

Journal of Development Economics
Mental Health, News Consumption, and Political Behavior*
--Manuscript Draft--

Manuscript Number:	DEVEC-D-23-01841R1
Article Type:	Registered Report Stage 1: Proposal
Section/Category:	Experimental Papers, credit, insurance
Keywords:	mental health; news consumption; belief updating; fake news; polarization
Corresponding Author:	Francesco Capozza Berlin Social Science Center GERMANY
First Author:	Francesco Capozza
Order of Authors:	Francesco Capozza Valentin Bolotnyy Siddharth George
Abstract:	We seek to understand how poor mental health, through its effects on cognition and perception, affects behavior with political implications. We will implement a randomized controlled trial around the 2024 general elections in India in which the treatment group will be offered one-month of subsidized mental health care through an online app. We will use this intervention to study how improvements in mental health change the news that people want to consume and affect their political attitudes and behaviors.
Response to Reviewers:	See the response letter attached

Mental Health, News Consumption, and Political Behavior*

Valentin Bolotnyy[†] Francesco Capozza[‡] Siddharth George[§]

February 15th, 2024

Pre-Registration Report

Abstract

We seek to understand how poor mental health, through its effects on cognition and perception, affects behavior with political implications. We will implement a randomized controlled trial around the 2024 general elections in India in which the treatment group will be offered one-month of subsidized mental health care through an online app. We will use this intervention to study how improvements in mental health change the news that people want to consume and affect their political attitudes and behaviors.

Keywords: mental health, news consumption, belief updating, fake news, polarization

JEL Classification codes: C83, C93, D72, D83, D91, I31

*We are grateful to Michael Thaler, Johannes Haushofer, Chris Roth, Frank Schilbach, Arkadev Ghosh, Ruben Durante, and Ro'ee Levy for their helpful comments, and to Andy Teo for research assistance.

[†]Hoover Institution, Stanford University. vbolotnyy@stanford.edu

[‡]WZB Berlin Social Science Center and Berlin School of Economics. francesco.capozza@wzb.eu

[§]National University of Singapore. segeorge@nus.edu.sg

1 Introduction

Mental health issues, misinformation, and political polarization are all growing concerns in many developing countries. These problems are typically seen as distinct and studied separately, but the recent COVID-19 period suggests they might be linked. Lockdowns worsened mental health (Altindag et al., 2022), providing fertile ground for the spread of COVID-related conspiracy theories (Sadish et al., 2021), which may have widened divisions in already polarized societies (Alsan et al., 2023). Prior research suggests that mental health changes the way people allocate attention (Suslow et al., 2020), acquire and remember information (Ash et al., 2023; Moran, 2016), and form beliefs (Bhat et al., 2022). Thus, conditions like depression and anxiety might influence the news that people watch or read and shape how they think about current events. Some scholars even argue that declining mental health contributes to an information crisis in society, where many citizens have deeply inaccurate beliefs about the world and take inappropriate actions as a result (Cichocka, 2020). Yet, we have almost no direct evidence on how mental health affects news consumption and beliefs about public issues.

In this study, we experimentally evaluate how mental health affects news consumption and political behavior by conducting a randomized control trial (RCT) in India. To induce exogenous variation in mental health, we partner with *Intellect*, a leading Asian mental health platform, and offer randomly selected participants subsidized access to their mobile app. We plan to recruit approximately 3,000 individuals via social media advertisements. After completing a baseline survey, treated participants will receive a one-month subscription to *Intellect's* app with incentives for regular use.¹ The app contains self-guided cognitive behavioral therapy (CBT) programs to build healthy habits, change thought patterns, and address issues like depression, stress, and anxiety. Midline and endline surveys after two weeks and one month, respectively, measure changes in mental health, news consumption, beliefs, and preferences.² Additionally, a plug-in captures browser and app usage data, and we observe activity on Twitter (now X).

India is a good context to study the links between mental health, misinformation, and political behavior. Mental illness is common: even before the pandemic, 10.6% of adults, or about 150 million people, suffered from a mental disorder that

¹*Intellect* will also provide us data on app usage, so we can measure compliance.

²In addition, if we find treatment effects after 1 month, we will conduct a second endline at the 2-month mark to assess whether treatment effects persist after the intervention ends.

required active intervention.³ The vast majority face common conditions, such as depression and anxiety, that (prior research has shown) can usually be effectively treated with CBT (Layard and Clark, 2014). Nevertheless, treatment gaps are significant, with 83% of individuals experiencing mood and stress-related disorders receiving no treatment in the past year.⁴ These gaps are especially concerning for vulnerable groups, like women and the poor, who suffer higher rates of mental illness. Given India's strained health infrastructure, scarcity of mental health professionals, prevalence of smartphones and affordable data costs, mobile-based CBT offers a cost-effective, scalable solution to improve mental health treatment access.

India is also an important theatre in the global battle against misinformation. Nearly 60% of Indians view misinformation as a problem and 46% believe social media has increased polarization. Political actors actively use social media to disseminate (true and fake) information in an environment charged with religious tensions (Carney, 2022). Moreover, since WhatsApp, the most popular social media platform, is encrypted and thus has no scope for content moderation, the primary way to fight misinformation is to reduce citizens' susceptibility to it.

We begin by verifying whether treated individuals display improvements in their mental health. Prior experiments have found that using *Intellect's* app for 1 week reduced anxiety by 0.2 standard deviations (SD), depression by 0.11SD, and stress by 0.23SD (Ong and Sündermann, 2022; Kosasih et al., 2023; Toh et al., 2022). Thus, we expect a strong first stage in our study.

We study how mental health impacts *five* aspects of news consumption: *demand, attention, belief formation, sharing* and the *reason for consuming news*. First, *demand*. We measure the quantity of news consumed in two ways — (i) by surveying respondents about time spent reading or watching news (à la Allcott et al. (2020)) and (ii) using our browser data to track visits to news websites (as in Levy (2021)). Mental health has an ambiguous impact on the overall quantity of news consumed, as some disorders (e.g. anxiety) cause individuals to obsessively check news while others (e.g. depression) may lead individuals to disengage from news.

We also identify the medium and source of news consumption, specifically capturing the importance of social media as a source of news. While prior work high-

³These figures come from the Indian Mental Health Survey, which in 2015 interviewed a representative sample of over 34,000 Indian adults.

⁴Indian Mental Health Survey, 2015-16. The government's report also argued that closing treatment gaps would help India achieve target 3.4 of the Sustainable Development Goals (SDGs), which focuses on promoting mental health and well-being and reducing premature mortality from mental health disorders.

lights the mental health costs of social media use (Braghieri et al., 2022; Allcott et al., 2020, 2022), ours is one of the first studies to examine causality in the other direction — how mental health impacts social media use. To measure social media activity, we complement self-reported measures of usage and digital addiction (Allcott et al., 2022) with actual time spent on different apps from a plug-in and publicly observable measures of user activity on X. Browser data enables us to identify news sources and (in some cases) topics. This allows us to assess whether treatment increases mainstream news consumption while reducing reliance on fringe sources.

Second, we investigate how mental health influences respondents' preferences over tone and slant in news. Psychological findings indicate that depression and anxiety lead to selective attention to negative or threatening stimuli (Armstrong and Olatunji, 2012; Suslow et al., 2020), potentially increasing focus on and recall of negative news (Kelly and Sharot, 2023). To measure demand for different types of news, we ask respondents to select articles they would like to read based on the article headlines (in the same vein as Chopra et al. (2022)). This enables us to test whether mental health affects respondents' demand for negative news and news that is aligned with their prior beliefs.

Third, we directly measure whether mental health affects respondents' attention and memory. We measure attention in several ways. First, we test whether treated individuals are more likely to pass attention checks that measure their ability to read beyond sensationalist or misleading headlines. Second, to measure what is salient, we ask respondents to highlight key words and phrases in a news article. We test specifically whether (i) respondents' attention is swayed by visually salient (but uninformative) content and (ii) respondents are differentially attentive to negative words.

Fourth, we study how mental health affects belief formation. A core aim of CBT is to slow down thinking and promote reflection (Pennycook and Rand, 2019; Bago et al., 2020, 2023). This may reduce a person's susceptibility to fake news (WalDROP, 2023), enabling them to form more accurate beliefs. We elicit respondents' beliefs about two polarising topics which have been the subject of extensive misinformation in India — COVID-19 and the relative population growth of Hindus and Muslims. We assess whether treated respondents are more likely to have accurate beliefs about the efficacy of the COVID-19 vaccine and the average fertility of Hindus and Muslims. Furthermore, we test whether treatment impacts belief updating in response to true news and fake news. If better mental health makes individu-

als more judicious news readers, we should find increased updating in response to true news and weaker updating in response to fake news.

We explore several channels through which mental health may result in the formation of more accurate beliefs about the world — improved cognition, increased ability to detect fake news, and a decrease in motivated reasoning. Prior work (e.g. [Cramer et al. \(2016\)](#)) shows that mental health therapy affects cognitive functions such as memory and concentration, which can affect how individuals process information. We measure cognition using Raven’s matrices, following other studies that measure cognitive bandwidth in low-income countries ([Shah et al., 2012](#); [Haushofer and Fehr, 2014](#)).

The cognitive and emotional aspects of mental health could shape an individual’s susceptibility to particular political narratives, potentially influencing their ideological alignment ([Baysan, 2022](#); [Hüning et al., 2022](#); [Kubin et al., 2021](#)). Thus, we measure the ability to identify fake news at both baseline and endline by asking respondents about the veracity of a series of (true and fake) news headlines.

Improved mental health may enable individuals to incur the cognitive and psychological costs of consuming news that conflicts with their beliefs ([Engelmann et al., 2022](#)). To capture motivated reasoning, we assess whether respondents respond more to news aligned with their prior beliefs. We also evaluate whether treated individuals express a different motivation for reading news, placing more weight on accuracy rather than belief confirmation.

Fifth, we examine whether mental health has downstream effects on beliefs and preferences, and explore the importance of news consumption as a mediating channel. We measure the accuracy and polarization of respondents’ beliefs about a health issue (the efficacy of the COVID-19 vaccine) and a political issue (the relative fertility of Muslims and Hindus) before and after presenting a news article about the topic. The pre-news treatment-control differences in belief accuracy and polarization capture the direct impacts of improved mental health on these outcomes. However, if treatment-control gaps widen after the provision of news, it would imply that treatment improves belief accuracy and reduces polarization in part through more judicious reading of news. This allows us to shed some light on the importance of news consumption as a mediating channel.

Finally, we measure impacts on social preferences. We base this hypothesis on neuroimaging evidence, which suggests that mental health therapy affects brain areas associated with cooperative behavior, potentially mitigating divisive attitudes.

To capture social preferences, we measure respondents' attitudes towards other ethnic and political groups using both validated questionnaires (i.e. thermometer rating and perspective-taking survey items) and incentivized behavioral measures such as a dictator game with non-coethnics and the decision to join a partisan WhatsApp group.

