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

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Abstract

Misinformation remains a global threat to public health and democratic governance, yet research continues to disproportionately focus on highly connected, Western contexts. This paper asks: under what conditions do individuals share false information in largely offline environments? To address this question, we conducted a large-scale, in-person vignette-based conjoint experiment with nearly 6,000 adolescents across 583 villages in Bihar, India, a setting characterized by limited internet access and high exposure to misinformation. Respondents evaluated randomized information scenarios varying in veracity, transmitter identity, social endorsement, source, and topic, using a forced-choice design to simulate real-world oral information sharing. We find, first, that even without explicit veracity cues, respondents place a premium on truthfulness: true information is significantly more likely to be shared than false information. Second, ethnic and religious identity powerfully shape sharing behavior: Muslim transmitters are penalized even when sharing true information, whereas Hindu transmitters are judged more by the accuracy of the message. These results highlight how offline information sharing is shaped not only by content but also by social group dynamics. The findings underscore the importance of expanding misinformation research to low-connectivity populations and demonstrate methodological innovations for adapting experimental designs to offline, face-to-face environments.

Keywords: Misinformation, Vignette Experiment, India, Sharing Behavior

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1 Introduction

Misinformation remains one of the most pressing threats to public health and democratic governance across the globe. Yet, despite its global reach, academic research on misinformation has remained disproportionately concentrated in the West, in contexts that differ systematically from much of the rest of the world (Blair et al., 2024). A critical point of divergence lies in the stark digital divide (Kashyap et al., 2020; Blumenstock and Eagle, 2012). Whereas over 90% of individuals in North America and Europe regularly access the internet, approximately 70% of people in Sub-Saharan Africa and around 60% in South Asia remain fully offline or experience only intermittent connectivity. While the implications of this divide are profound, we note that the absence of constant internet access does not imply the absence of misinformation. On the contrary, misinformation continues to thrive in these offline or semi-connected environments, often with devastating consequences. In Myanmar, for example, unverified rumors spread via word of mouth and low-cost mobile technologies fueled ethnic tensions, culminating in episodes of violent conflict and mass displacement. Similarly, vaccine hesitancy driven by conspiracy theories and misinformation has undermined public health campaigns in offline communities across South Asia and Sub-Saharan Africa. These examples serve as reminders that the fight against misinformation cannot be confined to digitally saturated environments.

Yet despite this reality, the vast majority of empirical studies on misinformation either implicitly or explicitly assume a highly connected, digitally literate population (Badrinathan and Chauchard, 2024). Cross-national studies, though growing in number, typically draw samples from English-speaking, online-accessible populations, leaving critical offline dynamics underexplored (for example, see Arechar et al. (2023)). As a result, we lack not only a theoretical understanding of how misinformation spreads in less digitally connected societies, but also practical methodological tools to study these contexts effectively. This is a crucial gap: before designing interventions to combat misinformation, we must first undertake the necessary descriptive task of understanding the conditions that facilitate misinformation sharing in offline environments.

This paper addresses these gaps by examining patterns of misinformation sharing in rural India. Although internet penetration in India has grown markedly, reaching approximately 48% nationwide, rural areas continue to lag behind sharply, with only about 30% of residents enjoying reliable internet access. Bihar, where our study is located, highlights these challenges: it remains one of India's poorest states, with limited infrastructure and minimal digital penetration. In our sample, only one in five households reported regular access to the internet, while simultaneously reporting high levels of belief in misinformation stories.

Our first major contribution is thus to explore how misinformation circulates in these largely offline and rural populations. Specifically, we ask: under what conditions are individuals most likely to share false information? What factors encourage or inhibit such behavior? To answer these questions, we conducted a large-scale, in-person survey of nearly 6,000 adolescents aged 13 to 18, spanning 583 villages across Bihar. Our second contribution, then, is our explicit focus on adolescents. Theoretically, adolescence represents a critical developmental window: attitudes, cognitive heuristics, and social behaviors are still relatively malleable, offering opportunities for meaningful intervention before patterns of misinformation consumption and sharing become entrenched (Jennings and Niemi, 1968; Niemi and Jennings, 1991).

Conducting this study in a predominantly offline context necessitated substantial methodological innovation. To examine how source credibility shapes misinformation sharing (Bauer and Clemm Von Hohenberg, 2021; Berinsky, 2023; Wittenberg et al., 2023), we introduce a novel distinction between the original source of a claim and its transmitter, the individual conveying the information. This separation is crucial in offline settings, where information circulates interpersonally rather than through impersonal digital media (Gadjanova, Lynch, and Saibu, 2022). In such environments, we hypothesize that the identity of the transmitter can influence the credibility assigned to the message, an aspect largely overlooked in existing misinformation research rooted in Western, online populations. We further incorporate the transmitter's religious and ethnic identity into our design, drawing from extensive comparative politics literature documenting the role of ethnic biases in shaping trust and decision-making (Habyarimana et al., 2009). While prior misinformation studies have emphasized partisan and ideological biases, we highlight how different identity-based considerations may be salient in multiethnic offline societies.

To adapt our survey for an offline population, we developed a vignette-based conjoint experiment. Departing from typical online conjoint formats that display attribute lists on screens (Hainmueller, Hopkins, and Yamamoto, 2014), we embed randomized attributes within orally delivered information scenarios, closely mirroring the way individuals naturally encounter information in face-to-face exchanges. In each vignette, we independently randomize the topic (politics, vaccines, health, science), veracity (true, false), transmitter identity (Hindu stranger, Muslim stranger, local doctor, community leader, relative), original source (reputable newspaper, government, social media, or no cue), and social endorsement (endorsed, controversial, rejected) of each message. Respondents – nearly 6,000 adolescents – were then asked which piece of information they would be more inclined to share, either offline or online. These methods help underscore ecological validity in our study, offering a template for studying misinformation dissemination in environments where traditional online survey tools are infeasible.

We outline three key findings. First, respondents exhibited a clear preference for sharing true over false information: true claims were 9 percentage points more likely to be shared than false ones. This finding is especially striking given the structure of our experiment, which deliberately provided no veracity cues to respondents. Participants had to first independently assess the truthfulness of the information and then decide whether or not to share it: a three-step cognitive process (assessing veracity, then caring about, then acting on it). Despite our setup, respondents consistently placed a premium on truthfulness. This suggests that when information presents multiple competing attributes, as it often does in the real world, truthfulness continues to play a significant, if imperfect, role in shaping sharing behavior. Nevertheless, the persistence of false information sharing even in this setting underscores that while truth matters, it is far from the only factor at play.

Our second key finding is that the identity of the information transmitter significantly shapes sharing behavior. We find a systematic bias against minority (Muslim) transmitters: information shared by Muslim strangers was significantly less likely to be shared compared to information from Hindu strangers. However, this bias is not symmetric across veracity. Interacting transmitter identity with veracity reveals that Muslim sources are penalized regardless of whether they share true or false information. In other words, even when Muslim sources do share accurate information, they are penalized for it. On the other hand, Hindu sources only incur a penalty for sharing false information, suggesting that veracity matters only for ingroup sources. This highlights how ethnic identity interacts with informational content, aligning with a substantial body of comparative politics research showing that ethnic biases heavily influence decision-making in many parts of the world (Chauchard, 2016; Adida et al., 2017). Third, we find that social endorsement shapes information sharing, but its effects differ across online and offline contexts. Respondents were more likely to share controversial statements in person, while statements characterized by broad agreement or disagreement were shared more frequently if respondents think they are received online. These differences suggest that norms governing information dissemination are context-specific, with interpersonal environments potentially rewarding different signals of credibility or social relevance than digital ones.

