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Digital Empowerment for Youth: Experimental Evidence from India

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Digital Empowerment for Youth: Experimental Evidence from India

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Abstract

Concerns about the impacts of smartphones and social media have risen alongside their surging use in developing countries. One potential solution is educational interventions that encourage users to optimize their interactions with digital technologies. We co-created a multi-week, evidence-based digital empowerment curriculum designed to expand students' ability to exert deliberate control over their use of social media and smartphones. We implement this curriculum with college students in India as a classroom-based course and as a text message-based course. Using a randomized controlled trial, we evaluate both versions of the curriculum and estimate the effects of exposure to the curriculum on social media consumption, mental health, misinformation discernment, sleep and concentration, and academic outcomes.

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Proposed timeline

Jul 23 – Aug 23:	Scoping and team hiring
Aug 23 – Sep 23:	Pitching the study to universities
Aug 23 – Sep 23:	Focus group discussions
Sep 23 – Nov 23:	App development and testing
Sep 23 – Nov 23:	Preparation of baseline and endline survey instruments
Sep 23 – Jun 24:	Development and testing of digital empowerment curriculum
Nov 23 – Dec 23:	Survey and intervention piloting
Jan 24 – Feb 24:	Formally onboarding the universities
Feb 24 – Aug 24:	Baseline surveys
Sep 24 – Oct 24:	Classroom intervention
Oct 24 – Nov 24:	First round of endline surveys
Dec 24 - Jan 25:	Winter break in universities
Nov 24 – Feb 25	Microlearning intervention
Feb 25 – March 25	Second round of endline surveys
Mar 25 – Mar 25:	Wrap up field activities

At the time of the registered report initial submission, we have launched baseline surveys across four universities and completed the baseline data collection for around 16% of the planned sample. We are doing baseline surveys in waves (before and after the summer break) to accommodate the different schedules of the universities in our sample.

Contents

1 Introduction

People around the world spend an average of over five hours per day on their smartphones and about two and a half hours on social media (Kemp, 2024a). This widespread usage has drawn significant regulatory attention, especially due to its potential impact on younger populations. In 2023, the US Surgeon General issued an advisory highlighting the potential adverse effects of social media on youth mental health and emphasized the urgent need for additional research, recommending education as a potential solution (HHS, 2023). Educators have developed and implemented school-based programs to empower users of social media. However, most of these programs have been implemented in developed countries, and their effectiveness has not been rigorously evaluated (Weinstein and James, 2022).

Our study addresses this gap by introducing a digital empowerment curriculum for young adults in urban India. India is the world's largest market for Facebook, Instagram, WhatsApp, and YouTube (Kemp, 2023, 2024b), and is home to approximately 800 million smartphone users (Das, 2024) and 460 million active social media users (Kemp, 2024a). We evaluate the efficacy of this program using a randomized controlled trial (RCT). To the best of our knowledge, it will be the first large-scale RCT to evaluate the effectiveness of a digital empowerment program in any setting.

Implementing a digital empowerment curriculum in this context could have high returns. While there is significant regulatory attention in developed countries, youth in developing countries —who constitute a sizable proportion of global social media users — remain highly vulnerable and understudied. Furthermore, unlike their counterparts in developed countries, youth in developing countries may be particularly vulnerable due to the lack of implicit guidance from parents and teachers, who are often themselves new to navigating the digital world.[1] We target students in college as this is the period when youth in our context typically begin to spend substantial amounts of time on social media and smartphones.

We partner with universities in Punjab, India to implement a multi-week digital empowerment curriculum involving approximately 6,000 students. This program encourages mindful use of

[1]In the US, around three-quarters of parents prioritize managing the amount of time their teenagers spends on their phones. About half of these parents report looking through their child's smartphone and setting limits on phone use (Pew Research Center, 2024). In contrast, while the incidence of cyberbullying in India exceeds the global average, parental concern about this issue remains lower than the global average (McAfee, 2022).

smartphones and social media and teaches students to make better choices about their digital media consumption ("digital empowerment"), going beyond just teaching how to use digital tools ("digital literacy"). We co-created the curriculum with local educators, adapting existing evidence-based materials for Indian college students.

The goal of the curriculum is to teach learners how to exert deliberate control over their use of smartphones and social media. These digital technologies can be addictive, involving significant self-control problems and habit formation, and potential misperception of self-control problems and inattention to habit formation (Allcott et al., 2022). The program aims to inform learners about platform design features and their influence on mind and behaviors, thereby developing a deeper understanding of their relationship with technology. The curriculum does not suggest that all levels of digital use are harmful; it instead aims to enable learners to optimize their interactions with digital technologies. Rather than being passively led by technology, learners are encouraged to make active decisions (Carroll et al., 2009) and exert greater agency over their digital use.