We recruit a large sample of 3,000 respondents through targeted advertisements on social media platforms. This gives us considerable statistical power, enabling us to detect treatment effects of 0.05-0.11 SD, which are considerably lower than other studies examining the same outcomes. The advertisement campaign will prominently feature the offer of complimentary access to a mental health app for a one-month duration. While not representative of Indian society on the whole, the sample will be representative of the population (e.g. younger, urban) that is most exposed to online misinformation and suffers a higher incidence of mental illness. To incentivise compliance, we provide incentives for using *Intellect's* app and measure compliance by collecting administrative data from *Intellect* on usage of different app features. To mitigate attrition, we incentivise participation in the midline and endline surveys. To keep Control group respondents engaged, we implement a phase-in design, where the control group receives access to the app 2 months later than the respondents in the treatment group. To mitigate concerns about experimenter demand effects, we capture not only self-reported measures of news consumption, but also actual browsing and app usage data.

Contributions to literature. Our study contributes to a number of literatures. First, we shed light on the link between mental health and media consumption. Prior work has focused on the mental health impacts of media exposure. [Braghieri et al. \(2022\)](#) show that the diffusion of social media worsened mental health. [Allcott et al. \(2020\)](#) finds that deactivating Facebook improved mental health, in part because social media use shows signs of addiction ([Allcott et al., 2022](#)). We contribute to this literature by presenting experimental evidence on the reverse link — i.e. how mental health affects news consumption, a question on which there is almost no empirical evidence.

Second, we contribute to a growing literature studying the impacts of mental health in low-income settings ([Ridley et al., 2020](#); [Lund et al., 2022](#)). Several influential papers document how mental health therapy can have lasting economic impacts in low-income settings ([Baranov et al., 2020](#)), often by changing risk pref-

erences ([Angelucci and Bennett, 2021](#)) and beliefs about oneself ([Bhat et al., 2022](#)). Mental health treatments like CBT are often effective at reducing crime and violence in polarized societies ([Blattman et al., 2017, 2023](#)) by changing thought patterns, automatic associations, and social identities ([Heller et al., 2017](#)). We contribute to this literature by examining another channel through which mental health may affect beliefs about the world and social preferences — news consumption.

Third, we will contribute to a burgeoning literature on misinformation ([Barrera et al., 2020](#); [Henry et al., 2022](#); [Berger et al., 2023](#)). There is generally limited research on misinformation in developing countries ([Badrinathan, 2021](#)). Moreover, most studies have examined training interventions that educate people about misinformation and teach them to detect fake news ([Guess et al., 2020](#); [Ali and Qazi, 2023](#); [Hirshleifer et al., 2022](#)). Our contribution is to examine the link between mental health and susceptibility to fake news and conspiracy theories and the accuracy of their beliefs about the world.

The remainder of the paper proceeds as follows. Section 2 provides background. Section 3 illustrates the experimental design and Section 4 describes the data we are planning to collect. We then present our pre-specified empirical strategy in Section 5. Finally, Section 6 illustrates the timeline for the execution of the study, Section 7 shows evidence from a small pilot to substantiate our hypotheses, and Section 8 outlines the potential limitations and how we plan to address them.

2 Background

2.1 Mental Health in India

There are growing policy concerns about mental health in India. Approximately 11% of the Indian population, covering nearly 200 million people, suffers from some kind of mental health challenge — primarily depression, anxiety, or schizophrenia ([Bhat et al., 2022](#)). Social stigma against mental illness exacerbates these issues, hindering individuals from seeking help. A lack of awareness about mental health and the limited availability of mental healthcare services further compound the problem, especially in rural areas where access is very limited. The COVID-19 pandemic added another layer of complexity by exacerbating mental health issues due to lockdowns, loss of loved ones, economic uncertainty, and isolation.

One of the primary obstacles to improving mental health in India is the shortage

of qualified professionals, including psychiatrists, psychologists, and social workers, resulting in delayed or inadequate treatment. Additionally, mental health services have historically been underfunded and underprioritized in the healthcare system, though the government recently increased resourcing of mental health professionals via the Mental Healthcare Act of 2017.

In this context, mobile-based mental health resources and platforms, such as the app we partner with and study, represent a cost-effective and scalable solution to mental health challenges.

2.2 Mental Health and Polarization

Intergroup polarization in India is a multifaceted issue with a deep connection to mental health. Religious and communal polarization, such as that between Hindu and Muslim communities, can result in heightened stress, anxiety, and even trauma. When individuals from these groups experience discrimination, fear, or conflict, their mental well-being is significantly impacted. These negative mental health outcomes can further contribute to an 'us versus them' mentality, increasing polarization. Thus, mental health and polarization can exhibit a dangerous feedback loop.

Political polarization amplifies feelings of uncertainty and insecurity, which can take a severe toll on the mental health of individuals. The media, especially social media, amplifies these divisions and can heighten mental health distress (Levy, 2021). Economic disparities and historical communal tensions can create additional mental health challenges, further straining marginalized communities.

It is essential to recognize that mental health and polarization are interconnected, and addressing one issue can positively impact the other (Landwehr and Ojeda, 2021). Tackling mental health challenges in a polarized society is a vital aspect of reducing polarization itself, as improved mental well-being can lead to more open dialogue, empathy, and unity among diverse groups. Mental health services may play a crucial role in breaking this negative feedback loop.

2.3 Misinformation and the Indian Political Landscape

Misinformation has become a significant challenge in the Indian political landscape, fueled by a combination of social, technological, and political factors. In recent years, the rapid growth of social media platforms, especially WhatsApp, has

played a pivotal role in the spread of misleading information, leading to a distortion of public discourse and influencing political opinions.

One key aspect of misinformation in India is its role in shaping public perceptions during election campaigns. False narratives, manipulated images, and fabricated stories often circulate widely, creating a polarized information environment. This misinformation can sway public opinion, impact voter behavior, and even contribute to the rise of populist movements.

The decentralized nature of information dissemination on social media makes it challenging to regulate and monitor the spread of misinformation. In some instances, political actors themselves have been accused of using misinformation as a strategic tool to influence public opinion, create division, and advance their agendas. Like in other countries, right-wing parties, such as the ruling BJP, are thought to have wielded this more effectively as a campaign tool.

Religious and communal tensions in India further amplify the impact of misinformation. False narratives that exploit religious sentiments or promote divisive ideologies can lead to real-world consequences, including social unrest and violence. This underscores the need for interventions that address factors that make individuals more receptive to such information, such as the online mental health intervention we study. This can complement fact-checking and other efforts to combat misinformation in the Indian political landscape and improve communal tensions.

The most viral examples of misinformation in India often relate to communal tensions. For instance, in 2013, a fake video purported to show Muslim youth in the district of Muzaffarnagar, Uttar Pradesh, attacking a Hindu victim.⁵ In reality, the video was an old Taliban propaganda clip. Communal passions were inflamed by the video, which was widely circulated after being shared by a BJP legislator from a neighbouring town. A riot ensued, which killed at least 62 people and displaced over 50,000 people.

In 2019, several travellers were killed in multiple episodes due to fake news about roaming child kidnappers.⁶ India has also been considered the biggest source of misinformation about COVID (*Al-Zaman, 2022*).

⁵More details are available [here](#).

⁶An article about the incident can be viewed [here](#).

3 Research Design

3.1 Intervention and Basic Methodological Framework

In our experimental design, participants will be required to engage with a mental health application for a duration of one month. We leverage a collaboration with *Intellect*, a leading mental health company whose app has been shown to be effective in medical trials (Ong and Sündermann, 2022; Kosasih et al., 2023; Toh et al., 2022). Our recruitment strategy will focus on identifying individuals who express interest in using Intellect’s app to improve their mental health. This approach aims to optimize initial participation rates and reduce the likelihood of attrition post-treatment.

Recruitment Our respondent recruitment strategy will leverage Facebook, Instagram, and X advertisements, a method used by similar studies both in the US (Shreekumar and Vautrey, 2022; Beknazar-Yuzbashev et al., 2022) and in developing countries (Beam, 2023). These advertisements will be meticulously crafted to target individuals encompassing the entire political spectrum in India.

In our ad campaign, we will clearly communicate to potential participants that we are offering complimentary access to a mental health application, which they will actively engage with for a one-month duration. Additionally, we will emphasize that participants have the opportunity to earn supplemental compensation based on their survey responses.

Upon clicking on our advertisements, prospective participants will be prompted to confirm their Indian citizenship and that they are over 18 years of age. Subsequently, we will collect fundamental demographic information, which will serve to evaluate self-selection in the experiment. Furthermore, we will request their email addresses, through which we will distribute subsequent surveys and provide access to the mental health service.

We will oversample individuals with moderate and severe depression and anxiety at baseline, so as to ensure sufficient sample across the mental health distribution. This will enable us to detect first stage and treatment effect by baseline mental health.

We will explore sampling via survey panels if we are unable to achieve sufficiently broad coverage of respondents across the mental health distribution.

Baseline Measurement We will conduct a baseline survey measurement of the key variables in our experiment. First, we will collect the respondents' demographic information (age, gender, region, political affiliation, income level, religion). Then, we will measure the relevant outcomes that we will potentially change over the course of the study. We will group them in different thematic blocks:

- Reciprocity: we will measure the respondents' positive and negative reciprocity in terms of willingness: a) to return a favor; b) to take revenge; c) to punish if you are treated unfairly; d) to punish if others are treated unfairly.
- Emotions: we will elicit the extent to which the respondents have been happy, sad, angry, and worried in the past four weeks using the same wording as [Meier \(2022\)](#).
- Mental health status: we will measure the respondents' mental health status using validated scales to measure anxiety symptoms (GAD-7) and depression symptoms (PHQ-9).⁷
- Reasons to read news and sources of information: we will ask the respondents to state the motives behind their news consumption. We will show them two possibilities based on [Chopra et al. \(2023\)](#): accuracy motives and confirmation motives. Then, we will measure how much they consume political news and from which sources (online and offline).
- Fake news detection: we will measure the proclivity of the respondents to believe in fake news at the baseline. We will repeat this measurement in the midline survey using a different set of statements. Crucially, we will not provide feedback on how well the respondents will perform in recognizing fake news. To benchmark our measures against other studies of misinformation in the Indian context, we recycle some of the questions used by [Badrinathan and Chauchard \(2021\)](#).
- Screen time and digital addiction: we will measure the time respondents spend in front of a screen and how the screen time breaks down into different apps using a constant sum rank task (e.g. Instagram, Facebook, etc).

⁷The GAD-7 and the PHQ-9 have been shown to be suitable for measuring the prevalence and severity of anxiety and depression symptoms, respectively, in India. See [De Man et al. \(2021\)](#).

- **Thermometer ratings:** we will measure their 'sentiment' towards their own political group and their opponents using thermometer ratings. These are commonly used in political surveys like the American National Election Studies (ANES) and the Cooperative Election Study (CCES).

The survey modules outlined above constitute the central components of our study. We will administer these modules during both the midline and endline survey measurements to track changes over time.

Additionally, we will assess respondents' susceptibility to social desirability bias using a series of questions adapted from [Dhar et al. \(2022\)](#). These questions will present a list of personal attributes associated with moral or virtuous qualities, and respondents will be asked to indicate whether they possess these attributes. A higher score on the social desirability index will indicate a greater propensity for social desirability bias.