Together, these findings carry important implications. Theoretically, they underscore the need to expand misinformation research beyond partisan frameworks to account for ethnic and social biases that influence credibility judgments. Empirically, they highlight the importance of incorporating more diverse, less digitally saturated populations into studies of misinformation. Methodologically, they demonstrate how conjoint designs can be successfully adapted for offline, face-to-face survey environments, providing a blueprint for future experimental work in contexts where digital survey infrastructure is limited.

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 are 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 conjoint 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 a largely offline population in India, highlighting responses from a rural and less privileged context. 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 to get information, 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 even when such populations access the internet, 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 scope conditions that shape information processing in large parts 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.

We note that conjoint-style experiments focusing on news sharing are not new to the literature. For example, Mukerjee and Yang (2021) employ a conjoint design to examine how different cues influence information consumption, manipulating three attributes: the source, headline, and social endorsement. Similarly, Trexler (2024) investigates demand for news through a conjoint experiment that randomizes news style, topic, and source. However, both studies are conducted within U.S. contexts, where populations are accustomed to encountering news and making credibility judgments in online environments. Adapting this methodology to the Indian context required rethinking both the substantive attributes under study and the method of delivery. This necessitated the introduction of the distinction between the transmitter (the person conveying the information) and the original source (where the information originated). This separation reflects local realities more accurately than existing models that conflate these roles. Second, logistical adaptation was also necessary: while Mukerjee and Yang (2021) present respondents with bullet-point lists of randomized attributes and Trexler (2024) displays them in stylized headline formats, both suited to literate, screen-based decision-making, in our context such formats would poorly approximate how people actually encounter news face-to-face in India. Drawing on insights from fieldwork, we know that the modal pattern of information transmission in rural India involves, for example, a person verbally relaying a piece of news they themselves heard from a third party (transmitter), sometimes mentioning the news's origin (source) and the social reactions surrounding it (endorsement). Our study design therefore embeds all these dimensions into orally delivered vignettes, mirroring the natural flow of information in offline settings.

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, regardless of perceived credibility of the original source.

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. We expect that the credibility of sources matters in determining whether or not to share information.

A large body of comparative politics research has documented the role of ethnic bias in shaping a range of social and political behaviors, particularly in domains such as voting, political accountability, and public goods provision (Habyarimana et al., 2009). However, this literature has largely overlooked information sharing, despite its central role in the formation of beliefs that ultimately drive downstream behaviors. Understanding whether and how ethnic biases influence information sharing is therefore a critical, yet underexplored, question. By examining this dynamic among adolescents, we place an additional constraint on ourselves: adolescents' beliefs are likely to be less firmly entrenched than those of adults, making identity-based biases potentially harder to detect. Nevertheless, adolescence represents a formative stage for belief formation, and identifying ethnic biases at this stage provides crucial insight into the early roots of selective information processing and dissemination.

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).

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.

2.2 Social norms

We next randomize respondents' perceptions of social norms surrounding each piece of information. The goal of this attribute is to vary levels of social endorsement or controversy attached to a news story, thereby highlighting potential bandwagon dynamics that could influence the spread of misinformation (Roozenbeek et al., 2020). This dimension is especially important in offline settings, where individuals often discuss rumors or information by referencing how widely a story has circulated within their social networks. Specifically, we indicate whether "most people agreed," "most people disagreed," or "some agreed and some disagreed" with the statement, thus manipulating perceptions of social consensus. By varying this attribute, we aim to capture how the "common knowledge" aspect of misinformation—its power derived from being seen as widely circulated—affects willingness to share. Drawing on the literature on social norms, we expect that information perceived to be widely believed will be more likely to be shared (Tankard and Paluck, 2016). Beyond the inherent attributes of the information itself, the perception of broad social endorsement provides a descriptive norm that signals credibility through consensus. Thus, we hypothesize that information perceived as enjoying greater social support will be shared at higher rates.

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.

We note that respondents were not explicitly informed whether a statement was true or false. While we experimentally vary the veracity of the information pool, respondents must independently assess the truthfulness of each piece based on cues embedded within other attributes of the vignette. Thus, if we observe that, all else equal, respondents are more likely to share true information over false information (or vice versa), this behavior reflects a two-stage cognitive process: respondents first infer veracity based on available cues, and then incorporate that inference into their sharing decisions. Importantly, by withholding explicit veracity labels, we deliberately make it more difficult for respondents to engage in the normatively "correct" behavior of privileging true information. Any systematic preference for true over false information under these conditions thus reflects active cognitive evaluation rather than mere compliance with overt signals.

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. This is especially crucial 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 centers, 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 may 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).

Further, for India specifically, citizens still rely on traditional media platforms such as television and newspapers to a large extent. Consequently, the exploration of offline communication channels emerges as a pivotal and indispensable endeavor. To incorporate this, our vignette design orthogonally randomizes attributes across priming online and offline settings.

3 Research Design

To answer our research questions, we field an in-person survey in Bihar, India, the main component of which is a vignette conjoint experiment (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 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. Sampling strategy and household selection is detailed in Appendix A[1]. The composition of the final sample is detailed in Table 2.

We selected India – and specifically Bihar – as the setting for this study for several reasons. India represents a crucial context: it is one of the world's fastest-growing economies, yet it remains deeply unequal in digital access. This makes India one of the few places where large populations remain substantially offline even as misinformation remains pervasive and consequential. Within India, Bihar presents an especially compelling case. It is the country's poorest state, with over one-third of its population living below the poverty line. Bihar's underdevelopment is reflected not only in limited access to basic services such as healthcare and education, but also in low rates of digital connectivity: as per our baseline data, only 11.5% of adolescent respondents reported owning a personal cellphone, and among those with access to an internet-enabled device, just 19% reported using the internet. Most information exchange thus occurs offline, mediated through family and community networks where misinformation can circulate unchecked, compounded by strong cultural norms around deference to elders and authority figures. Even among households with internet access, device sharing is common, in stark contrast to the individualized access typical of Western settings (Steenson and Donner, 2017).

Bihar's political and informational environment further heightens its relevance for studying misinformation. While Bihar is not directly under single-party BJP rule, the party heading the

[1] We note here that this experiment is embedded in the endline survey of an 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.

central government in India, it is governed by a BJP-led coalition and situated within a broader northern Indian media ecosystem that has witnessed multiple instances of elite-driven disinformation leading to violence and fatalities (Badrinathan, Chauchard, and Siddiqui, 2024). These dynamics unfold against a backdrop of declining state capacity, shrinking independent media spaces, and increasing state capture of informational institutions (Mohan, 2021; Sen, 2023). In this context, misinformation thrives, and vulnerable populations face particular challenges in accessing credible information. Although misinformation is a country-wide concern, Bihar's combination of structural underdevelopment, political incentives for elite-driven disinformation, and deep-rooted cultural narratives creates a uniquely difficult environment for information correction efforts. Understanding misinformation dynamics in such a setting is therefore critical for designing interventions tailored to contexts of low connectivity, weak institutions, and high social vulnerability.