The curriculum consists of three modules that seek to enhance the learners' capacity to optimize their smartphone and social media use by (i) providing information about the design and functioning of digital platforms, raising awareness of self-control problems, and developing attentiveness to habit formation; (ii) equipping them with skills and tools, such as commitment devices to align their behavior with the preferences of the long-run self; and (iii) offering information and tools to combat misinformation on social media.

We evaluate two versions of the curriculum: a classroom-based and a text message-based version ("microlearning"). The microlearning course is designed to be a light-touch version of the classroom-based course, and is implemented after the completion of the classroom-based curriculum. Students assigned to the microlearning course will receive a condensed version of the curriculum in the form of text messages. Evaluating these two versions of the program allows us to determine the relative efficacy of the two modes of delivery, which has policy implications for scaling up the program to non-collegiate settings.

As a first stage outcome, our study evaluates the effects of the program on social media consumption using both self-reported and actual usage measures. We also evaluate the impact of the program on mental health, including reported symptoms of anxiety and depression, subjective well-being, and digital addiction. We estimate the effects on adoption of commitment devices for overall phone use, as well as app-specific use for the most popular apps. To evaluate the impact on the ability to identify misinformation, we present respondents with a series of news snippets and ask them to judge the accuracy of each item. Additionally, we evaluate the impact of the program on student GPA, usage of smartphones during class hours or bedtime, and sleep behavior.

We collect high-frequency smartphone usage data from the participants using a custom-built Android app. This app unobtrusively tracks foreground app activity every five seconds, providing objective measures of total screen time, app-specific usage patterns, bedtime habits, pick-up frequency, and notifications. Participants in both treatment and control groups are incentivized to download the app to track their smartphone usage. In addition to tracking usage, the app also serves as a commitment device, allowing users to set usage limits at the app level.

We combine this app data with survey data and administrative records from the universities to develop and test novel measures to understand whether the curriculum affects mental health and academic outcomes through concentration during class and bedtime behaviors. To assess effects of curriculum modules on outcomes like digital use and well-being, we supplement app data with short check-in surveys before the start of each session, along with a corresponding check-in with students in the control group. The modular structure of our curriculum enables us to isolate the impact of learning components on short-term outcomes.

Finally, to shed light on the differential impacts of the intervention, we explore heterogeneity across several dimensions, such as gender, baseline social media usage, age when student acquired their first smartphone, and whether they come from a rural area. For example, we hypothesize that the curriculum may have different impacts for students from rural versus urban backgrounds. Students from rural areas, having limited prior exposure to digital environments, may particularly benefit as the curriculum is introduced before their digital habits are fully developed.

Our study contributes to the growing body of literature on the economics of social media (Aridor et al., Forthcoming). Prior research in the US finds that while users place high value on their access to social media (Brynjolfsson et al., 2019; Mosquera et al., 2020; Allcott et al., 2020), a large fraction of use is caused by self-control problems exacerbated by habit formation (Allcott et al., 2022). This can significantly impact the well-being of adolescents and young adults, as high-speed internet and social media use have been shown to lead to worse mental health (Donati et al., 2022; McDool et al., 2020; Braghieri et al., 2022). Our study aims to provide evidence on how a curriculum-based intervention that targets social media use affects mental health outcomes for college students.

More specifically, our study provides evidence on how a digital empowerment intervention can affect how people engage with digital technologies in a developing country. In developing countries, access to technology is rapidly increasing, but resources and support systems to ensure its responsible and beneficial use are lagging behind (World Bank, 2016). Smartphones and social media act as temptation goods (Allcott et al., 2022), and self-control problems may disproportionately impact poorer populations by diverting time and resources away from education and economic opportunities towards unproductive digital use, such as binge entertainment (Ramdas and Sungu, 2022), further locking them into poverty (Bernheim et al., 2015).

A key component of the curriculum is to encourage participants to use commitment devices. Earlier work has documented demand for commitment devices to manage smartphone and social media use (Ek and Samahita, 2023; Allcott et al., 2022). Hoong (2021) shows that nudging participants to adopt a soft commitment device, which was readily available on their smartphones, led to a significant reduction in their Facebook usage. Our study adds to this literature on demand-side interventions to regulate digital technology use. Compared to Allcott et al. (2022), which provided a commitment device and a nudge for the treatment group to use it, our classroom-based intervention not only includes a commitment device and a nudge, but also raises awareness about the extent of self-control problems both for themselves and for people around them. In addition, the curriculum provides a forum for people to discuss digital technology use with their friends, which could facilitate coordination to move them out of the product market trap (Bursztyn et al., 2024).