Randomization Our study will employ a randomization process, wherein respondents will be evenly distributed into two distinct experimental conditions: a Treatment group and a Control group. The sole differentiation between these groups lies in the timing of access to the mental health app. Specifically, participants assigned to the Treatment group will receive immediate and complimentary access to the mental health app immediately following the baseline survey. They will retain this access for a duration of one month. In contrast, participants designated to the Control group will gain access to the mental health app only after 2 months — after Treatment group participants have completed their one-month usage period and an additional month (to allow us to estimate any persistence effects). This staggered access approach allows us to explore the effects of mental health app utilization on our key variables, comparing those who have access from the outset with those who gain access after a delay. The app is available in English and Hindi. Therefore, we will restrict our sample to respondents who can understand these languages.

Compliance We will be able to carefully measure compliance, as Intellect will provide us granular data on app usage. We will have information about time spent on the app and modules completed.

Midline Measurement Two weeks after the randomization, we will conduct a midline survey measurement. In this second survey, we will repeat the measure-

ment of the core modules listed in the baseline measurement section above. In addition, we will measure additional outcomes:

- **Belief updating:** we will assess how changes in mental health affect how people process information and update their beliefs. For this purpose, we will measure the respondents' beliefs about inflation and GDP growth in the next year in India. We will focus on this topic because it constitutes a reasonable and politically neutral topic that people are interested in. After the core module, we will ask the respondents to read an article from an economic expert on how India's macroeconomic conditions might evolve in the next year. After being exposed to the article, we will measure the respondents' beliefs about inflation and GDP growth again.
- **Attention:** we will display an article with multiple paragraphs on COVID-19, its origin, its implications, and its remedies. We will ask respondents to answer different questions about the content of the text they have read. We will also record the time spent on the article by each respondent. Both measures, namely the number of questions answered correctly and the time spent on the page, will be our proxies for attention. Finally, we will present a short article to the respondents on the myth about Muslims taking over Hindus in the following years. We will ask respondents to highlight the parts of the text that summarize, in their opinion, the content of the message.
- **Fake news detection:** we will measure whether improving one's mental health enhances one's ability to detect fake news. We will follow the methodology proposed in [Bago et al. \(2020\)](#), where we will display different pieces of news to respondents and will ask them to evaluate how likely they think the news are to be fake.
- **Cognitive bandwidth:** we will measure whether respondents free up their cognitive bandwidth after improving their mental health ([Shreekumar and Vautrey, 2022](#)). We will ask the respondents to complete Raven matrices. We will incentivize the task by giving a bonus to the respondents for every correct answer they report.

Endline Measurement Two weeks after the midline measurement and four weeks after the baseline measurement we will conduct an endline measurement survey.

The survey will repeat the core survey modules in the baseline and midline surveys as well as ask additional questions:

- **Doomscrolling:** Our study will explore individuals' inclination to prefer negative news over positive news. To investigate this tendency, we will present respondents with five pairs of article headlines. Each pair will include two distinct headlines, both covering the same news event. However, one headline will carry a negative connotation, while the other will have a positive one. Respondents will be asked to select the headline from each pair that they find more interesting or engaging. It is important to note that respondents will have a genuine incentive to reveal their true preferences, as they will receive a curated list of news articles similar in tone to those they found more interesting after the study. This approach allows us to assess individuals' natural inclinations toward negative or positive news content, providing valuable insights into their news consumption preferences. We will create a doomscroll index equal to $\frac{\#negativenews - \#positivenews}{10}$. One might be concerned that measuring news consumption using survey data does not capture people's actual news consumption behavior in real life. [Peterson and Iyengar \(2020\)](#) show that the correlation between news consumption in a survey has a correlation of 0.6 with actual news consumption behavior. This evidence reassures us about the external validity of the measurement. To capture whether the respondents spend more time reading negative news relative to positive news, we will use actual browsing data captured with a web browsing extension, which we will explain in the next paragraph.
- **Perspective taking:** we will investigate whether the respondents are more inclined to take into account others' points of view in their reasoning. Following ([Levy, 2021](#)), we will ask whether they agree with the following questions: "I find it difficult to see things from the opponent's point of View"; "I think it is important to consider the perspective of the opponent".
- **Punishment:** we will measure the attitudes of respondents towards their political opponents using an incentive-compatible measure. We will tell the respondents that they have been matched with an individual who belongs to a different ethnic group. We will ask them how much of a \$1 bonus they would like to share with them ([Bursztyn et al., 2020](#)).

- Donation to charity: we will ask the respondents whether they are willing to donate extra money to a NGO that promotes communal activities and harmony across ethnic groups.
- Joining WhatsApp group: at the end of our endline, we will ask respondents whether they want to follow one of two WhatsApp accounts that we will run. One of the two profiles will share politically slanted content, while the other will share moderate content. Upon choosing which profile to follow, we will add the phone number of the respondents to the WhatsApp group. At the moment of joining the group, the respondents will not know how many people have actually joined prior to them. Then, we will check whether the respondents will follow the account. We decide to focus on WhatsApp groups because of their relevance to shape political preferences in the Indian political context ([Carney, 2022](#)).

Post-intervention survey If we find that the intervention affected news consumption at endline, we will conduct a post-intervention survey to assess persistence. This post-intervention survey will be conducted at the 2-month mark (when the control group will receive access to the app). This survey will be very similar to the endline survey.

Observational data We will explore an avenue to collect data on the actual online behavior of respondents in our experiment. We will collaborate with the behavioral company PY Insights to collect respondents' data about their news browsing behavior (for a similar approach in the Indian context see [Miller et al. \(2021\)](#)). To do so, in the last steps of the endline survey, respondents will be asked to install a browsing extension that will collect data on their desktop browsing history from the previous 90 days. In particular, we will be interested in data about the respondents' news consumption online. By matching the answers from our experiment to the news browsing history, we will be able to document any change in news consumption due to an improvement in the mental health of the respondents in the Treatment group. In addition to this measure, we will ask our respondents to give us their X handle in the baseline survey. Conditional on obtaining enough X handles, we will scrape the publicly available X activity of the respondents in terms of engagement with political news (number of likes, posts, reposts, and comments). We will compare the engagement of the respondents with respect to political news across

Treatment and Control groups.

Experimenter Demand Effects To address potential experiment demand effects, we will implement several robustness measures aimed at minimizing these concerns. While experimenter demand effects are typically of moderate magnitude (de Quidt et al., 2018), we are committed to ensuring the integrity of our study. First, we will elicit the main behavioral measures of the study in an incentive-compatible fashion. In addition, the experiment will be designed in such a way as to preserve the respondents' anonymity, which also makes the respondents less prone to the experimenter demand effect. Furthermore, we will obfuscate the main purpose of the experiment, which is establishing a link between mental health status and news consumption. Finally, we will measure the degree to which the respondents are prone to social desirability bias using a validated scale by Dhar et al. (2022) in an Indian setting, and we will perform a heterogeneity analysis along this dimension.

3.2 Hypotheses and Key Outcomes

In this project, we will investigate how mental health impacts people's ability to recognize fake news, what type of news they consume, whether improved mental health affects how people process and recall information, and the potential mechanisms behind these effects. Moreover, we will study whether mental health affects political behavior and reduces affective polarization. Through this comprehensive exploration, we aspire to uncover significant insights into the complex interplay between mental health and information processing, with implications for individual decision-making, public discourse, and political polarization.

In the remaining part of the section, we list our main hypotheses, the theoretical premises that guide our reasoning, and the potential mechanisms we seek to investigate:

Hypothesis 1: *Improving respondents' mental health will cause an improvement in their ability to detect fake news.*

Considerable empirical evidence indicates that deliberation and reflective thinking have a mitigating effect on individuals' susceptibility to believing in fake news (Pennycook and Rand, 2019; Bago et al., 2020, 2023). This effect appears to be par-

ticularly pronounced among individuals who are inclined to endorse conspiracy theories (Bago et al., 2022). Notably, the enhancement of deliberation aligns with one of the primary objectives of CBT, a core component of the exercises available on the mental health app that will be provided to respondents in our experiment.

Based on this substantial body of evidence, Hypothesis 1 posits that improvements in mental health, particularly through enhanced deliberation facilitated by CBT exercises, will lead to a decreased propensity to believe in fake news.

Hypothesis 2: *Improving respondents' mental health will make them less likely to gravitate towards negative news relative to positive news.*

The definition of depression as “the negatively biased filter with which to view the world,” as articulated by Gotlib and Joormann (2010), resonates with a substantial body of research in psychology that investigates the relationship between mental health disorders and attention patterns, often utilizing eye-tracking methodologies.

For instance, Armstrong and Olatunji (2012) conducted a meta-analysis that revealed how anxious individuals tend to exhibit heightened attention toward threats during free viewing and information search tasks. Moreover, they found that anxious individuals face challenges disengaging their attention from threatening stimuli during information search.

Conversely, individuals experiencing depression tend to display reduced orientation towards positive stimuli and struggle to maintain their focus on such positive cues (Suslow et al., 2020). This pattern is further supported by studies demonstrating that individuals with depression tend to allocate more attention to dysphoric images and faces, while paying less attention to positive ones.

These findings are also corroborated by experimental studies involving larger samples, which reveal that individuals with pessimistic beliefs and a negative outlook on the future exhibit information acquisition behaviors akin to “doomscrolling” (Faia et al., 2022a; Sharot et al., 2012). In essence, these individuals tend to selectively engage with negative or distressing content while diverting their attention away from positive or uplifting information.

This convergence of research underscores the intricate interplay between mental health and attention patterns, shedding light on how cognitive biases may contribute to the manifestation of various mental health disorders, including depres-

sion and anxiety.

Hypothesis 3: *Improving respondents' mental health will change how people pay attention to information, how they update their beliefs, and their agreement with stereotypes.*

According to Beck's model of depression (Disner et al., 2011), latent schemas, which could be related to genetics and experiences, lead to the creation of depressive schemes (negative self-reliant views) that might be triggered by external factors (stressors). The effect of stressors alters people's views about self, future, and the world (also known as the negative cognitive triad). Depression alters the brain's information process with effects on biased attention, interpretation, and memory. Research by Cramer et al. (2016) affirms the influence of mental health therapy, particularly meditation, on cognitive functions such as memory, concentration, and energy levels. This suggests that therapeutic interventions can have a direct and positive impact on cognitive processes, potentially counteracting some of the cognitive biases associated with depression. The improvement of cognitive processes could have a spillover on whether people agree with stereotypical thinking, which is a form of heuristics used to decode reality in a fast way. Allowing for more mental space to understand reality allows people to engage less in stereotypical thinking.

Hypothesis 4: *Improving respondents' mental health will reduce affective polarization.*

Affective polarization measures people's attitudes toward individuals who belong to their own group and to opposite groups. There is evidence that mental health therapy affects social preferences and attitudes toward others. Iwamoto et al. (2020) suggests that therapy acts on the reward-processing areas of the brain, including the rostral anterior cingulate cortex (rACC), which is known to modulate fear processing in the amygdala, as well as the ventromedial prefrontal cortex (vmPFC), nucleus accumbens (NAcc), and caudate. These areas are associated with the cooperative behavior of individuals.