3.1 Vignette Experiment

To estimate effects of different characteristics of hypothetical pieces of information on sharing intentions, we utilize a forced-choice vignette experiment. To emphasize better our focus on offline sharing, we first wanted to prime respondents to think about the physical context in which they were receiving information. To do so, we first randomize respondents into one of two conditions:

1. **Priming Offline Settings**: Before viewing the conjoint tasks, respondents in this condition were primed to think an *offline* setting by prompting them to talk about an in-person meeting with people they know well.[2] Then, for each profile pair in the conjoint, 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. **Priming Online Settings**: Here respondents were primed to think about sharing in online settings.[3] For each information profile pair in the conjoint, they were then 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?"*

[2]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?"

[3]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?"

Once respondents were randomized into the online versus offline priming settings, 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:

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

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 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****.* ***When Rajesh shared this news with you in person, among others who were around****,* ***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.*

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%)

After being randomized into either the online or offline condition, each respondent was 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.

Given the unique context of sampling adolescents in a developing context who predominantly lack access to phones, the design choices we made were carefully chosen 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 these 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 respondents, 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 an average marginal component effect (AMCE) measuring change in the value of each attribute, 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. 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. Results from our the baseline specification are presented in Figure 1.[4] Marginal means shown in Appendix C and all tabular results are in Appendix G.

4.1 Emphasis on veracity

One of the most striking results to emerge from Figure 1 is regarding the emphasis respondents place on the veracity of statements, demonstrating how likely respondents were to make accuracy judgments 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. This finding is important for several reasons. While we cannot exclude more nuanced explanations,[5] 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

[4]We omit displaying the coefficients from our Topic attribute as variation in topic was mainly included to increase the realism of the vignettes rather than for theoretical reasons.

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

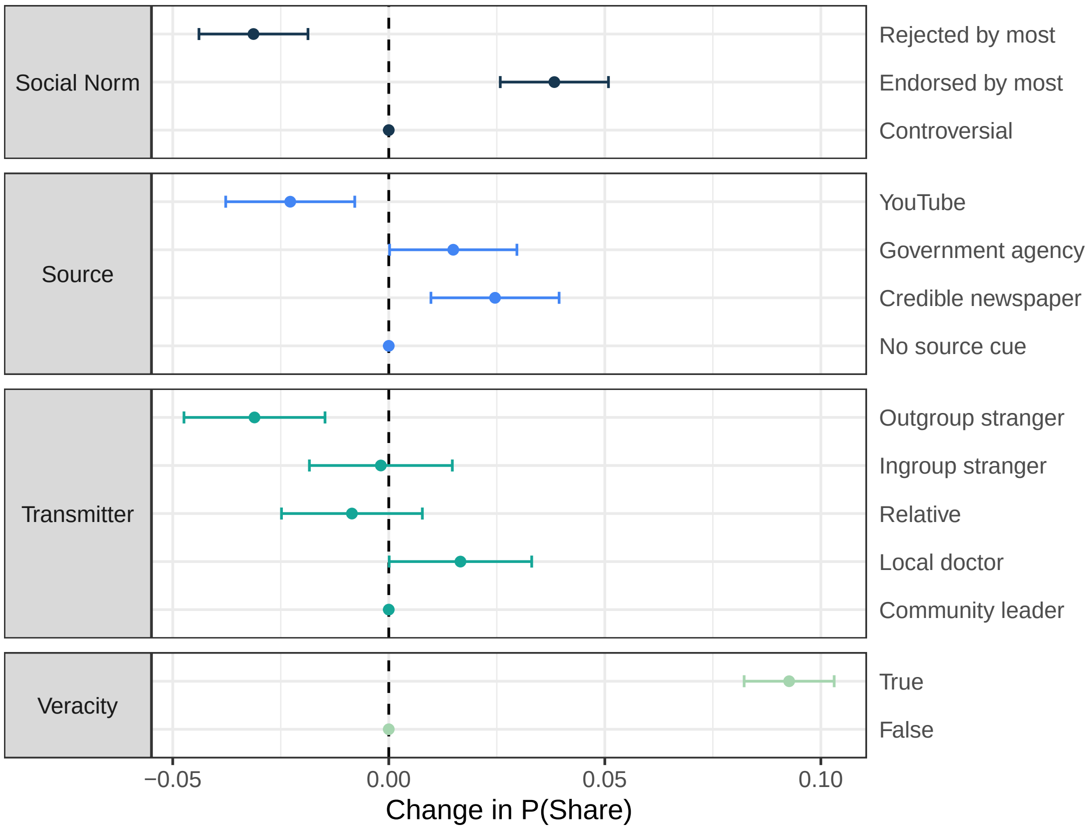

Figure 1: Main Effects of Different Attributes on Sharing

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 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 provide respondents with explicit cues to assist in identifying or prioritizing true messages—for example, by emphasizing accuracy prompts or providing fact-checks, as in prior work (Pennycook and Rand, 2019; Porter and Wood, 2019). Additionally, the use of multiple randomized attributes within our vignette design helped obscure the purpose of the study, reducing the likelihood that respondents' choices reflected a social desirability bias toward truthfulness rather than authentic evaluation.

This finding also carries important policy implications. Much of the existing misinformation literature has focused on the spread of false information in isolation, without simultaneously considering how true information competes with misinformation within the broader information environment. Yet what ultimately matters for the integrity of informational ecosystems is the composition of content that circulates. If individuals occasionally share misinformation but predominantly share accurate information – as our findings suggest may be possible – then the cumulative effect may favor truth, with true information eventually ”drowning out” falsehoods. By pitting true and false information directly against each other within the same experimental framework, our study thus underscores the dynamics of information competition, a perspective that remains underexplored in the existing literature.

Despite finding that respondents overall prioritize true information, a central question our design allows us to address is: under what conditions is false information nevertheless shared? To investigate this, 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. We first visualize the predictors of false information being chosen over true information by plotting $\mathbb{P}(\text{Chosen}|\text{False chosen over True})$. The resulting graph is striking. In Figure 2 we see that although there is an overall penalty for false information, there are specific conditions under which false information does become attractive. The strongest predictor is the perception of social endorsement. When false information is presented as being endorsed by most others, the penalty for its falsity diminishes sharply: respondents become more willing to share it. Conversely, when false information is framed as being rejected by most, it is penalized most heavily. These findings underscore the powerful role that perceived social norms play in driving misinformation sharing, suggesting that the social context in which information is embedded can override concerns about veracity. This also bodes with the main effect that we find for social norms: in Figure 1 we find that respondents place significant value on social norms: on balance 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).

Source credibility also emerges as a critical factor. False information attributed to credible sources—whether original sources such as reputable newspapers or government bodies, or transmitters such as local doctors—is significantly more likely to be shared than false information from less trusted actors. In these cases, the credibility of the source or transmitter appears to outweigh independent assessments of truthfulness. These results have important policy implications. They suggest that individuals do not exhibit an inherent preference for false information; rather, when trusted authorities disseminate misinformation, individuals become vulnerable to sharing it. Improving the quality and accuracy of information disseminated by official and trusted sources could therefore have substantial downstream effects on limiting misinformation spread.