We also contribute to the literature on digital literacy for combating misinformation. A substantial body of research has explored the role of social media in the spread of misinformation and its impact on political, social, and health outcomes (Zhuravskaya et al., 2020; Aridor et al., Forthcoming). There are significant concerns about the role of social media in propagating misinformation in India (Nielsen, 2019; Murali, 2023; Ponniah, 2019). Digital literacy education is among the more effective interventions in combating misinformation (Aridor et al., Forthcoming). Rather than focusing solely on debunking specific claims, our program aims to equip individuals to critically evaluate the veracity of online information across content (List et al., 2024) and increases awareness of how the sharing of misinformation is perceived by others (Guriev et al., 2023). Our intervention trains learners on how to discern fake news and offers practical strategies for identifying misinformation based on evidence-based approaches (Guess et al., 2020; Badrinathan, 2021; Athey et al., 2023; Ali and Qazi, 2023; Berger et al., 2023; Bowles et al., 2023).

More generally, our paper also relates to the literature on how educational interventions shape individuals' beliefs and preferences (Cantoni et al., 2017; Dhar et al., 2022; Arold, 2024; Lazuka and Elwert, 2023; Arold et al., 2022). Most of these studies focus on high school students, while we examine university students. Lastly, our study contributes to a small literature on the behavioral economics of education (Lavecchia et al., 2016), specifically focusing on mitigating behavioral barriers to improve learning outcomes of college students (Cappelen et al., 2017; Himmler et al., 2019; Patterson, 2018; Burger et al., 2011; Giuntella et al., 2024).

The rest of this report is structured as follows: Section 2 provides information on the study context and describes the intervention. Section 3 discusses the data collection procedures, and Section 4 describes the study design. Section 5 outlines the study hypotheses and construction of outcomes. Section 6 describes the empirical framework. Section 7 provides administrative details about the study.

2 Intervention

2.1 Study context

We conduct our study in the state of Punjab, India. In 2011, Punjab had a population of 27 million, with 37% residing in urban areas according to the latest census data. The literacy rate in Punjab was 88%, which is higher than the national average (Census of India, 2011). Punjab has nearly 86 internet subscribers per 100 population, which is above the national average of around 64 per 100 population (TRAI, 2022). In 2023, over 90% of rural households in Punjab owned smartphones (ASER, 2023).

We collaborate with universities in and around the city of Ludhiana, the largest and most populous city in the state of Punjab. Our sample comprises students enrolled in these institutions. At the time of the registered report initial submission, we have launched baseline surveys in four universities and completed approximately 16% of the planned data collection. We discuss the characteristics of our sample based on this partial data in Section 4.

2.2 Digital empowerment curriculum

To the best of our knowledge, a digital empowerment curriculum tailored to our specific context does not exist. Several module-based curricula[2] are available but they are designed for school students in the United States, and not for an international or developing country setting.[3]

To fill this gap, we curated a three-session digital empowerment curriculum using state-of-the-art content from Common Sense Media, the Digital Wellness Institute, the Digital Inquiry Group, the University of Iowa Libraries, and Boom Live.[4] The curriculum is designed to develop skills for intentional use of digital media among college students. It encourages students to reflect on their interactions with digital technologies, and raises awareness of self-control problems and attention to habit formation. Students are also exposed to practical strategies to regulate and monitor their usage, including the use of commitment devices to manage screen time. Additionally, to train students to combat misinformation, the program teaches skills such as fact-checking and lateral reading.

The content will be delivered in a mix of English and Punjabi, the preferred communication mode in universities in Punjab. In-person sessions will be held during regular class slots to ensure maximum student attendance. The curriculum is structured into three modules: the first two focus on recognizing and managing self-control problems, while the third module addresses the topic of misinformation.

- **Session 1:** The first session focuses on building awareness about digital media platform design and encouraging students to reflect on their relationship with digital technologies. Using relatable examples, the module covers the 'hook model' (Eyal, 2014) and explains how social media platforms and advertisements keep users engaged. Students then learn about how the body and mind respond to such designs and online content, and discuss a range of thought patterns and thinking traps associated with the use of social media (Billari et al.,

[2]For example, Cyber Civics is one popular curriculum (`https://www.cybercivics.com`).

[3]For a detailed review, see Weinstein and James (2022).