Mechanism 1: *Improving respondents' mental health changes time spent online and digital addiction.*

Mechanism 2: *Improving respondents' mental health reduces the experience of negative emotions.*

Category	Outcome	MDE	BL corr.	Reference TE
Mental health	Depression	0.031	0.9	0.37 (Shreekumar and Vautrey, 2022)
	Anxiety	0.031	0.9	0.46 (Shreekumar and Vautrey, 2022)
	Stress	0.031	0.9	0.33 (Shreekumar and Vautrey, 2022)
	Cognitive Load	0.031	0.9	0.13 (Shreekumar and Vautrey, 2022)
News	Fact-checking	0.087	0.3	0.15 (Chopra et al., 2022)
	Fake news recognition	0.087	0.3	0.38 Bago et al. (2023)
	Sharing fake news	0.087	0.3	0.14 Henry et al. (2022)
	Demand for news	0.087	0.3	0.10 Chopra et al. (2023)
	Digital Addiction	0.087	0.3	0.50 (Allcott et al., 2022)
	News Consumed Online	0.11	0.8	
Beliefs	Belief updating	0.067	0.6	0.37 (Faia et al., 2022b)
Polarization	Thermometer rating	0.046	0.8	0.06 (Levy, 2021)
	Punishment	0.046	0.8	0.08 (Bursztyjn et al., 2020)

Table 1. Power calculations

Mechanism 3: *Improving respondents' mental health increases their cognitive bandwidth.*

Mechanism 4: *Improving respondents' mental health increases their ability of perspective taking and increases reciprocity.*

3.3 Power Calculations

In this subsection, we describe our power calculations for mental health, news consumption, and belief and attitudinal outcomes. We conducted multiple rounds of a baseline survey and found that the within-subject correlation of mental health outcomes is 0.9. This significantly improves our power to detect even small effect sizes of about 0.031 SD. This is considerably lower than estimated in the literature. Table 1 presents minimum detectable effect (MDE) sizes for different outcomes. For example, Shreekumar and Vautrey (2022) finds that a similar treatment (access to a self-directed mental health app) reduces depression by 0.37 SD, anxiety by 0.46 SD, and stress by 0.33 SD in 4 weeks. This gives us significant confidence that we are likely to find a strong first stage, enabling us to identify downstream outcomes. For news consumption, our MDEs are in the range of 0.09-0.11 SD, which is still significantly lower than changes identified by studies that use fact-checking, fake news recognition and fake news sharing as an outcome.

4 Data

Our study will involve a sample of 3,000 respondents from India, recruited through targeted advertisements on X, Facebook and Instagram. Our recruitment strategy will be designed to encompass individuals representing a wide range of political ideologies within the Indian context.

The advertisement campaign will prominently feature the offer of complimentary access to a mental health app for a one-month duration. Additionally, we will communicate to potential participants that they have the opportunity to receive financial bonuses and rewards based on their responses in subsequent surveys.

This approach aims to attract a diverse group of respondents who are genuinely interested in improving their mental well-being and are motivated to actively engage with the study. By offering both access to the mental health app and potential rewards, we hope to maximize participation and foster meaningful insights into the relationships between mental health, information processing, and political polarization.

The study is designed as an RCT, which is the most suitable approach for evaluating the impact of the treatment, considering the substantial concerns surrounding endogeneity in the field of mental health. The RCT involves random allocation of the treatment, ensuring that the effects observed can be confidently attributed to the intervention.

Our study comprises three waves of surveys:

1. **Baseline Survey:** This initial survey serves as the starting point, capturing the respondents' characteristics and beliefs before any intervention.
2. **Midline Survey:** Conducted two weeks after the Treatment group receives access to the mental health app, this survey provides insights into short-term changes following the introduction of the intervention.
3. **Endline Survey:** Administered one month after the Treatment group gains access to the mental health app, this survey assesses the longer-term effects of the intervention.
4. **Post-intervention Survey:** administered at the 2-month mark. This will only be conducted if we find that the treatment impacts news consumption at endline.

In addition to the survey data, we have established a valuable collaboration with *Intellect*, a renowned Asian mental health service provider with a track record of validated apps from medical trials. This collaboration facilitates the collection of crucial information regarding respondents' utilization of the mental health app.

Through this partnership, we will obtain insights into whether respondents are actively using the app and the extent to which they engage with its features. This supplementary data is instrumental in enhancing our comprehension of how the treatment is being implemented and its potential impact on the respondents. By combining survey responses with real-world app usage data, we gain a more comprehensive and nuanced understanding of the intervention's effects and its role in improving mental well-being.

Finally, we will leverage a collaboration with the company PY Insights to collect respondents' online behavior. This should minimize concerns that any treatment effect on survey outcomes is due to experimenter demand effects.

The main focus of the project is to link how mental health affects respondents' news consumption, in particular news related to the political sphere. Therefore, we will tightly connect the content of the news the respondents will consume to the general election in India in May 2024. For this reason, our timeline will revolve around that milestone, when we will have to complete the data collection.

5 Empirical Analysis

We will test for equality of the mean of baseline characteristics measured before randomization to check if the Control and Treatment groups look similar. For this purpose, we will use t-test equality of means, and a χ^2 test for zero difference between all the characteristics⁸.

Controlling for the individual characteristics X_i , we will check if the individuals in either the treated group or the active control group are more likely to leave the sample before finishing the experiment. Defining C_i to be 1 if the individual finishes the experiment and 0 otherwise, we will use a linear probability model as follows:

$$C_i = \alpha + \beta_1 t_i + \Gamma^T X_i + \epsilon_i$$

where t_i is 1 if the individual is in the treated group. Testing for $\beta_1 = 0$ gives us

⁸We first standardize the differences and look at the sum of squared differences as the test statistics.

an indication of differential attrition across the Treatment and Control groups. We will repeat the analysis for the midline and endline surveys.

In case of rejection of balancing tests, or differential attrition across groups, we will use propensity scores to check the robustness of the results.

Descriptives

We will explore the correlates of mental health in the Control group that does not receive access to the app in the first month. Specifically, we will regress their level of mental health on the demographic variables we will elicit.

First Stage

We will assess whether allocating the respondents to the Treatment group improves their mental health status relative to the mental health status of the respondents in the Control group. Our key outcomes for mental health status are PHQ-9 score and GAD-7 score. We will standardize both scores using the mean and the standard deviation of the answers from the control group, and then we will average them to create a Mental Health Distress Index.

We will use the following regression:

$$y_i = \alpha + \beta_1 t_i + \Gamma^T X_i + \epsilon_i$$

Where y_i is the Mental Health Distress Index score, t_i is a dummy variable that gets a value equal to 1 if the respondent is allocated to the Treatment group, and X_i is a vector of controls (age, gender, political affiliation, ethnicity, income, education, and baseline mental health where for each regression we use the baseline measure of each variable).

Hypothesis 1 - Effect on Fake News (Primary Outcome)

We will assess the impact of an improvement in the mental health status among the respondents in the Treatment group on the ability of the respondents to detect fake news. We compute a fake news detection index which computes how many fake news have been correctly detected divided by the number of news seen, which will be our main outcome of interest for this hypothesis. We will create these indexes for

both baseline and midline surveys, and we will subtract the index of the baseline from the index of the midline.

We will use the following regression:

$$y_i = \alpha + \beta_1 t_i + \Gamma^T X_i + \epsilon_i$$

Where y_i is the difference in fake news recognition index between midline and baseline, t_i is a dummy variable that gets a value equal to 1 if the respondent is allocated to the Treatment group, and X_i is a vector of controls (age, gender, political affiliation, ethnicity, income, and Mental Health Distress Index at baseline).

Hypothesis 2 - Doomscrolling (Primary Outcome)

We will assess the impact of an improvement in mental health status among respondents in the Treatment group on the tone of the news to which they gravitate. We compute a doomscrolling index, which will be the main outcome by which test this hypothesis.

We will use the following regression:

$$y_i = \alpha + \beta_1 t_i + \Gamma^T X_i + \epsilon_i$$

Where y_i is $\frac{\#negativenews - \#positivenews}{10}$, t_i is a dummy variable that gets a value equal to 1 if the respondent is allocated to the Treatment group, and X_i is a vector of controls (age, gender, political affiliation, ethnicity, income, and Mental Health Distress Index at baseline).

Hypothesis 3 - Beliefs updating and Attention (Primary Outcome)

We will measure the effect of improved mental health among the respondents in the Treatment group on their ability to process information and update their beliefs. We will elicit quantitative prior and posteriors about two different topics: one is related to India's macroeconomic fundamentals (in Midline) and the other one to demographic trends in India (in Endline). We will compute an index of belief updating equal to $Posterior_i - Prior_i$.

We will use the following regression:

$$y_i = \alpha + \beta_1 t_i + \Gamma^T X_i + \epsilon_i$$

Where y_i is the belief updating index, t_i is a dummy variable that gets a value equal to 1 if the respondent is allocated to the Treatment group, and X_i is a vector of controls (age, gender, political affiliation, ethnicity, income, and Mental Health Distress Index at baseline).

To measure attention, we will use two different variables. One is a continuous variable with the time spent on the article on COVID-19. The second measure is an index combining the number of correct answers to questions about the COVID article. Both variables will be the outcomes of a specification like the one above. Finally, we will code with a dummy equal to 1 whether they highlight the main correct conclusion from the text on Muslims taking over Hindus, and we will repeat the same analysis as above.

Hypothesis 4 - Effect on Polarization (Primary Outcome)

We will assess the impact of an improvement in mental health status among the respondents in the Treatment group on affective polarization and attitudes toward political opponents. We will measure polarization using two different measures. An incentivized measure is a dictator game where the respondents are matched with a political opponent and the unincentivized measures are thermometer ratings for people who belong to their own party and the opponent party (we will measure these ratings at the endline and baseline, so we will subtract the baseline measurement from the endline measurement).

We will use the following regression:

$$y_i = \alpha + \beta_1 t_i + \Gamma^T X_i + \epsilon_i$$

Where y_i is the share of money that the respondent kept or the thermometer indexes for fellow party members and opponents, t_i is a dummy variable that gets a value equal to 1 if the respondent is allocated to the Treatment group, and X_i is a vector of controls (age, gender, political affiliation, ethnicity, income, and Mental Health Distress Index at baseline).

Finally, we will compare whether the respondents in the Treatment group are

more willing to follow a political WhatsApp group by regressing a dummy that takes value 1 if the respondents want to follow one of the two groups on the treatment indicator and the usual controls. Conditional on following a group, we will assess whether the treatment makes the respondents follow the politically moderate WhatsApp group more relative to the politically extreme WhatsApp group.

Effect on online behavior (Exploratory)

By matching respondents with their online browsing history profiles, we will be able to retrieve their pre-intervention and during-intervention news consumption. This will allow us to study how the online behavior of the respondents changes across Treatment and Control before and after the mental health intervention. For this purpose, the specification will be analogous to a difference-in-differences specification:

$$y_{it} = \alpha + \beta_1 t_i + \beta_2 Post_t + \beta_3 t_i \times Post_t + \Gamma^T X_i + FE_i + FE_t + \epsilon_{it}$$

where y_{it} will refer to the number of news consumed i , which will be a measure of individual engagement, t_i is a dummy that takes value 1 if the respondents are allocated to the Treatment group and $Post_t$ is an indicator for the post mental health intervention period. FE_i are individual fixed effects and FE_t are time fixed effects at the week level. We will perform two different sets of additional analyses on the online browsing of the respondents. First, we will classify news websites as “slanted” to assess whether the treated respondents are consuming slanted news relative to the overall number of news. Second, we will also perform this analysis where the outcome is the standardized number of negative news that the respondent engages with relative to the total news consumed. Following [Robertson et al. \(2023\)](#), we will compute two scores for the headlines of the news they read based on the number of negative words and positive words relative to the total number of words used.

