0.007	0.488	0.514
Source	Credible newspaper	offline	0.533	0.007	0.520	0.546
Source	Government agency	offline	0.497	0.006	0.485	0.510
Source	YouTube	offline	0.469	0.007	0.456	0.482
Social Norm	Controversial	offline	0.508	0.005	0.498	0.518
Social Norm	Endorsed by most	offline	0.532	0.005	0.522	0.543
Social Norm	Rejected by most	offline	0.459	0.005	0.449	0.470
Topic	Health	online	0.499	0.007	0.486	0.512
Topic	Politics	online	0.510	0.006	0.497	0.523
Topic	Science	online	0.494	0.007	0.481	0.507
Topic	Vaccines	online	0.498	0.007	0.485	0.511
Veracity	False	online	0.451	0.004	0.443	0.458
Veracity	True	online	0.551	0.004	0.543	0.558
Transmitter	Community leader	online	0.504	0.008	0.489	0.519
Transmitter	Local doctor	online	0.512	0.008	0.497	0.527
Transmitter	Relative	online	0.497	0.008	0.483	0.512
Transmitter	Hindu stranger	online	0.507	0.008	0.492	0.522
Transmitter	Muslim stranger	online	0.481	0.008	0.466	0.496
Source	No source cue	online	0.494	0.007	0.481	0.507
Source	Credible newspaper	online	0.509	0.007	0.496	0.521
Source	Government agency	online	0.521	0.006	0.508	0.533
Source	YouTube	online	0.477	0.007	0.464	0.490
Social Norm	Controversial	online	0.487	0.005	0.477	0.497
Social Norm	Endorsed by most	online	0.540	0.005	0.530	0.551
Social Norm	Rejected by most	online	0.473	0.006	0.463	0.484

[a] Statistic: Subgroup MMs.

Table 10: AMCEs by Accuracy Discernment

Feature	Level	Subgroup	Estimate	SE	lower	upper
Topic	Health	Below Median	0.000	NA	NA	NA
Topic	Politics	Below Median	0.007	0.011	-0.015	0.029
Topic	Science	Below Median	-0.001	0.011	-0.023	0.021
Topic	Vaccines	Below Median	-0.012	0.011	-0.034	0.010
Transmitter	Community leader	Below Median	0.000	NA	NA	NA
Transmitter	Local doctor	Below Median	0.008	0.013	-0.017	0.032
Transmitter	Relative	Below Median	-0.002	0.012	-0.026	0.022
Transmitter	Hindu stranger	Below Median	-0.011	0.012	-0.036	0.013
Transmitter	Muslim stranger	Below Median	-0.036	0.012	-0.060	-0.012
Veracity	False	Below Median	0.000	NA	NA	NA
Veracity	True	Below Median	0.071	0.008	0.056	0.087
Source	No source cue	Below Median	0.000	NA	NA	NA
Source	Credible newspaper	Below Median	0.022	0.011	0.000	0.044
Source	Government agency	Below Median	0.015	0.011	-0.006	0.037
Source	YouTube	Below Median	-0.019	0.011	-0.041	0.003
Social_Norm	Controversial	Below Median	0.000	NA	NA	NA
Social_Norm	Endorsed by most	Below Median	0.031	0.010	0.012	0.050
Social_Norm	Rejected by most	Below Median	-0.032	0.010	-0.051	-0.013
Topic	Health	Above Median	0.000	NA	NA	NA
Topic	Politics	Above Median	0.033	0.011	0.011	0.054
Topic	Science	Above Median	0.004	0.011	-0.018	0.026
Topic	Vaccines	Above Median	0.014	0.011	-0.008	0.036
Transmitter	Community leader	Above Median	0.000	NA	NA	NA
Transmitter	Local doctor	Above Median	0.025	0.012	0.001	0.049
Transmitter	Relative	Above Median	-0.017	0.012	-0.041	0.008
Transmitter	Hindu stranger	Above Median	-0.003	0.013	-0.027	0.022
Transmitter	Muslim stranger	Above Median	-0.022	0.013	-0.047	0.003
Veracity	False	Above Median	0.000	NA	NA	NA
Veracity	True	Above Median	0.115	0.008	0.099	0.130
Source	No source cue	Above Median	0.000	NA	NA	NA
Source	Credible newspaper	Above Median	0.027	0.011	0.005	0.049
Source	Government agency	Above Median	0.016	0.011	-0.006	0.038
Source	YouTube	Above Median	-0.025	0.011	-0.047	-0.003
Social_Norm	Controversial	Above Median	0.000	NA	NA	NA
Social_Norm	Endorsed by most	Above Median	0.044	0.009	0.026	0.062
Social_Norm	Rejected by most	Above Median	-0.033	0.009	-0.052	-0.015