[4]We use materials from Common Sense Media (`https://www.commonsensemedia.org`) and course content in the certificate program from Digital Wellness Institute (`https://www.digitalwellnessinstitute.com`). The goal of the latter certificate program is to train educators to teach digital wellness strategies that promote healthy technology use and reduce digital stress. Additionally, we incorporated resources from the Digital Inquiry Group (`https://inquirygroup.org/`), the University of Iowa Libraries' guide on types of misinformation (`https://guides.lib.uiowa.edu/c.php?g=849536&p=6077637`), and Boom Live's Ultimate Fact Checking Kickstarter course (`https://workshop.boomlive.in/courses/Ultimate-Fact-Checking-Kickstarter-627b70040cf2cf6d6b6edc61`).

2018; Leong and Chee, 2023; Avery et al., 2022; Vogel et al., 2014; Feinstein et al., 2013). Students learn how naiveté about self-control problems and inattention to habit formation leads to mispredictions about future use and over-consumption (O'Donoghue and Rabin, 1999; Allcott et al., 2022).

- **Session 2:** In the second session, students are introduced to how commitment devices work to manage self-control problems (Bryan et al., 2010; Allcott et al., 2022). The session provides information on various tools, such as advertisement blockers, user-set limits on screen time, and *do not disturb* mode, which are easily available to participants. The session also introduces the idea of goal setting as an internal commitment device that may allow students with low self-control to implement their plans (Clark et al., 2020).

- **Session 3:** The final session explores how misinformation spreads through social media and discusses its potential negative impacts (Pennycook et al., 2020; Badrinathan and Chauchard, 2023). It examines why individuals are vulnerable to the harmful effects of misinformation and provides evidence-based strategies for recognizing and curtailing misinformation (List et al., 2024; Berger et al., 2023; Athey et al., 2023; Zhuravskaya et al., 2020; Van Der Linden, 2022; Guess et al., 2020).

Adaptation Before the study began, we held focus group discussions to ensure that our intervention is pertinent and practical for the everyday lives of college students. Appendix A reports on this qualitative exploration. The content was adapted to be age-appropriate and contextually relevant for college students in India. This involved selecting relevant themes, incorporating contextual examples, and adding translations to the local language. We received feedback from US-based content developers as well as local experts.[5] Additionally, we collaborated with Initiators of Change, a Punjab-based youth development NGO, to localize and fine-tune the curriculum. They helped ensure that the material was culturally relevant for youth in the state. See appendix B for examples of how the content was adapted to fit the local context.

[5]We sought and incorporated inputs on the curated curriculum from experts at the Center for Digital Thriving, Harvard University and the National Institute of Mental Health and Neurosciences (NIMHANS), India.

In-class activities To encourage self-reflection and problem-solving, we make use of worksheets and a web-based audience response system. Worksheets will be distributed at the end of each session to reflect on the concepts discussed during the session (see Figure A3). The audience response system allows participants to anonymously vote on questions during the presentation using their phones, with the results displayed in real time on the screen (see Figure A4). Further, we also encourage students to create a written report on intervention sessions, which would count for credit towards some of their practicum courses. This provides an additional reinforcement component for the training content.

Selection of facilitators The facilitators for the course were selected in collaboration with a professor at Punjab Agricultural University, one of our partner universities. They were chosen for their proficiency in public speaking and experience with young audiences. The team included speakers with expertise in journalism, teaching, personality development, neuroscience and counseling.

Facilitator training The facilitators underwent training by the research team on the content and curriculum for the sessions. They are familiarized with the technical terminology used in the materials. A detailed script corresponding to each slide presentation is provided to ensure standardization across facilitators. However, they are also afforded some flexibility to include relevant examples of their own to explain concepts clearly, as long as the examples adhere to the core subject matter.

Student attendance We will gauge intervention take-up by recording student attendance in the sessions. Field managers are trained to collect attendance using a standardized template at the beginning of each session.

Student feedback After each session, students will be asked to provide feedback on the session and rate the content and usefulness on a five-point scale. The feedback form includes the following areas of evaluation: relevance of content, interaction and engagement, perceived effectiveness of audience response system and worksheets, effectiveness of facilitator, perceived gain in knowledge, and suggestions for improvement.

2.3 Microlearning

The microlearning treatment is designed to be a light-touch version of the full curriculum. Previous research has shown that text messages can be an effective way to induce behavioral change (Armanasco et al., 2017). In addition to being relatively low-cost to develop and distribute, the text message course delivery mechanism makes the content more accessible to users in lower-income countries than in-person or classroom instruction due to fewer time and resource requirements.