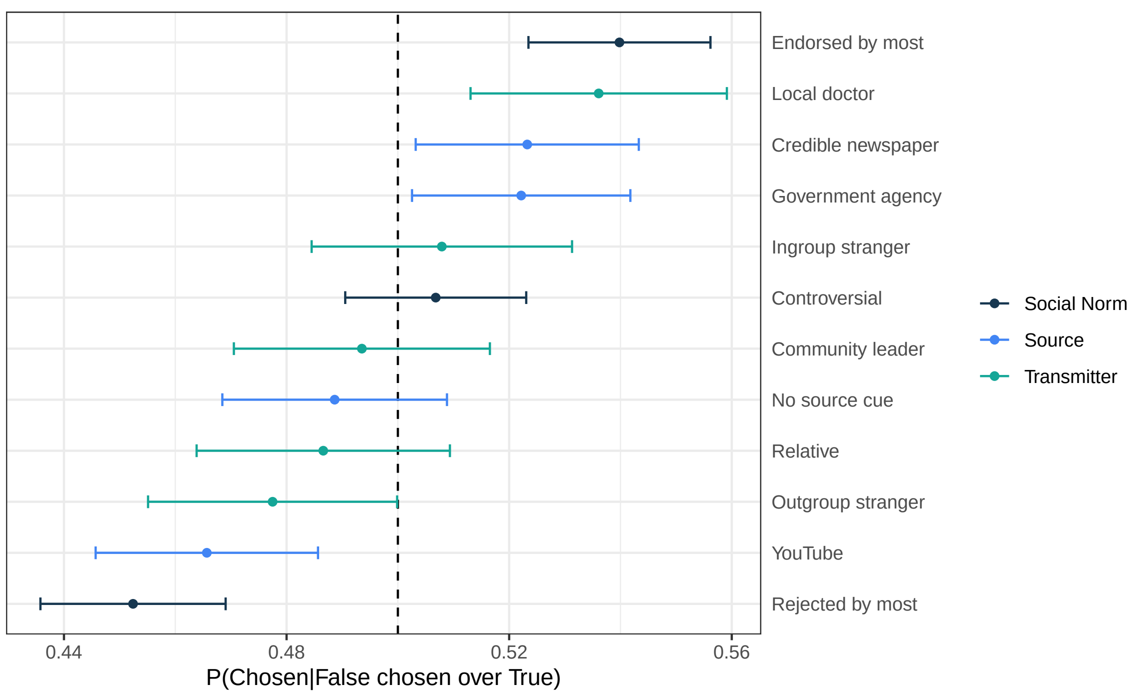

Figure 2: Predictors of Choosing to Share Misinformation

4.2 The effect of transmitter identity

Next, we observe that both the source and the transmitter of information condition and influence intentions to share. In the main effect (Figure 1), respondents do prioritize more credible sources, such as news from a government agency or a reputable newspaper, and are more likely to share information from such sources compared to situations where no source cues are provided. Further, our findings indicate that respondents consider not only the source but also the transmitter of the information. Statements from local doctors, who hold a lot of context-specific credibility, 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 religious identity of the transmitter matters.

In particular, we find that respondents significantly penalize information transmitted by outgroup strangers. Given the composition of our sample – approximately 90% Hindu respondents, reflecting the demographic structure of Bihar – the outgroup category disproportionately consists of Muslim transmitters. When the transmitter is identified by a Muslim name, respondents are significantly less likely to share the information, regardless of its content. Figure 3 presents AMCEs separately by veracity and illustrates the differences between responses to true and false information. This allows us to directly assess how the identity of the transmitter interacts with the truthfulness of the information. Among outgroup transmitters, both true and false information are penalized: respondents are less likely to share information from Muslim strangers, even when the information is true. This finding highlights that, although respondents generally value true information—as shown previously in our results—ethnic identity can override veracity considerations when evaluating the credibility of outgroup sources.

By contrast, for ingroup transmitters (Hindu strangers), we observe a marked distinction between true and false information: respondents are more likely to share true information and less likely to share false information from ingroup members. In other words, veracity becomes salient primarily when the transmitter is part of the ingroup. Taken together, these results suggest that when information is accompanied by ethnic identity cues, respondents prioritize social group membership over truthfulness. Only in interactions with ingroup members does the veracity of the information meaningfully influence sharing behavior.

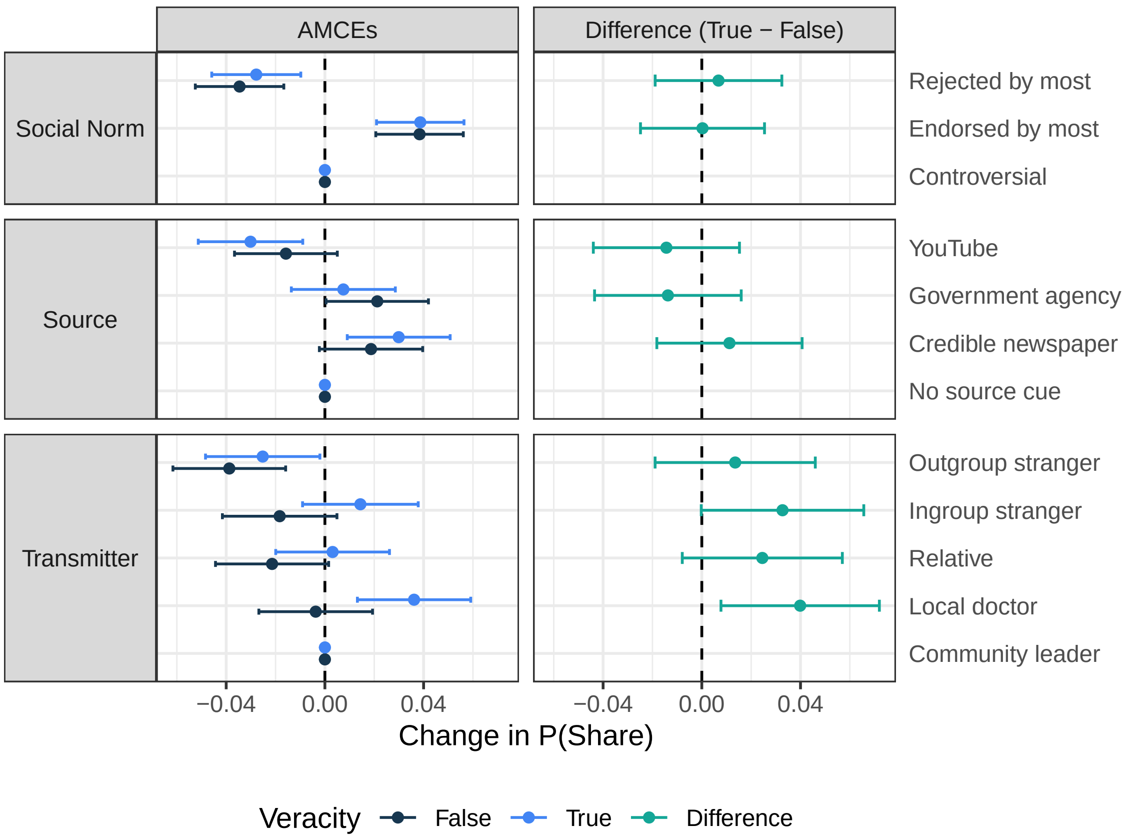

Figure 3: AMCE by Veracity

To further probe these dynamics, in Figure 4 we subset the data to choice-pairs where (1) one piece of information was transmitted by an outgroup member and the other by an ingroup member, and (2) the respondent chose the outgroup transmitter's information over the ingroup's. We then plot $\mathbb{P}(\text{Chosen}|\text{Outgroup chosen over Ingroup})$, visualizing the predictors of this choice. This approach allows us to examine an important question: although information from outgroup transmitters is generally penalized, under what conditions can other attributes "compensate" for outgroup status and still make a statement sharable? Two patterns emerge. First, veracity remains highly influential: when respondents do choose information from an outgroup transmitter, they are substantially more likely to do so when the information is true, and significantly less likely when it is false. Second, we find some evidence that perceived social endorsement also matters, though the effects are weaker. Together, these results reinforce that even in contexts of strong ethnic bias, truthfulness can partially mitigate identity-based penalties.