Heterogeneity Analysis (Secondary Outcome)

We will look at the heterogeneity of the baseline results by the individual characteristics using a linear regression similar to Equation 5, but interacting the treatment t_i and the characteristic of interests x_i , which changes in each separate regression.

$$y_i = \alpha + \beta_1 t_i + \beta_2 x_i + \beta_3 t_i \times x_i + \Gamma^T X_i + \epsilon_i$$

y_i is one of the outcome variables we have described in the previous sections from Hypothesis 1 to Hypothesis 4. X_i are the usual controls.

x_i is one of following variables: Political affiliation ($BJP_i = 1$) and baseline mental health status ($MH_{baseline}$). This heterogeneity analysis by baseline mental health is policy-relevant. Even if CBT has larger impacts on those with severe mental health issues, these individuals constitute a small share of the population. Small impacts on individuals with mild or moderate depression and anxiety — who are much more numerous in the population — may be quantitatively more important in aggregate terms. Our heterogeneity results could thus inform both the cost-effectiveness and optimal targeting of mental health interventions.

Mechanisms (Secondary Outcome)

We will explore the potential mechanisms that are driving changes in the outcome variables after a change in the mental health status of the respondents in the Treatment group. For all the mechanisms that we will explore, we will standardize the answers of the respondents with the mean and standard deviation from the Control group to ease the interpretation of the results.

We will use the following regression:

$$y_i = \alpha + \beta_1 t_i + \Gamma^T X_i + \epsilon_i$$

Where y_i is one of the mechanism measures listed below, t_i is a dummy variable that gets a value equal to 1 if the respondent is allocated to the Treatment group, and X_i is a vector of controls (age, gender, political affiliation, ethnicity, and income).

We will consider different outcome variables:

- We will investigate whether changes in mental health lead to a reduction in the time spent online and digital addiction. We will measure both sets of variables at baseline and endline. For the digital addiction questions, we will compute an index both at baseline and endline. We will, then, compute the difference between the endline and baseline measures of time spent online and the digital addiction index.

- We will assess the impact of improved mental health on reducing negative emotions. We will create an index of emotions combining fear, anger, and sadness for this purpose.
- We will measure the impact of improved mental health on the cognitive bandwidth of the respondents, which we will measure using performance on Raven matrices.
- We will also construct measures of the accuracy of beliefs and test whether treatment impacts belief accuracy.
- We will create an index of perspective-taking by combining the two questions we will use to measure how well the respondents are able to put themselves in the shoes of political opponents. Moreover, we will compute an index of reciprocity using four questions. We will measure reciprocity at the baseline and endline. Then, we will compute a difference between these two measures which will be used as an outcome for the mechanisms.

Robustness Checks

We will conduct additional robustness checks:

- We will perform the estimations with and without the respondents in the 1st and 99th percentile of the time spent on the survey.
- We will assess whether social desirability bias is affecting the estimates. We will run a heterogeneity analysis where we interact the treatment dummy with the social desirability index. The outcomes of the regressions are the 4 main outcome variables and the mental health status.
- We will assess whether there is differential attrition in participation to the follow-up among participants originally allocated to Treatment and Control. In order to do so, we will run the regression described in Section 5. If the Treatment dummy coefficient is significant with a p-value smaller than 0.05, we will use Lee Bounds to provide estimates of the next regression.
- We will address concerns of multiple hypothesis testing in different ways. First, we will index whatever variables belong to the same family of outcomes.

Second, we will account for multiple hypotheses by computing False Discovery Rate (FDR) q-values within each family when relevant. We will correct for 2 outcomes in Hypothesis 3 related to belief updating and 3 outcomes in Hypothesis 3 related to Attention and 3 outcomes in Hypothesis 4. We do not correct secondary outcomes for multiple-hypothesis testing and their analysis should be interpreted as exploratory.

6 Proposed Timeline

Below we indicate an expected timeline for our project. The earlier we manage to recruit our desired sample, the earlier we will start delivering access to the mental health app.

- April -May 2024: Recruitment of the respondents via X, Facebook, Instagram
- May-June 2024: Treatment group receives access to the mental health app and first outcomes are measured
- July-Aug 2024: Control group gets access to the mental health app
- Sep 2024: Conclusion of the study and payment of standing bonuses

7 Pilot Data

We have conducted a pilot study to explore whether there are correlations between mental health and background characteristics as well as between mental health and some of the outcomes that are relevant to the study. We recruited our sample on *Prolific* in two waves of data collection. The sample consists of U.S. respondents who are the majority on the platform. These results should be interpreted as a proof of concept of the plausible link between mental health and news consumption.

Table [A1](#) shows the correlation between the respondents' mental health status and their background characteristics. A higher value of the Mental Health Distress Index implies worse mental health for the respondents. Younger respondents and white respondents report better mental health (we defined white as whoever does not constitute an ethnic minority in the U.S.). In contrast, female respondents and respondents who are self-reported conservatives report significantly lower mental health. These correlations emphasize the importance of exploring potential hetero-

geneous effects between mental health and political behavior along political affiliation and ethnicity of the respondents.

Table A2 displays a negative correlation between the mental health of the respondents and the index of digital addiction. This seems to suggest that the respondents with worse mental health are less digitally addicted.

Table A3 shows that the respondents with worse mental health are more likely to believe in fake news (p-value = 0.14) and less likely to believe in true news. This piece of evidence seems to suggest that the channel between mental health and fake news recognition is plausible.

Finally, Table A4 shows that worse mental health is negatively correlated with how much the respondents update their beliefs about inflation and the unemployment rate. This evidence seems to corroborate the link that mental health has with the belief updating process.

8 Limitations and Challenges

The main challenge that might jeopardize the implementation of the study concerns the engagement of the respondents in the Control group. The respondents in the Control group might drop out of the study, leading to a high differential attrition rate. We will take two main steps to address this concern:

- We will pay the respondents in the Control group significant amounts to incentivize engagement in the study across the different waves of data collection.
- We will follow [Shreekumar and Vautrey \(2022\)](#) to keep the respondents in the Control group engaged by implementing a delayed provision of the app to the respondents in the Control group, right after the respondents in the Treatment group finish the treatment.

9 Administrative Information

This work was supported by the Centre for Trusted Internet and Community at the National University of Singapore. The project has received IRB approval at the National University of Singapore. The authors have no conflicts of interest to declare.

References

- Al-Zaman, Md Sayeed**, "Prevalence and source analysis of COVID-19 misinformation in 138 countries," *IFLA journal*, 2022, 48 (1), 189–204.
- Ali, Ayesha and Ihsan Ayyub Qazi**, "Countering misinformation on social media through educational interventions: Evidence from a randomized experiment in Pakistan," *Journal of Development Economics*, 2023, 163, 103108.
- Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow**, "The welfare effects of social media," *American Economic Review*, 2020, 110 (3), 629–676.
- , **Matthew Gentzkow, and Lena Song**, "Digital addiction," *American Economic Review*, 2022, 112 (7), 2424–2463.
- Alsan, Marcella, Luca Braghieri, Sarah Eichmeyer, Minjeong Joyce Kim, Stefanie Stantcheva, and David Y Yang**, "Civil liberties in times of crisis," *American Economic Journal: Applied Economics*, 2023, 15 (4), 389–421.
- Altindag, Onur, Bilge Erten, and Pinar Keskin**, "Mental health costs of lockdowns: Evidence from age-specific curfews in turkey," *American Economic Journal: Applied Economics*, 2022, 14 (2), 320–343.
- Angelucci, Manuela and Daniel Bennett**, "The economic impact of depression treatment in India," 2021.
- Armstrong, Thomas and Bunmi O Olatunji**, "Eye tracking of attention in the affective disorders: A meta-analytic review and synthesis," *Clinical psychology review*, 2012, 32 (8), 704–723.
- Ash, Elliott, Daniel Sgroi, Anthony Tuckwell, and Shi Zhuo**, "Mindfulness reduces information avoidance," *Economics Letters*, 2023, 224, 110997.
- Badrinathan, Sumitra**, "Educative interventions to combat misinformation: Evidence from a field experiment in India," *American Political Science Review*, 2021, 115 (4), 1325–1341.
- and **Simon Chauchard**, "Religious messaging against COVID-19 misinformation: Experimental evidence from India," *Unpublished manuscript*]. Retrieved from: <https://sumitrabadrinathan.github.io/Assets/paper-covid.pdf>, 2021.
- Bago, Bence, David G Rand, and Gordon Pennycook**, "Fake news, fast and slow: Deliberation reduces belief in false (but not true) news headlines.," *Journal of experimental psychology: general*, 2020, 149 (8), 1608.
- , – , and – , "Does deliberation decrease belief in conspiracies?," *Journal of Experimental Social Psychology*, 2022, 103, 104395.

—, —, and —, “Reasoning about climate change,” *PNAS nexus*, 2023, 2 (5), pgad100.

Baranov, Victoria, Sonia Bhalotra, Pietro Biroli, and Joanna Maselko, “Maternal depression, women’s empowerment, and parental investment: Evidence from a randomized controlled trial,” *American economic review*, 2020, 110 (3), 824–859.

Barrera, Oscar, Sergei Guriev, Emeric Henry, and Ekaterina Zhuravskaya, “Facts, alternative facts, and fact checking in times of post-truth politics,” *Journal of public economics*, 2020, 182, 104123.

Baysan, Ceren, “Persistent polarizing effects of persuasion: Experimental evidence from turkey,” *American Economic Review*, 2022, 112 (11), 3528–3546.

Beam, Emily A, “Social media as a recruitment and data collection tool: Experimental evidence on the relative effectiveness of web surveys and chatbots,” *Journal of Development Economics*, 2023, 162, 103069.

Beknazar-Yuzbashev, George, Rafael Jiménez Durán, Jesse McCrosky, and Mateusz Stalinski, “Toxic content and user engagement on social media: Evidence from a field experiment,” *Available at SSRN*, 2022.

Berger, Lara Marie, Anna Kerkhof, Felix Mindl, and Johannes Munster, “Debunking “Fake News” on Social Media: Short-Term and Longer-Term Effects of Fact Checking and Media Literacy Interventions,” 2023.

Bhat, Bhargav, Jonathan De Quidt, Johannes Haushofer, Vikram H Patel, Gautam Rao, Frank Schilbach, and Pierre-Luc P Vautrey, “The long-run effects of psychotherapy on depression, beliefs, and economic outcomes,” Technical Report, National Bureau of Economic Research 2022.

Blattman, Christopher, Julian C Jamison, and Margaret Sheridan, “Reducing crime and violence: Experimental evidence from cognitive behavioral therapy in Liberia,” *American Economic Review*, 2017, 107 (4), 1165–1206.

—, **Sebastian Chaskel, Julian C Jamison, and Margaret Sheridan**, “Cognitive Behavioral Therapy Reduces Crime and Violence over Ten Years: Experimental Evidence,” *American Economic Review: Insights*, 2023, 5 (4), 527–545.