This intervention will be conducted after the digital empowerment intervention. Students assigned to the microlearning treatment will receive a condensed version of the digital empowerment lesson each week, followed by a question from the lesson. Based on their response, the user will receive another message that informs them whether they answered correctly, with an explanation of the correct and incorrect responses (Athey et al., 2023). We plan to send three sets of text messages corresponding to each of the three digital empowerment sessions.

This will allow us to compare the relative efficacy of a classroom intervention with that of a microlearning intervention, allowing us to address questions of scalability, across high-touch and low-touch versions. Appendix C includes drafts of the texts planned for this intervention.

3 Data

The data used in this study consists of survey data, mobile application usage data, Instagram activity data, and administrative data from partner universities.

3.1 High-frequency mobile application data

We collect high-frequency data on smartphone usage through *YouthWell Punjab Dashboard* (henceforth *Dashboard*), an Android application custom-made for this project.[6] Android users across both the treatment and control groups are encouraged to download the app to track their smartphone usage. The app serves a dual purpose: tracking usage and as a commitment device.

[6]The app builds on *Phone Dashboard*, the usage-tracking app developed as a part of Allcott et al. (2022). Beyond additional features that optimize data collection and fit for the local setting, a key difference in the design of the app is the availability of commitment devices. In Allcott et al. (2022), the control group did not have the limit functionality on the app, whereas, in our setting, both treatment and control groups have access to the built-in commitment device. We made this choice so that any effect of the mere provision of commitment device cancels out. The treatment group receives a curriculum that encourages the use of commitment devices, and therefore, any change in the use of commitment devices could be attributed to the curriculum treatment.

Dashboard tracks smartphone usage by recording the app displayed in the foreground at five-second intervals. This granular level of tracking provides an objective measure of total smartphone usage, as well as other measures of phone use, such as total usage by app, usage before bedtime, and the frequency of phone pickups. In addition, Dashboard records notifications, logging which apps are sending them and how users respond. To ensure privacy, the software does not capture the specific content viewed within each app or the details of the notifications. The user interface features a dashboard that summarizes daily and weekly screen time by individual apps.

Dashboard also includes a feature that allows users to set usage limits at the app level. The limits set by the user become active on the next calendar day. Like most in-built system apps (such as *Digital Wellbeing* on Android and *Screen Time* on iOS), once a daily usage limit for an app is reached, users have the option to relax these limits. However, a unique feature of Dashboard is that if the user chooses to relax the limit, usage can only resume after a specified delay. Users have the choice to set delay of up to 20 minutes or disable limit extensions altogether, potentially making the app a more powerful commitment device. Dashboard records the limits users set, and whether and how much a user chooses to extend to have additional use, once the daily limit for an app is reached.

For iOS users (the minority of students in our sample), we track their total phone use by partnering with a commercial app *BePresent*. The app records screen time at 30-minute intervals[7] Similar to Dashboard on Android, BePresent tracks foreground app usage.[8] Due to constraints on iOS, the app cannot collect data at the same granularity as Dashboard. Consequently, for iOS users, we have data on overall phone use at threshold levels, but no app-specific usage and other granular measures.

3.2 Baseline survey

Our baseline surveys consist of questions to assess various aspects of current digital media consumption, well-being, mental health, and behavior, in addition to standard demographic information. We use a multiple price list procedure (Andersen et al., 2006) to measure how much people value using social media and separately how much they value their data.

[7] The screen-time is recorded based on minimum threshold crossed. For example, if a user has 1 hour and 59 minutes of screen time, it is recorded as 1 hour and 30 minutes since the two hour threshold has not been crossed.

[8] For privacy reasons, it does not track browser use in private mode and the use of FaceTime.

Our ability to conduct baseline surveys is constrained by the program-specific schedules of students across different universities. Due to the wide variation in student schedules across universities, we conduct our baseline surveys in waves. The field teams work closely with a point of contact in each university to choose date and time for survey activities that ensures maximum attendance. The field teams at J-PAL South Asia began collecting baseline data on February 14, 2024. Within a collaborating institution, all students who are enrolled in a specific major in our partner universities are invited to participate and complete the baseline survey. Consenting students become a part of the study sample. Given that we work with college students with high levels of literacy, surveys are self-administered in a monitored setting with field monitors available to provide technical support.

The survey instrument was primarily in English, with selective translations into Punjabi. This bilingual approach was adopted based on multiple pilot rounds with out-of-sample students. Students felt more comfortable comprehending the material when presented bilingually, rather than fully in Punjabi or English alone. The survey underwent thorough testing and revision before deployment to ensure accurate comprehension by respondents.