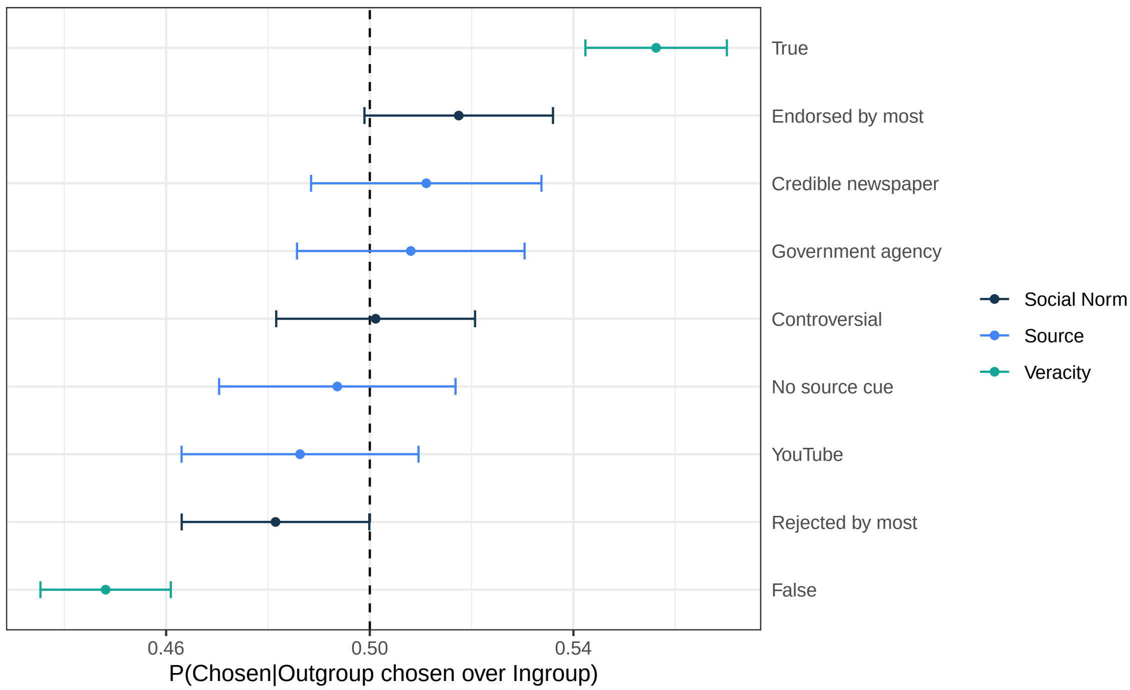

Figure 4: Predictors of Choosing Outgroup Information

Finally, breaking down the results by respondent' own religious identity, we see that among Hindu respondents, statements transmitted by Muslim strangers are shared significantly less often compared to Hindu strangers (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.

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.

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. To ensure that the observed effects around veracity were not simply driven by any form of identity, we looked at subgroup AMCEs on veracity by partisanship (measured at the household level) as well as by other pre-treatment demographic variables, including age, gender, and household income (proxied by an asset index). Across these subgroups, we find no significant differences in sharing behavior for true versus false information (Appendix F). These results support our intuition that in this context, religious identity – not partisanship or other demographic factors – is the primary axis along which information sharing decisions are shaped. In short, identity matters, but it is religious affiliation, rather than political or socioeconomic markers, that most powerfully influences the spread of information in this setting.

4.3 Priming online and offline contexts

Finally, we examine whether priming online versus offline sharing contexts affects sharing behavior. We first trained random forest models on our data and extracted estimates of variable importance, with bootstrapped standard errors. Consistent with earlier results, veracity emerges as the most important predictor of sharing overall, but its importance is significantly greater when respondents are primed to think about online sharing (Appendix E). We corroborate this finding using an alternative measure, the maximum absolute difference in marginal means across attribute levels, which similarly shows that true information is shared more, and false information less, in the online condition compared to offline. Conversely, source and transmitter identity matter more offline, suggesting that offline sharing is more influenced by contextual and relational cues than by truthfulness. These results align with the idea that the public nature of online spaces increases scrutiny, making respondents more cautious about sharing false information.

Social norms also operate differently across contexts. Positive endorsement (”most agree”) boosts sharing in both settings, but more strongly online. Negative endorsement (”most disagree”) reduces sharing more offline than online. Controversial information elicits opposite effects: it is shared less offline but more online, highlighting how anonymity and distance on online platforms may encourage the sharing of polarizing content, whereas offline settings, with closer social ties and greater reputational risks, may discourage such behavior (Gurgun et al., 2023; Asenbaum, 2018). In sum, online sharing behavior places a premium on social endorsement and veracity, while offline sharing is more sensitive to rejection cues and source identity. These patterns underscore the need to consider platform-specific dynamics when designing interventions to combat misinformation, particularly in close-knit offline communities where factors beyond factual accuracy shape the spread of rumors.

5 Discussion and Conclusion

In this paper, we conducted an in-person study with about 6,000 adolescents in rural Bihar, India, to investigate the factors that influence individuals' decisions about which information to share and under what conditions they disseminate false news. To do so, we implemented a vignette-based experiment that emphasized attributes often overlooked in the existing literature, including the identity of the transmitter, the context of sharing (online versus offline), and factors such as social endorsement, topic, and source. Using a forced-choice design in which respondents were presented with news-sharing scenarios, we highlight two key findings. First, respondents placed a strong emphasis on veracity: they were significantly more likely to share true information over false information. Notably, this occurred without any explicit cues about a story's accuracy – we did not provide fact-check labels, veracity indicators, or other prompts –

meaning that respondents had to independently infer truthfulness based on contextual attributes alone. Second, we find that the religious identity of the transmitter strongly shapes sharing behavior. Specifically, there is a pronounced bias against Muslim transmitters: respondents were less likely to share information from Muslim sources, and this penalty persisted even when the information was true. By contrast, when the transmitter was Hindu, veracity played a greater role, with respondents more willing to reward true information and penalize false information. Together, these findings suggest that while truthfulness matters for information sharing, ethnic and religious identity can override veracity considerations, especially when evaluating information from outgroup members.

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 mediums and sources, 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. The implications of 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.