Braghieri, Luca, Ro’ee Levy, and Alexey Makarin, “Social media and mental health,” *American Economic Review*, 2022, 112 (11), 3660–3693.

Bursztyn, Leonardo, Georgy Egorov, and Stefano Fiorin, “From extreme to mainstream: The erosion of social norms,” *American economic review*, 2020, 110 (11), 3522–3548.

Carney, Kevin, “The effect of social media on voters: experimental evidence from an Indian election,” *Job Market Paper*, 2022, pp. 1–44.

- Chopra, Felix, Ingar Haaland, and Christopher Roth**, “Do people demand fact-checked news? Evidence from US Democrats,” *Journal of Public Economics*, 2022, 205, 104549.
- , – , and – , “The demand for news: Accuracy concerns versus belief confirmation motives,” *NHH Dept. of Economics Discussion Paper*, 2023, (01).
- Cichocka, Aleksandra**, “To counter conspiracy theories, boost well-being,” *Nature*, 2020, 587, 177.
- Cramer, Holger, Helen Hall, Matthew Leach, Jane Frawley, Yan Zhang, Brenda Leung, Jon Adams, and Romy Lauche**, “Prevalence, patterns, and predictors of meditation use among US adults: A nationally representative survey,” *Scientific reports*, 2016, 6 (1), 36760.
- de Quidt, Jonathan, Johannes Haushofer, and Christopher Roth**, “Measuring and Bounding Experimenter Demand,” *American Economic Review*, 2018, 108 (11), 3266–3302.
- Dhar, Diva, Tarun Jain, and Seema Jayachandran**, “Reshaping adolescents’ gender attitudes: Evidence from a school-based experiment in India,” *American economic review*, 2022, 112 (3), 899–927.
- Disner, Seth G, Christopher G Beevers, Emily AP Haigh, and Aaron T Beck**, “Neural mechanisms of the cognitive model of depression,” *Nature Reviews Neuroscience*, 2011, 12 (8), 467–477.
- Engelmann, Jan, MaÃ LeBreton, Nahuel Salem-Garcia, JoÃ van der Weele et al.**, “Anticipatory Anxiety and Wishful Thinking,” Technical Report, CEPR Discussion Papers 2022.
- Faia, Ester, Andreas Fuster, Vincenzo Pezone, and Basit Zafar**, “Biases in Information Selection and Processing: Survey Evidence from the Pandemic,” *The Review of Economics and Statistics*, 03 2022, pp. 1–46.
- , – , – , and – , “Biases in information selection and processing: Survey evidence from the pandemic,” *Review of Economics and Statistics*, 2022, pp. 1–46.
- Gotlib, Ian H and Jutta Joormann**, “Cognition and depression: current status and future directions,” *Annual review of clinical psychology*, 2010, 6, 285–312.
- Guess, Andrew M, Michael Lerner, Benjamin Lyons, Jacob M Montgomery, Brendan Nyhan, Jason Reifler, and Neelanjan Sircar**, “A digital media literacy intervention increases discernment between mainstream and false news in the United States and India,” *Proceedings of the National Academy of Sciences*, 2020, 117 (27), 15536–15545.

- Haushofer, Johannes and Ernst Fehr**, “On the psychology of poverty,” *science*, 2014, 344 (6186), 862–867.
- Heller, Sara B, Anuj K Shah, Jonathan Guryan, Jens Ludwig, Sendhil Mulinathan, and Harold A Pollack**, “Thinking, fast and slow? Some field experiments to reduce crime and dropout in Chicago,” *The Quarterly Journal of Economics*, 2017, 132 (1), 1–54.
- Henry, Emeric, Ekaterina Zhuravskaya, and Sergei Guriev**, “Checking and sharing alt-facts,” *American Economic Journal: Economic Policy*, 2022, 14 (3), 55–86.
- Hirshleifer, Sarojini, Mustafa Naseem, Agha Ali Raza, and Arman Rezaee**, “The spread of (mis) information: A social media experiment in Pakistan,” 2022.
- Hüning, Hendrik, Lydia Mechtenberg, and Stephanie Wang**, “Using Arguments to Persuade: Experimental Evidence,” *Available at SSRN 4244989*, 2022.
- Iwamoto, Sage K, Marcus Alexander, Mark Torres, Michael R Irwin, Nicholas A Christakis, and Akihiro Nishi**, “Mindfulness meditation activates altruism,” *Scientific reports*, 2020, 10 (1), 6511.
- Kelly, Christopher and Tali Sharot**, “Knowledge-Seeking Reflects and Shapes Well-Being,” 2023.
- Kosasih, Feodora Roxanne, Vanessa Tan Sing Yee, Sean Han Yang Toh, and Oliver Sündermann**, “Efficacy of Intellect’s self-guided anxiety and worry mobile health programme: A randomized controlled trial with an active control and a 2-week follow-up,” *PLOS Digital Health*, 2023, 2 (5), e0000095.
- Kubin, Emily, Curtis Puryear, Chelsea Schein, and Kurt Gray**, “Personal experiences bridge moral and political divides better than facts,” *Proceedings of the National Academy of Sciences*, 2021, 118 (6), e2008389118.
- Landwehr, Claudia and Christopher Ojeda**, “Democracy and depression: a cross-national study of depressive symptoms and nonparticipation,” *American Political Science Review*, 2021, 115 (1), 323–330.
- Layard, Richard and David M Clark**, *Thrive: The Power of Evidence-Based Psychological Therapies*, Penguin UK, 2014.
- Levy, Ro’ee**, “Social media, news consumption, and polarization: Evidence from a field experiment,” *American economic review*, 2021, 111 (3), 831–870.
- Lund, Crick, Kate Orkin, Marc Witte, Thandi Davies, John Walker, Johannes Haushofer, Sarah Murray, Judy Bass, Laura Murray, and Vikram Patel**, “Treating Mental Health Conditions Improves Labor Market and Other Economic Outcomes in Low and Middle-Income Countries,” *University of Oxford, Working Paper*, 2022.

- Man, Jeroen De, Pilvikki Absetz, Thirunavukkarasu Sathish, Allissa Desloge, Tilahun Haregu, Brian Oldenburg, Leslie CM Johnson, Kavumpurathu Raman Thankappan, and Emily D Williams,** “Are the PHQ-9 and GAD-7 Suitable for Use in India? A Psychometric Analysis,” *Frontiers in Psychology*, 2021, 12, 676398.
- Meier, Armando N,** “Emotions and risk attitudes,” *American Economic Journal: Applied Economics*, 2022, 14 (3), 527–558.
- Miller, Amalia R, Kamalini Ramdas, and Alp Sungu,** “Browsers Don’t Lie? Gender Differences in the Effects of the Indian COVID-19 Lockdown on Digital Activity and Time Use,” *Gender Differences in the Effects of the Indian Covid-19 Lockdown on Digital Activity and Time Use (September 24, 2021)*, 2021.
- Moran, Tim P,** “Anxiety and working memory capacity: A meta-analysis and narrative review.,” *Psychological bulletin*, 2016, 142 (8), 831.
- Ong, Wen Yi and Oliver Sündermann,** “Efficacy of the mental health app “Intellect” to improve body image and self-compassion in young adults: a randomized controlled trial with a 4-week follow-up,” *JMIR mHealth and uHealth*, 2022, 10 (11), e41800.
- Pennycook, Gordon and David G Rand,** “Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning,” *Cognition*, 2019, 188, 39–50.
- Peterson, Erik and Shanto Iyengar,** “Partisan Gaps in Political Information and Information-Seeking Behavior: Motivated Reasoning or Cheerleading?,” *American Journal of Political Science*, 2020.
- Ridley, Matthew, Gautam Rao, Frank Schilbach, and Vikram Patel,** “Poverty, depression, and anxiety: Causal evidence and mechanisms,” *Science*, 2020, 370 (6522), eaay0214.
- Robertson, Claire E, Nicolas Pröllochs, Kaoru Schwarzenegger, Philip Pärnamets, Jay J Van Bavel, and Stefan Feuerriegel,** “Negativity drives online news consumption,” *Nature human behaviour*, 2023, 7 (5), 812–822.
- Sadish, D, Achyuta Adhvaryu, and Anant Nyshadham,** “(Mis) information and anxiety: Evidence from a randomized Covid-19 information campaign,” *Journal of Development Economics*, 2021, 152, 102699.
- Shah, Anuj K, Sendhil Mullainathan, and Eldar Shafir,** “Some consequences of having too little,” *Science*, 2012, 338 (6107), 682–685.
- Sharot, Tali, Ryota Kanai, David Marston, Christoph W Korn, Geraint Rees, and Raymond J Dolan,** “Selectively altering belief formation in the human brain,” *Proceedings of the National Academy of Sciences*, 2012, 109 (42), 17058–17062.

Shreekumar, Advik and Pierre-Luc Vautrey, “Managing emotions: The effects of online mindfulness meditation on mental health and economic behavior,” Technical Report, Tech. Rep., MIT 2022.

Suslow, Thomas, Anja Husslack, Anette Kersting, and Charlott Maria Bodenschatz, “Attentional biases to emotional information in clinical depression: a systematic and meta-analytic review of eye tracking findings,” *Journal of Affective Disorders*, 2020, 274, 632–642.

Toh, Sean Han Yang, Jessalin Hui Yan Tan, Feodora Roxanne Kosasih, and Oliver Sündermann, “Efficacy of the mental health app intellect to reduce stress: randomized controlled trial with a 1-month follow-up,” *JMIR Formative Research*, 2022, 6 (12), e40723.

Waldrop, M Mitchell, “How to mitigate misinformation,” *Proceedings of the National Academy of Sciences*, 2023, 120 (36), e2314143120.

A Appendix One

Appendix Table A1. MH and Background Characteristics

	<i>Dependent variable:</i>
	Mental Health Distress Index
Age	−0.110*** (0.031)
Income	−0.012 (0.093)
Conservative	0.971** (0.392)
Employed	0.033 (0.062)
High Education	−0.107 (0.277)
White	−0.559*** (0.200)
Female	1.821*** (0.689)
Religiosity	0.073 (0.235)
Observations	200
R ²	0.195
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

Appendix Table A2. Correlations between MH, Digital Addiction, Doomscrolling, and Polarization

	<i>Dependent variable:</i>		
	Digital (1)	Doom (2)	Polarization (3)
Mental Health Distress Index	-0.074*** (0.014)	-0.004 (0.006)	0.011 (0.012)
Conservative	0.124 (0.085)	-0.033 (0.039)	-0.072 (0.076)
Observations	102	102	102
R ²	0.227	0.017	0.013

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix Table A3. Correlations between MH and Fake News Recognition

	<i>Dependent variable:</i>	
	Believe in Fake (1)	Believe in True (2)
Mental Health Distress Index	0.004 (0.003)	-0.002 (0.003)
Conservative	0.010 (0.015)	-0.036** (0.015)
Observations	200	200
R ²	0.016	0.039

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix Table A4. Correlations between MH and Belief Updating

	<i>Dependent variable:</i>	
	Updating Inflation (1)	Updating Unemployment (2)
Mental Health Distress Index	-0.073 (0.057)	-0.022 (0.042)
Conservative	-0.141 (0.353)	0.068 (0.263)
Observations	102	102
R ²	0.023	0.003

Note:

*p<0.1; **p<0.05; ***p<0.01

B Instructions

B.1 Baseline

1. Demographics

What is the gender you identify yourself with? [Male/Female/Other/Prefer not to answer]

What is your year of birth? [Open text]

What is your religion? [Hindu/Muslim/Sikh/Christian/Other]

What is your highest completed level of education? [None/Primary School (Grade 1-5)/Middle School (Grade 6-8)/High School (Grade 9 or 10)/Pre University College (Grade 11 or 12)/Diploma/College Degree/Post Graduate Degree/Other]

What type of work do you do? [None/ Farming (own land)/Farm labour (on someone else's land)/Government job/Private salaried employee/Daily wage earner/Own business/Housewife/Student/Other]

In which state do you reside? [Dropdown list]

With which party do you identify the most? [BSP/BJP/SP/Congress/Others/Don't know]

What is your phone number? We will use it to send you bonuses based on your answers [Open text]

2. PHQ-9 Questions (Depression)

Over the last 2 weeks, how often have you been bothered by any of the following?