[a] Statistic: Subgroup AMCEs. Models based on OLS with SEs clustered at respondent level.

Table 11: MMs by Accuracy Discernment

Feature	Level	Subgroup	Estimate	SE	lower	upper
Topic	Health	Below Median	0.501	0.007	0.488	0.514
Topic	Politics	Below Median	0.510	0.007	0.496	0.523
Topic	Science	Below Median	0.500	0.007	0.486	0.513
Topic	Vaccines	Below Median	0.490	0.007	0.477	0.504
Veracity	False	Below Median	0.465	0.004	0.457	0.473
Veracity	True	Below Median	0.536	0.004	0.528	0.544
Transmitter	Community leader	Below Median	0.510	0.008	0.494	0.525
Transmitter	Local doctor	Below Median	0.516	0.008	0.501	0.532
Transmitter	Relative	Below Median	0.508	0.008	0.493	0.523
Transmitter	Hindu stranger	Below Median	0.496	0.008	0.481	0.512
Transmitter	Muslim stranger	Below Median	0.471	0.008	0.456	0.487
Source	No source cue	Below Median	0.496	0.007	0.483	0.509
Source	Credible newspaper	Below Median	0.518	0.007	0.504	0.532
Source	Government agency	Below Median	0.511	0.007	0.498	0.524
Source	YouTube	Below Median	0.475	0.007	0.462	0.489
Social Norm	Controversial	Below Median	0.500	0.006	0.489	0.511
Social Norm	Endorsed by most	Below Median	0.532	0.006	0.521	0.543
Social Norm	Rejected by most	Below Median	0.468	0.006	0.457	0.479
Topic	Health	Above Median	0.488	0.007	0.475	0.502
Topic	Politics	Above Median	0.521	0.007	0.507	0.534
Topic	Science	Above Median	0.491	0.007	0.477	0.504
Topic	Vaccines	Above Median	0.502	0.007	0.488	0.515
Veracity	False	Above Median	0.443	0.004	0.435	0.451
Veracity	True	Above Median	0.558	0.004	0.550	0.566
Transmitter	Community leader	Above Median	0.504	0.008	0.489	0.520
Transmitter	Local doctor	Above Median	0.528	0.008	0.513	0.544
Transmitter	Relative	Above Median	0.487	0.008	0.471	0.502
Transmitter	Hindu stranger	Above Median	0.502	0.008	0.486	0.517
Transmitter	Muslim stranger	Above Median	0.480	0.008	0.465	0.496
Source	No source cue	Above Median	0.497	0.007	0.483	0.511
Source	Credible newspaper	Above Median	0.522	0.007	0.509	0.535
Source	Government agency	Above Median	0.511	0.007	0.498	0.524
Source	YouTube	Above Median	0.470	0.007	0.456	0.483
Social Norm	Controversial	Above Median	0.495	0.005	0.485	0.506
Social Norm	Endorsed by most	Above Median	0.540	0.006	0.530	0.551
Social Norm	Rejected by most	Above Median	0.464	0.006	0.453	0.475

[a] Statistic: Subgroup MMs.