Methodologically and empirically, this study offers several important contributions. First, we developed a novel approach to delivering conjoint experiments in-person through face-to-face surveys. This required a series of innovations, including adapting attribute presentation into vignette formats that more closely mirror real-world information transmission, and designing the survey in ways that ensured respondent engagement and comprehension. Empirically, by successfully implementing this delivery mechanism, we were able to generate insights about populations that are typically excluded from experimental research – specifically, individuals with limited or no internet access. Given that offline populations represent a substantial proportion of the global population, our study expands the reach of misinformation scholarship beyond the digitally connected, offering a more inclusive understanding of how information circulates and is evaluated in diverse contexts.

A final 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 a broader implication that misinformation can arise not only from trusting inaccurate news but also from distrust of certain individuals or communities.

Despite these important findings, we acknowledge some 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. Finally, while our study measures information sharing through self-reported intentions (consistent with standard practice in the literature) we recognize that it would be valuable to observe actual sharing behavior directly. Due to logistical constraints, we were unable to implement behavioral measures in this study. We hope that future research will build on our findings by developing methods to capture real-world sharing behaviors, particularly in offline and low-connectivity environments.

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. Understanding these descriptive patterns of what drives information sharing is a crucial first step toward designing effective interventions to combat the spread of misinformation. 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. But randomization in current study was independent of RCT treatment assignment. For the RCT the unit of randomization to treatment or control was the village. Villages were selected based on their proximity to 100 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 100 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 News 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 BJP 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 Indian classical music