To incentivize participation, students who completed the survey received a modest monetary compensation in the form of a gift card of INR 100 (USD 1.20) to remunerate their time. Additionally, we offered the opportunity to win a larger prize of INR 5,000 (USD 60) through a random draw, with one winner selected from each university. This combination of guaranteed compensation for all participants and the potential for a larger reward aimed to maximize survey response rates. Students also received certificates of study participation.

3.3 Endline survey

The endline survey protocol and instruments will largely mirror those of the baseline survey, with a few notable additions and omissions. Sections required solely during the recruitment phase, such as demographic details and app installation, will be omitted. However, new modules will be incorporated to assess critical outcomes of interest. These include evaluating participants' subject-matter knowledge gained from the intervention curriculum, their ability to distinguish misinformation from factual content, and their perspectives on goal-setting and various dimensions of the labor market.[9]

[9] These additional modules were not included in the baseline to accommodate completion within a single class period.

Similar to the baseline survey, all students will receive compensation for their time in the form of a Rs 100 (USD 1.20) gift card upon concluding the endline survey. Furthermore, a random draw will be conducted at each university site, offering one student the opportunity to win a larger prize of Rs 5,000 (USD 60).

3.4 Instagram activity data

We aim to collect social media usage data from a subset of participants who consent to share their Instagram activity data with us using a secure, guided platform data download. Using natural language processing methods, we will conduct text analysis of participants' social media posts and shares, allowing us to gauge how the intervention tangibly affects the user behavior on the platform (besides time use). We will use this data for exploratory analyses as it is unclear at this stage if we will have a sufficient number of participants willing to share their Instagram usage data to make any meaningful inference about changes in social media usage patterns. Figure 2 shows the distribution of Instagram data sharing prices at baseline.

3.5 Short check-in surveys

For the class-based intervention, we will administer a short survey containing modules on digital addiction, mental health, and ability to discern misinformation before the start of each session. This gives us a higher frequency measure of the main outcomes, allowing us to study short-term effects of individual sessions of the intervention. To ensure that treatment and control groups get similar exposure to the research team, we will also conduct three check-in surveys for the control groups between the baseline and the endline, mirroring the visits that the treatment groups receive. For microlearning, we will administer the same surveys over text messages to both treatment and control students.

3.6 Administrative data from partner universities

We will obtain data on the class schedules of participants and their attendance records from our partner universities. This data will be combined with the high-frequency mobile application data to analyze phone usage and social media usage during class hours. Additionally, data on student performance on university examinations will be collected to evaluate the impact of our interventions on academic achievement.

3.7 Follow-up survey

We will conduct follow-up data collection three months after our endline surveys. The survey will include a subset of modules from the endline survey that allow us to test for the persistence of effects on our primary outcomes. The survey will be self-administered and shared with participants via WhatsApp and email. Participants will be incentivized with gift cards to complete the survey.

4 Experimental Design

4.1 Sample

Our sample consists of students in the age group of 17-24 years enrolled in six higher education institutions in Punjab, India.[10] We collaborate with universities around the city of Ludhiana and recruit 6,000 students from these institutions.[11] Consenting students will become a part of the study sample.

For sample recruitment, we approached leadership across higher educational institutions around the Ludhiana city regarding program participation. To be included in the study, institutions formalized their commitment by signing a Memorandum of Understanding (MOU) with J-PAL South Asia. The MOU stipulated that the institution would facilitate the research activities being conducted on their premises.

Participating universities follow a hierarchical organizational structure. At the highest level are departments, which encompass various majors or degree programs. These majors are further divided into academic years. In cases where an academic year within a major has high enrollment, the students may be split into smaller sections. These sections follow the same curriculum but may have different instructors. Figure 3 illustrates how our partner universities are organized.

[10] We have a set of three backup universities to sample from if we are unable to meet the required sample from our current set of six institutions.

[11] Most of the students are enrolled in undergraduate programs. In two of the universities, the sample also includes a subset of students enrolled in masters programs.

Sample characteristics. At the time of the registered report initial submission, the baseline data collection has been launched across four universities. Summary statistics from the partial baseline sample covering roughly 16% of the total sample are presented in Table 1. The mean age of student participants is 20 years. 76% of students reside with their parents, and 15% have lived in an urban area before attending university. All respondents report a minimum of seven years of parental education, with around half of the participants having mothers who attended college.

Access to technology is widespread within the sample. 58% indicate having a WiFi connection at home, and 83% use an Android mobile device. The median age at which respondents first owned a smartphone is 16 years. Participants self report social media usage of over 5 hours per day on average.

While students who acquired their first phone before the age of 18 years exhibit higher digital literacy (knowledge about digital media processes), they also report higher self-reported social media usage.[12] Additionally, this group is associated with higher digital addiction and lower subjective well-being, suggesting potential challenges linked to early and frequent digital interaction (Figure 4a).