Statement	Possible Answers
Little interest or pleasure in doing things?	not at all, several days, half of the days, nearly every day
Feeling down, depressed, or hopeless?	not at all, several days, half of the days, nearly every day
Trouble falling or staying asleep, or sleeping too much?	not at all, several days, half of the days, nearly every day
Feeling tired or having little energy?	not at all, several days, half of the days, nearly every day
Poor appetite or overeating?	not at all, several days, half of the days, nearly every day
Feeling bad about yourself — or that you are a failure or have let yourself or your family down?	not at all, several days, half of the days, nearly every day
Trouble concentrating on things, such as reading the newspaper or watching television?	not at all, several days, half of the days, nearly every day
Moving or speaking so slowly that other people could have noticed? Or so fidgety or restless that you have been moving a lot more than usual?	not at all, several days, half of the days, nearly every day
Thoughts that you would be better off dead, or thoughts of hurting yourself in some way?	not at all, several days, half of the days, nearly every day

3. GAD-7 Questions (Anxiety)

Over the last 2 weeks, how often have you been bothered by any of the following?

Statement	Possible Answers
Feeling nervous, anxious, or on edge?	not at all, several days, half of the days, nearly every day
Not being able to stop or control worrying?	not at all, several days, half of the days, nearly every day
Worrying too much about different things?	not at all, several days, half of the days, nearly every day
Trouble relaxing?	not at all, several days, half of the days, nearly every day
Being so restless that it is hard to sit still?	not at all, several days, half of the days, nearly every day
Becoming easily annoyed or irritable?	not at all, several days, half of the days, nearly every day
Feeling afraid, as if something awful might happen?	not at all, several days, half of the days, nearly every day

4. Emotions

We will now list a number of feelings. Please indicate, for each feeling, how often or rarely you experienced this feeling in the last four weeks. How often have you felt:

Statement	Possible Answers
Angry	Very rarely, Rarely, Occasionally, Often, Very Often
Worried	Very rarely, Rarely, Occasionally, Often, Very Often
Happy	Very rarely, Rarely, Occasionally, Often, Very Often
Sad	Very rarely, Rarely, Occasionally, Often, Very Often

5. Reciprocity

People experience different emotions daily. We are interested in understanding emotions that come up in response to the scenarios provided below. There are no

right or wrong answers.

In general, when someone does me a favor I am willing to return it. Please use a scale from 0 to 10, where 0 means “completely unwilling to return it” and 10 means you are “very willing to return it”. [Slider 0 - 10]

If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to doing so. Please use a scale from 0 to 10, where 0 means “never” and 10 means “always”. [Slider 0 - 10]

How willing are you to punish someone who treats you unfairly, even if there may be costs for you? Please use a scale from 0 to 10, where 0 means “completely unwilling” and 10 means “very willing”. [Slider 0 - 10]

How willing are you to punish someone who treats others unfairly, even if there may be costs for you? Please use a scale from 0 to 10, where 0 means “completely unwilling” and 10 means “very willing”. [Slider 0 - 10]

6. Reasons to read news

The next two questions aim to understand your main reasons for reading the news. Please state how much you agree or disagree with the point of view that is presented.

When it comes to selecting which news on politics and public affairs to read, watch, or listen to, which of the following is most important to you? (Select only one) [Accuracy/Novelty/Relevance to people like me]

How much would you say you rely on social media for your news on politics and public affairs? [Very rarely/Rarely/Occasionally/Often/Very Often]

People can follow the news in a number of different ways. How do you follow the news on a typical day?

Below, we show a list of possible news sources. If you had 100 points to allocate

to these different news sources, with the most points going to the source you use the most for news, how would you allocate the points?

For example, if you only used one source to get your news, you should assign that source 100 points and 0 to all the other sources. If all of the sources we list are equally important for you, please assign 10 points to each of these sources.

- Facebook
- Instagram
- WhatsApp
- Physical newspapers
- Radio
- Television
- Online newspapers
- Twitter
- YouTube
- Reddit

7. Screen Time and Digital Addiction

We would like to know about your screen time and social media usage. Please pick the answer that is closest to reality.

How many hours do you spend in front of a screen per day (i.e., computer, laptop, mobile phone, tablet)? [0-1 h/1-2 h/2-4 h/4-6 h/6-8 h/8 or more]

How much time (in hours) do you spend on each of these social media platforms per day? [0-1 h/1-2 h/2-4 h/4-6 h/6-8 h/8 or more]

- Facebook

- Instagram
- WhatsApp
- Tiktok
- Twitter
- Snapchat
- YouTube
- Reddit

Over the past 2 weeks, how often have you. . .

Statement	Possible Answers
Been worried about missing out on things online when not checking your phone?	always, often, sometimes, rarely, never
Checked social media, text messages, or email immediately after waking up?	always, often, sometimes, rarely, never
Used your phone longer than intended?	always, often, sometimes, rarely, never
Found yourself saying “just a few more minutes” when using your phone?	always, often, sometimes, rarely, never
Used your phone to distract yourself from personal problems?	always, often, sometimes, rarely, never
Used your phone to distract yourself from feelings of guilt, anxiety, helplessness, or depression?	always, often, sometimes, rarely, never
Used your phone to relax in order to go to sleep?	always, often, sometimes, rarely, never
Tried to reduce your phone use without success?	always, often, sometimes, rarely, never
Experienced that people close to you are concerned about the amount of time you use your phone?	always, often, sometimes, rarely, never
Felt anxious when you don’t have your phone?	always, often, sometimes, rarely, never
Found it difficult to switch off or put down your phone?	always, often, sometimes, rarely, never
Been annoyed or bothered when people interrupt you while you use your phone?	always, often, sometimes, rarely, never
Felt your performance in school or at work suffers because of the amount of time you use your phone?	always, often, sometimes, rarely, never
Lost sleep due to using your phone late at night?	always, often, sometimes, rarely, never
Preferred to use your phone rather than interacting with your partner, friends, or family?	always, often, sometimes, rarely, never
Put off things you have to do by using your phone?	always, often, sometimes, rarely, never

8. Thermometer Rating

Please tell us about your feelings toward different groups of people.

Below is something we call a feelings thermometer.

Ratings between 0 degrees and 50 degrees mean that you don't feel favorable toward the group and that you don't care too much for that group of people.

Ratings between 50 degrees and 100 degrees mean that you feel favorable and warm toward the group.

You would rate a group at the 50 degree mark if you don't feel particularly warm or cold toward them.

- Hindu
- Muslims
- Congress supporters
- BJP supporters

9. Marlowe-Crowne Social Desirability Scale (Selected Questions)

Please indicate to what extent you agree that the following statements apply to you or are accurate descriptions of you.

Note: For each statement, we will use sliders from 0-100 with five labels: completely inaccurate, quite inaccurate, neither accurate nor inaccurate, quite accurate, completely accurate.

- I have deliberately said something that hurt someone's feelings.
- There have been times when I was quite jealous of the good fortune of others.
- I'm always willing to admit it when I make a mistake.
- There have been occasions when I took advantage of someone.

- I sometimes feel resentful when I don't get my way.
- No matter who I'm talking to, I'm always a good listener.
- I am always courteous, even to people who are disagreeable.

10. Voting Intentions

Do you plan to vote in the General Election next month? [Yes/No/I do not know]

11. Fake News Detection

To the best of your knowledge, how accurate is the following statement?

[All the statements have the following options: Definitely true/Probably true/Probably false/Definitely false. The news that are true are labeled with T and those that are false are labeled with F. This will not be shown to the respondents.]

- Australia has won cricket world cup most often (T)
- There is no cure for HIV/AIDS (T)
- The COVID-19 vaccine is ineffective and contributes to spreading the disease (F)
- The Muslim population will soon overtake the Hindu population (F)
- Polygamy is very common among Muslims (F)
- COVID19 vaccines are associated with autism(F)
- Drinking cow urine helps to build one's immune system (F)
- Netaji Bose did not die in a plane accident (F)
- BJP has hacked electronic voting machines (F)
- UNESCO declared PM Modi the best prime minister in the world in 2016 (F)
- The BJP's Anuppur district unit chief in Madhya Pradesh has started to wear shoes after 6 years (T)

B.2 Midline

1. Prior Beliefs about Indian Economy

Please share your expectations on two economic indicators for India: inflation and unemployment.

Remember that there are no right or wrong answers.

What do you think the inflation rate is going to be at the end of the year (2024)?
Slider 0 - 20

What do you think the unemployment rate is going to be at the end of the year (2024)?
Slider 0 - 20

Generally speaking, do you think India is headed in the right direction?

- Yes, definitely
- Not sure
- No, headed in the wrong direction

Sections 2 to Section 4 and Section 6 and Section 7 from the Baseline

7. Article about Indian Economy and Posterior Beliefs

Link: <https://economictimes.indiatimes.com/news/economy/indicators/indias-gdp-to-grow-6-7-1-pc-during-2024-2026-growth-prospects-remain-strong-sp/articleshow/105259406.cm>

Please share your expectations on two economic indicators for India: inflation and unemployment.

Remember that there are no right or wrong answers.

What do you think the inflation rate is going to be at the end of the year (2024)?
Slider 0 - 20

What do you think the unemployment rate is going to be at the end of the year (2024)?

Slider 0 - 20

8. Attention Check and Belief Updating

“Unveiling the Hidden Realities of COVID-19: What They Don’t Want You to Know!”

In the intricate tapestry of the COVID-19 pandemic, a web of misinformation has woven its way into public discourse. Join us on an eye-opening exploration as we unravel the unexpected truths behind the global crisis, revealing information that certain entities wish to keep obscured.

Origins Unveiled - “Laboratory Secrets Revealed?” The origins of COVID-19 have been shrouded in controversy, with some speculating about a hidden laboratory creation. However, a robust body of scientific evidence overwhelmingly supports the natural zoonotic origin of the virus, indicating likely transmission from bats to humans through an intermediate host. While the lab-origin theory may capture imaginations, the scientific consensus firmly asserts the virus’s natural emergence.