C Marginal Means

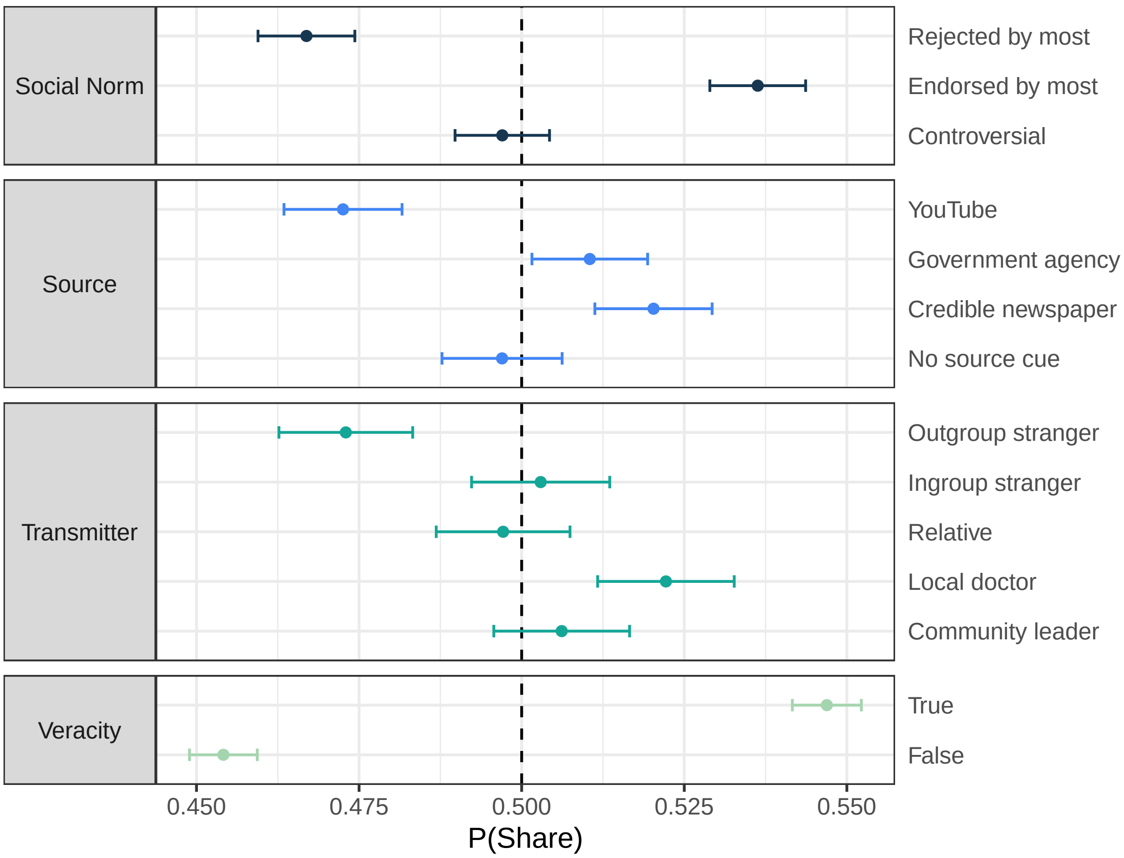

Figure 5: Main Effects Marginal Means

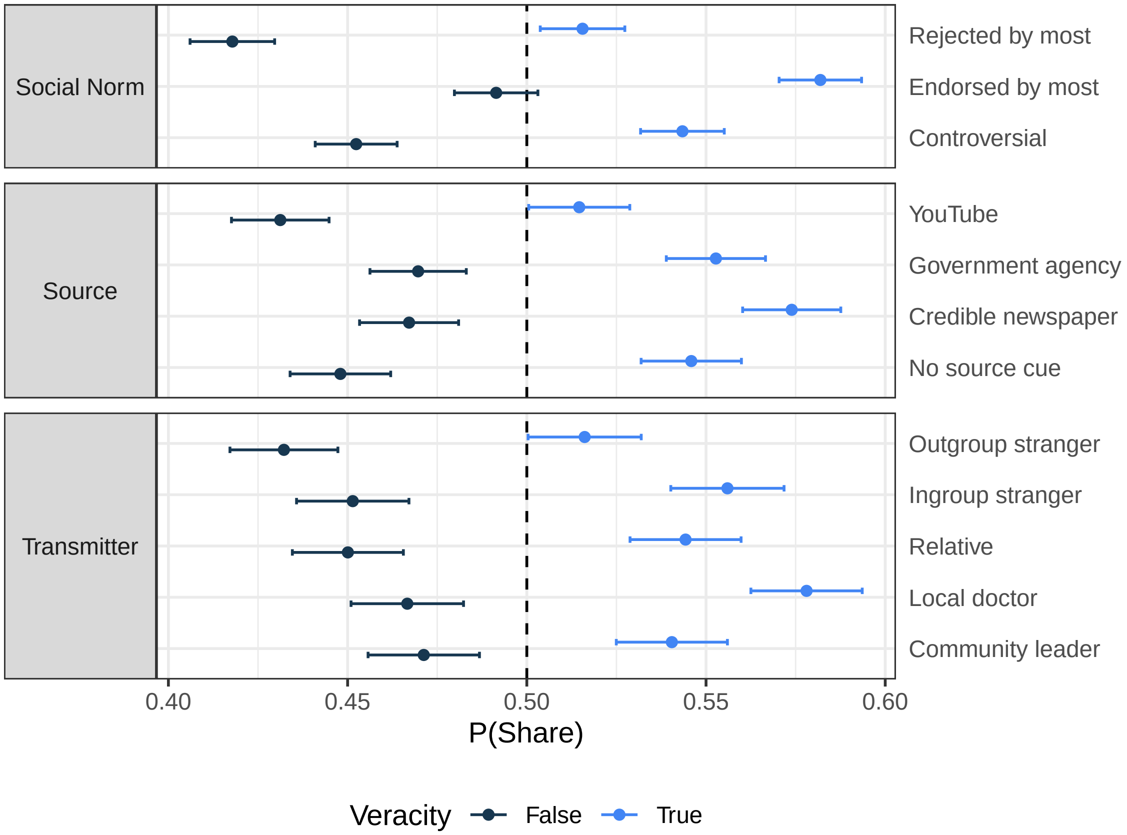

Figure 6: Marginal Means by Veracity

D Ethnicity Effects

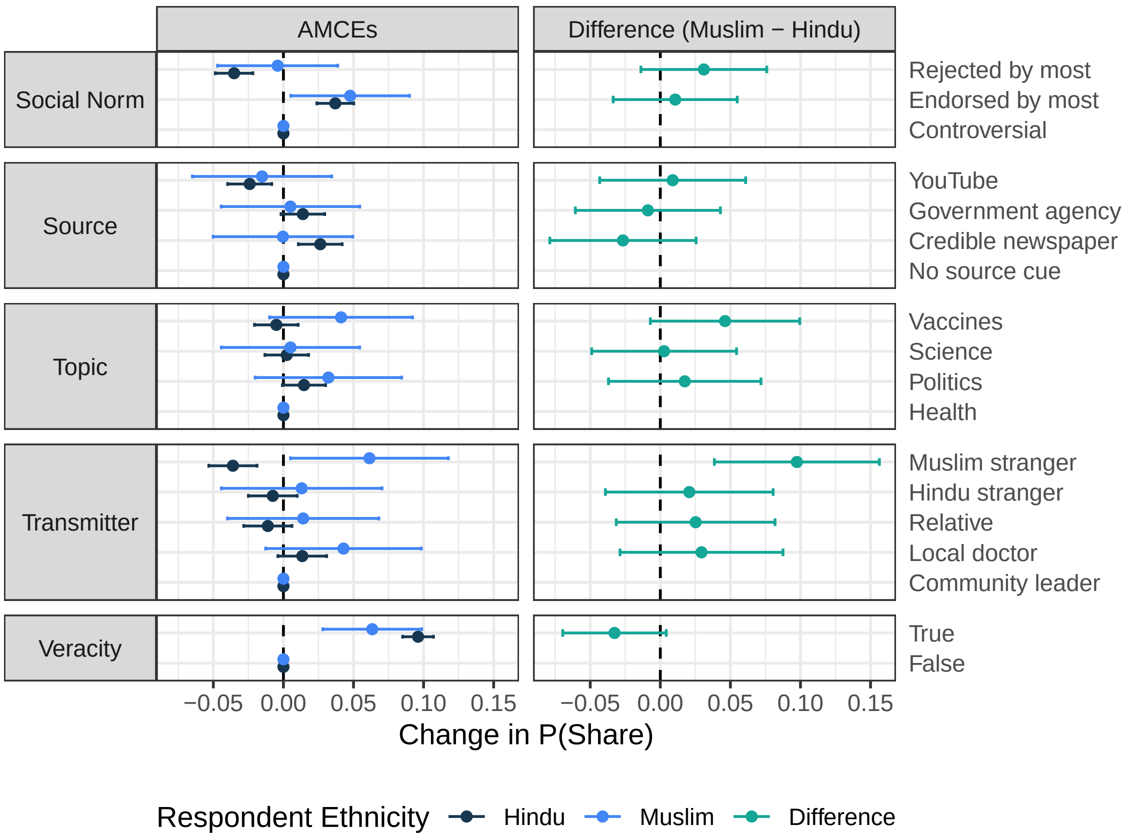

Figure 7: AMCEs by Respondent Ethnicity

E Online versus offline

In Figure 8 we look at estimates of variable importance from our random forest model, including bootstrapped standard errors. 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.