While we do not see variation in social media usage by gender, female students report higher levels of anxiety and depression symptoms (Figure 4b). Figure 4c shows that students from urban areas report higher levels of social media usage as well as exhibit higher digital literacy compared to those from rural areas. Similarly, students with higher parental education show higher levels of self-reported social media usage as well as higher levels of digital literacy (Figure 4d). Students in urban areas are more likely to have parents with more years of schooling and may also be more likely to acquire smartphones at an early age. Nevertheless, these patterns indicate potential sources of heterogeneity in student outcomes.

4.2 Treatment assignments

To evaluate the impact of the classroom-based and text message-based versions of the curriculum, the microlearning treatment is cross-randomized with the digital empowerment treatment. These two treatments are implemented sequentially with separate endline surveys to ensure cleaner tests.

[12] At the time of the registered report initial submission, data on actual usage is not yet available due to ongoing recruitment and data processing.

The full experimental design is illustrated in Figure 1.

The classroom-based digital empowerment intervention has two treatment arms: students in the treatment group will be exposed to the digital empowerment curriculum over several weeks, and students in the pure control group will only participate in surveys and not be exposed to this curriculum. To isolate the effects of the main components of the curriculum, the treatment arm (T) has two sub-treatments: (T1) the *self-control and misinformation* curriculum, which includes all three sessions, and (T2) the *self-control only* curriculum, covering sessions 1 and 2.[13] We are primarily interested in the intention-to-treat (ITT) effects of exposure to the curriculum.

We will conduct clustered random assignment for the digital empowerment intervention, considering students in a university-major-year as being in a cluster (henceforth, referred to as *cohort*).[14] We stratify our sample at the university-major level.[15] Within each university-major, we assign equal number of cohorts to treatment and to control. In case of odd number of cohorts within a major, we randomly assign the singleton unit to treatment or control. Within the treatment arm, we assign cohorts to one of the sub-treatments with equal probability. Given that students with different interests and motivations might self-select into different majors, stratification by major ensures balance across treatment and control on these unobservables. The analytic specifications account for strata fixed effects. Our sample will comprise 100 clusters with a median cluster size of 60 students.

Table 2 presents balance checks using baseline data. The digital empowerment treatment and control groups are balanced across nine of the 10 variables. There is a slight imbalance in whether the student lived in an urban area before starting university but the magnitude of difference is small. Furthermore, these balance tests were conducted using the partial baseline data we have collected from a subset of our partner universities at the time of the registered report initial submission.

The text message-based microlearning intervention is cross-randomized with the digital empow-

[13]We decided against including a misinformation only treatment arm for two reasons: (i) there is already a large body of existing evidence on training people to identify misinformation, some of which also feeds into the curriculum we are evaluating, and (ii) it would have substantially reduced the power of our tests to detect effects of the self-control curriculum, for which there is little existing evidence in the literature.

[14]In universities with a single section for each academic year within a program, the major-year combination is referred to as a cohort (e.g., BA Economics Year I and BA History Year II represent two separate cohorts). However, in universities with multiple sections, the cohort is defined as the major-year-section (e.g., BA Economics Year I Section A, BA Economics Year I Section B, and BSc Physics Year III are three distinct cohorts).

[15]For example, University X BA Economics, University X BSc Physics, and University Y BA Economics represent three different strata.

erment treatment. However, the two experiments are conducted sequentially and not in parallel to ensure cleaner tests from the different interventions. Given the possibility of spillovers, especially for text messages that can be easily shared, we will use a randomized saturation design to quantify both individual and network effects. We will first randomize the cohorts to two groups: the share of students receiving microlearning within the classroom being 0 or 50%. Within each cluster with 50% saturation, we will then randomize at the individual level and randomly assign 50% of the students to receive the microlearning treatment.[16]

4.3 Statistical power

Our study is powered to detect a minimum ITT effect of the digital empowerment curriculum of 0.15 SD for social media consumption, 0.07 SD for mental health index, and 0.25 SD for ability to identify misinformation (Figure 5a). For the microlearning treatment, our study is powered to detect a minimum ITT effect of 0.13 SD for social media consumption, 0.08 SD for mental health index, and 0.14 SD for ability to identify misinformation(Figure 5b).[17] The power simulations are formulated for a clustered-randomized controlled trial using a two-sided test with a significance level of five percent and power of 80%, assuming R^2 of 0.20 between the baseline and endline, using intracluster correlation derived from the baseline data, and an attrition rate of 10%.[18]

5 Outcomes, Measures and Hypotheses

5.1 Theory of change

We hypothesize that the curriculum leads students to develop better awareness of their self-control problems, leading to a more intentional use of digital media. Youth in environments lacking regulation or digital literacy can be particularly vulnerable to digital addiction and misinformation. Our intervention addresses these risks by promoting mindful use of smartphones and social media.