Vaccination Conspiracies - “Microchips and DNA Alteration Exposed!” Conspiracy theories surrounding COVID-19 vaccines have garnered attention, fueling fears of microchipping and DNA alteration. These claims, however, lack a factual basis. The vaccines approved for use have undergone rigorous testing and are proven to be safe and effective. Vaccination remains a critical tool in preventing severe illness, hospitalization, and death, contributing to the collective effort to curb the pandemic.

Global Manipulation - “Pandemic Plot or Natural Disaster?” The pandemic has, unfortunately, become a breeding ground for conspiracies, with some suggesting a deliberate plot rather than a natural disaster. Rigorous investigations and expert

analyses, however, consistently support the natural occurrence of the virus. The notion of intentional release or manipulation remains unfounded, emphasizing the importance of relying on evidence-based information.

Immunity Illusions - "Natural Immunity vs. Vaccination Showdown!" Confusion persists regarding natural immunity versus vaccination. While recovering from COVID-19 does confer some immunity, vaccines offer a more reliable and safer path to widespread immunity. The benefits of vaccination extend beyond individual protection, contributing to community-level immunity and reducing the overall impact of the virus.

Disinformation Dangers - "The Silent Spread of Lies Revealed!" As misinformation continues to permeate our information channels, the real danger lies in the silent spread of lies. Misleading narratives can have profound consequences, sowing seeds of doubt and eroding public trust. Combatting the infodemic requires not only accurate information but also a commitment to critical thinking and discernment, ensuring that the public is equipped to navigate these turbulent times.

Comprehension Questions:

1. *This is a simple question to check whether you are reading the instructions that we are providing. When asked about your views, please answer disagree.*

Based on the instructions above, do you think the COVID pandemic is over?

- A. Strongly agree
 - B. Agree
 - C. Disagree
 - D. Strongly disagree
2. *What is the widely accepted origin of COVID-19?*
 - A. Laboratory creation
 - B. Natural zoonotic origin (correct answer)
 - C. Human-engineered release
 - D. Extraterrestrial intervention

3. *What is the impact of the COVID-19 vaccine?*

- A. Enhancing the spread of the virus
- B. Contributing to community-level immunity (correct answer)
- C. Introducing harmful microchips
- D. Causing severe illness and side-effects, leading to hospitalization

9. Attention control

Please highlight the words that you think convey the key message of the article.

"Population Myths Unraveled: The Alleged Muslim Majority Takeover" In recent years, a pervasive myth has circulated, asserting that India is on the brink of becoming a majority-Muslim country due to the notion that Muslims have more children compared to their Hindu counterparts. This misinformation has fueled fears of demographic shifts, contributing to the narrative that Hindus are facing a potential minority status.

According to these claims, the idea is that Muslims, driven by religious beliefs, are outpacing Hindus in population growth, setting the stage for a significant demographic transformation. This narrative, however, oversimplifies complex demographic trends, leading to unfounded anxieties about the future composition of India.

In reality, demographic patterns are shaped by a myriad of factors, including socio-economic conditions, education, and access to healthcare. Numerous studies indicate that fertility rates are declining across religious communities in India, reflecting broader societal changes. Debunking this misinformation requires a nuanced understanding of demographic dynamics and a commitment to dispelling unfounded fears. By focusing on accurate and comprehensive demographic data, we can foster a more informed discourse that transcends divisive narratives and promotes unity in diversity.

10. Fake News detection

To the best of your knowledge, how accurate is the following statement?

[All the statements have the following options: Definitely true/Probably true/Probably false/Definitely false. The news that are true are labeled with T and those that are false are labeled with F. This will not be shown to the respondents.]

- On Navratri in 2023, Prime Minister Narendra Modi was participating in a Garba dance (F)
- Muslims were assaulting a Hindu gathering in Congress-ruled Karnataka (F)
- Indian drug manufacturers benefit from Big Pharma interest beyond China (T)
- Dry soil makes Indian farmers wary of planting wheat, despite rally (T)
- After the loss of the cricket match against Australia, Indian fans destroyed the posters of the national team's players (F)
- AIIMS Delhi is selling a medicine called Cardioton that can cure hypertension (F)
- US thwarted plot to kill Sikh separatist in America (T)
- New Delhi smog grows more intense as farm fires rage (T)
- Muslim men were assaulting an old man for chanting "Bharat mata ki jai" in Delhi (F)
- Kashmiri students were celebrating after Australia won against India at the Cricket World Cup (F)

11. Cognitive bandwidth

[The respondents will see a series of Raven matrices to complete at the end of the study]

You are going to see a series of pictures that represents a sequence of pictures or figures. For each figure, you need to pick the correct option that completes the sequence. You can win 10 Rupies for each correct answer.

B.3 Endline

1. Doomscroll

We are going to show you different headlines of news articles. They cover different topics regarding India's current state of affairs. The article headlines will be shown to you in pairs. We will ask you to state, for each headline, which article you would like to read.

Based on your preferences, we will send a link at the end of the survey with a newsletter that we have curated to match closely with your preferences.

[We will display the news headlines in pairs]

- "India's Economic Resilience Shines: Robust Growth and Innovative Reforms Propel Nation to New Heights"
- "Indian Economy Grapples with Challenges: Slowdowns and Uncertainties Cast Shadows on Growth Prospects"

-
- "Healthcare Renaissance in India: Innovative Policies and Advances Transforming Health Landscape for a Brighter Tomorrow"
 - "Healthcare Crisis Deepens in India: Strains on Infrastructure and Access Pose Grave Concerns"

-
- "Harmony Prevails: Muslims and Hindus in India Embrace Unity, Fostering Stronger Bonds for a Shared Future"
 - "Religious Tensions Escalate: Challenges to Integration Strain Muslim-Hindu Relations in India"

-
- "India's Foreign Policy Flourishes: Strategic Diplomacy and Global Alliances Propel the Nation onto the World Stage"

- "Foreign Policy Quandaries Emerge: India Grapples with Geopolitical Challenges and Diplomatic Strains"
-

- "Democracy Flourishes in India: Inclusive Governance and Citizen Participation Strengthen the Nation's Democratic Fabric"

- "Democracy at Crossroads: India Faces Challenges to Political Stability and Civic Liberties"
-

- "India Champions Sustainable Future: Bold Climate Initiatives and Green Innovations Spearhead Environmental Transformation"

- "Climate Crisis Intensifies in India: Rising Temperatures, Extreme Weather, and Environmental Challenges Cast a Pall Over the Nation"
-

- "AI Revolutionizes India: Innovation and Tech Advancements Propel the Nation into a Bright Future of Growth and Progress"

- "AI Disruption Raises Concerns in India: Job Displacements and Ethical Dilemmas Pose Challenges to Society"
-

- "Crime Rate on a Decline: India's Comprehensive Strategies Yield Positive Results, Fostering Safer Communities"

- "Crime Wave Grips India: Escalating Rates Pose Alarming Threats to Public Safety and Security"
-

- "China and India Forge Stronger Ties: Bilateral Cooperation and Diplomacy Foster Mutual Growth and Regional Stability"

- "Tensions Escalate: Strained Relations Between China and India Raise Geopolitical Concerns in the Region"
-

- "Education Revolution Unfolds in India: Progressive Policies Envision a Future of Inclusivity, Quality, and Global Competence"
- "Education Policy Challenges Loom: India Grapples with Issues of Accessibility, Quality, and Inequality in Schools"

Section 2 to Section 5 and Section 8 of the Baseline survey

9. Belief Updating

- What do you think is the average number of children a Hindu woman has?
[Slider]
- What do you think is the average number of children a Muslim woman has?
[Slider]

True News Article: "Examining India's Demographic Mosaic: Insights into the Muslim Community's Population Trends"

India, renowned for its rich cultural tapestry, experiences diverse demographic shifts, with each community contributing to the nation's dynamic growth. Recent studies examining census data offer valuable insights into the population trends of the Muslim community. A careful analysis debunks sensationalist claims, highlighting that the growth patterns among Muslims align with broader national trends. This comprehensive understanding underscores the need for nuanced discussions, fostering an environment where diversity is celebrated, and social cohesion is strengthened. By championing evidence-based reporting, we contribute to a more accurate portrayal of India's demographic landscape.

In an era where misinformation can fuel societal tensions, researchers emphasize the importance of responsible reporting. Acknowledging the unique demographic patterns within various communities allows for informed conversations, dispelling myths that may lead to unnecessary divisions. This evidence-based approach not only enriches public discourse but also promotes unity by appreciating the mosaic of identities that collectively shape India.

- What do you think is the average number of children a Hindu woman has?
[Slider]
- What do you think is the average number of children a Muslim woman has?
[Slider]

Fake News Article: "Population Explosion: The Unchecked Rise of India's Muslim Community"

Alarming reports are emerging, suggesting a shocking surge in the Muslim population that threatens to reshape India's demographic landscape. Claims, backed by questionable sources, assert that fertility rates among Muslims are soaring, painting a grim picture of an impending majority-Muslim India. The unverified information is igniting fears of a disproportionate demographic upheaval, with sensational headlines intensifying speculation and anxiety about the country's future.

As anxiety mounts, critics argue that unchecked population growth within the Muslim community poses a serious threat to the social fabric, potentially leading to heightened tensions and political instability. Urgent calls for intervention and policy changes are gaining traction, echoing the need for immediate action to avert a perceived crisis. It is crucial for the public to approach such information with skepticism, awaiting verified data to ensure responsible reporting and prevent the undue escalation of unfounded fears.

- What do you think is the average number of children a Hindu woman has?
[Slider]
- What do you think is the average number of children a Muslim woman has?
[Slider]

10. Perspective taking

[If the respondent is a Hindu, then the peer will be a Muslim and vice versa.]

How much do you agree or disagree with the following statements?

I find it difficult to see things from Muslims' [Hindu] point of view. [Strongly Disagree/Somewhat Disagree/Neither Agree nor Disagree/Somewhat Agree/Strongly Agree]

I think it is important to consider the perspective of Muslims [Hindu]. [Strongly Disagree/Somewhat Disagree/Neither Agree nor Disagree/Somewhat Agree/Strongly Agree]

11. Punishment

[If the respondent is a Hindu, then the peer will be a Muslim and vice versa.]

You are now on the last question of the survey. We will give you a bonus of 100 Rupies for fully completing our survey.

Please know, though, that we have matched you with another survey respondent. This respondent is a Muslim [Hindu].

You may, if you wish, split your bonus with this respondent. They will not make any decision that affects you.

Below, please move the slider to indicate how much of the 100 Rupies you want to keep for yourself. We will give the remaining amount as a completion bonus to the respondent you have been matched with.

[Slider from 0 to 100 with intervals of 10]

12. Voting Intentions

Do you plan to vote in the General Election? [Yes/No/I do not know]

13. Donating to NGO

You are given the opportunity to donate to an NGO that promotes communal harmony between communities in India. Would you like to contribute part of your payment for completing this survey to this group? Please click here to learn more about the NGO and select how much you would like to donate.

14. Joining a WhatsApp group

You are given the opportunity to join a WhatsApp group discussing the late political developments in India. We are going to show you two different groups that you

could join to stay always informed about what happens in the everyday life.
Of course, you can also choose to not join any group.

[Here, we describe the two different groups.]

If you state that you want to join a group, then you will receive a WhatsApp link to actually join the group.

Please select your most preferred option:

- I want to join Group A
- I want to join Group B
- I do not want to join any group