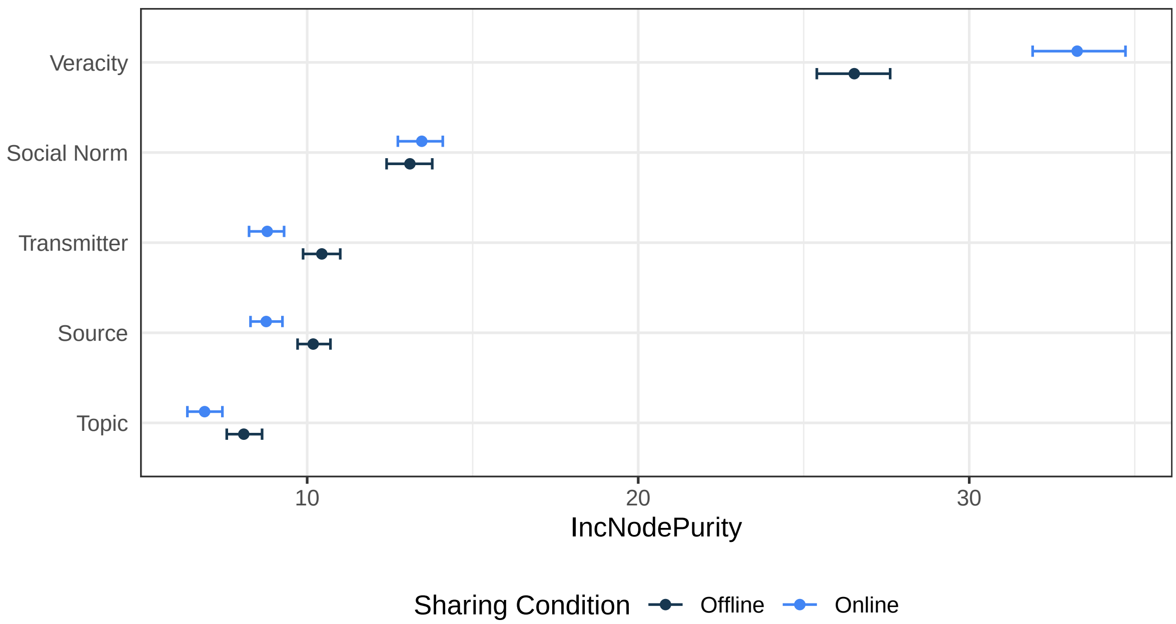

Figure 8: Attribute Importance across Sharing Conditions

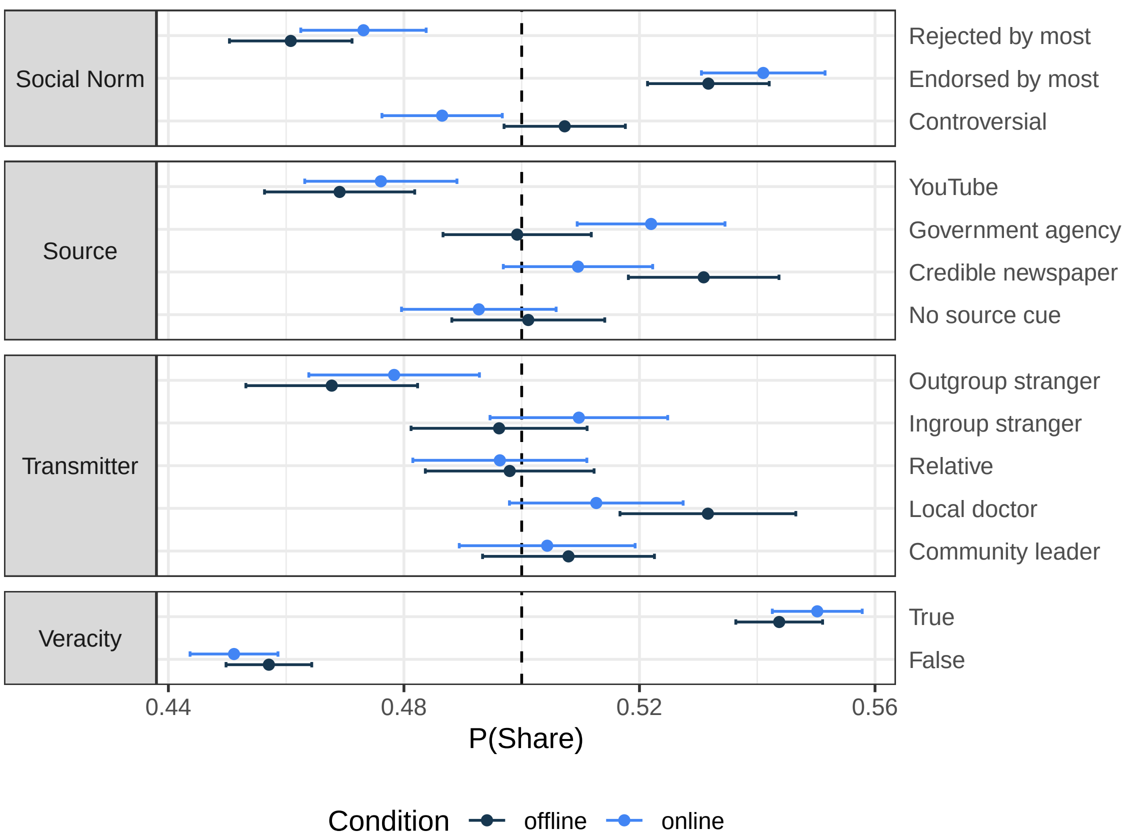

Figure 9: MMs by Online and Offline Sharing Condition

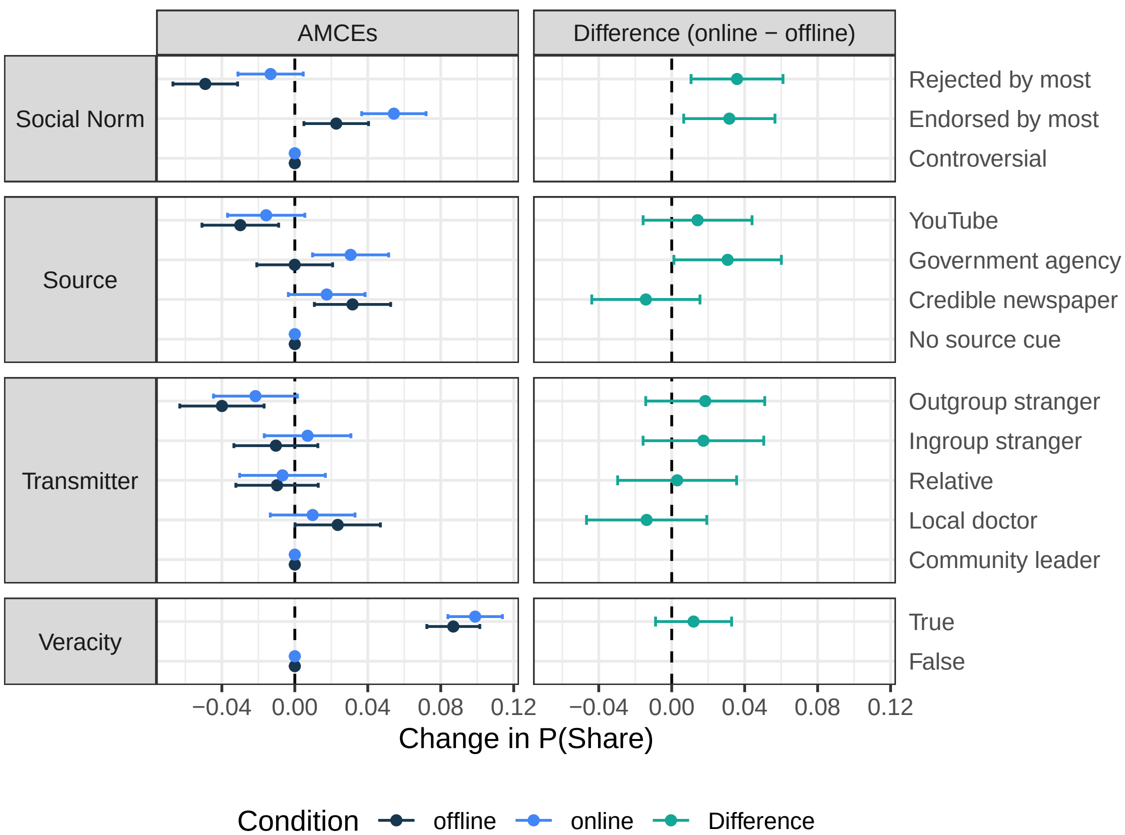

Figure 10: AMCE by Online and Offline Sharing Condition

F AMCE by Demographic Subgroups

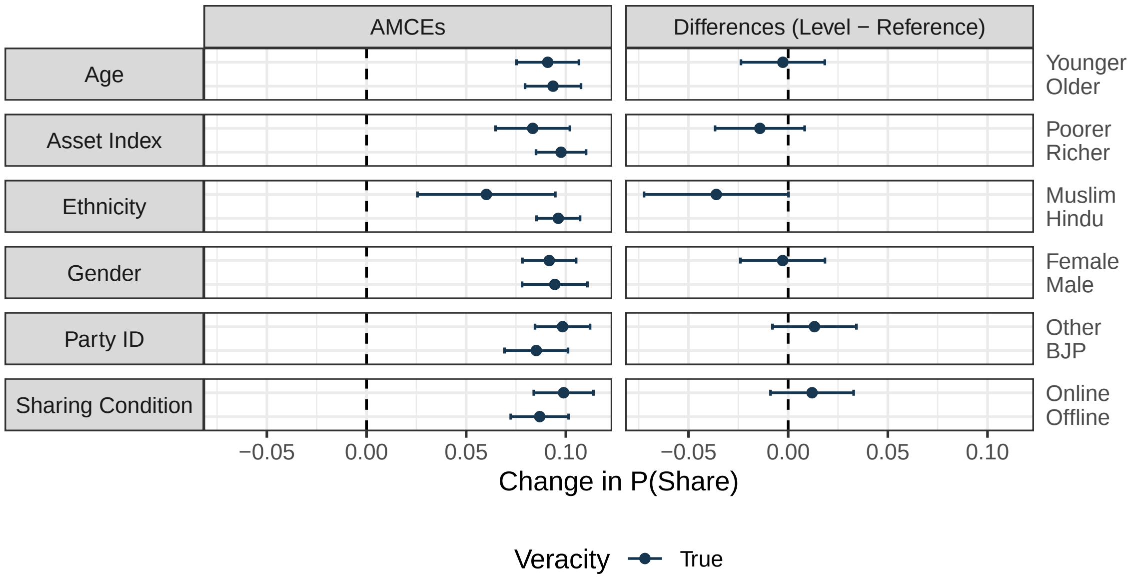

Figure 11: AMCE on Veracity by Subgroup Demographics

G 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.