[16]We do not present baseline balance checks for the microlearning intervention as the random assignment will be conducted after finalizing the baseline sample and collecting students' phone numbers in each university.

[17]These effect sizes are smaller than what has been previously estimated for other interventions in the literature: 0.19 SD for social media consumption (Allcott et al., 2022), 0.09 for mental health (Allcott et al., 2022), and 0.38 SD for ability to identify misinformation (Bago et al., 2020).

[18]Given that we survey students enrolled in higher education institutions, and provide incentives for participation in the study through cash vouchers and certificates, we assume attrition of 10%. Compared to settings where participants are recruited online, our institutional setting gives us higher fidelity in being able to track students over time.

In the immediate short term, the effect of the treatment may be reflected in social media consumption, self-reported digital addiction, use of commitment devices, and reduced phone usage during class hours and at bedtime. This may also lead to improved well-being as reflected in lower levels of depression and anxiety. Finally, this may have downstream effects on academic outcomes, labor market effort, and career aspirations. Table 3 presents a detailed theory of change.

5.2 Primary outcomes

Hypothesis 1: Exposure to treatment reduces social media consumption

The intervention emphasizes optimal use of social media and does not nudge students to reduce their social media consumption directly. However, given that more students report an overconsumption of social media (24%) than underconsumption (10%), we anticipate that the treatment leads to a reduction in social media consumption. We use the following outcomes to measure social media consumption: *(i) self-reported measures*: self-reported usage by asking students their perceived usage over the past three weeks; *(ii) objective measures*: daily usage outcomes constructed from the mobile application data. We will also test for differences in more granular outcomes (for example, if the treatment leads to reduction in Instagram usage but potentially an increase in the usage of Twitter).[19,20]

Hypothesis 2: Exposure to treatment leads to improvement in a composite index of mental health.

To circumvent inference problems associated with multiple hypotheses testing, we examine the effect of treatment on a composite index of mental health comprising (i) reported symptoms of anxiety, (ii) reported symptoms of depression, (iii) subjective well-being, and (iv) perceived digital addiction. We will create a single index aggregating across these four scales following Anderson (2008).

To measure symptoms of anxiety and depression, we use validated psychological scales including GAD-7 and PHQ-9 (Spitzer et al., 2006; Kroenke et al., 2001; De Man et al., 2021). Both scales

[19] Our ability to use the mobile application measure depends on the quality of mobile application data. We will use (ii) as the main measure if the attrition rate between those using the app at baseline and during the intervention period is lower than 30%, where using the app is defined as having non-zero use for at least 80% of the days during the relevant period.

[20] Our survey and administrative data will allow us to analyze selection into installation and retention of the Dashboard app.

ask respondents to report on symptoms associated with generalized anxiety disorder and major depressive disorder, rather than asking a direct question about anxiety or depression. We use the raw scale in the index construction to retain more variation relative to using a cut-off score. Following Allcott et al. (2020), we also measure subjective well-being by combining items across adapted versions of three scales: the Subjective Happiness Scale (Lyubomirsky and Lepper, 1999), the Satisfaction with Life Scale (Diener et al., 1985) and the Loneliness scale (Hughes et al., 2004).[21]

Finally, we capture perceived digital addiction using the addiction scale developed in Allcott et al. (2022) and adapted for the local context. The scale comprises 16 questions adapted from two established survey scales: the Mobile Phone Problem Use Scale (Bianchi and Phillips, 2005) and the Bergen Facebook Addiction Scale (Andreassen et al., 2012). This set of questions aims to evaluate the six principal aspects of addiction as outlined in the literature: salience, tolerance, mood modification, relapse, withdrawal, and conflict (Griffiths, 2005) and asks participants to report the frequency of behaviors that relate to each category. The possible responses on the scale are never, rarely, sometimes, often, and always, which will be coded as 0, 0.25, 0.5, 0.75, and 1 respectively. We will use the sum of these scores as a measure of perceived digital addiction.

Hypothesis 3: Exposure to treatment improves the ability to identify misinformation

We present respondents with screenshots of four news snippets from well-known media sources in a randomized sequence; among these, two tweets contain accurate information, and the other two contain false news (Guriev et al., 2023). Given that the language of the content could influence the participants' ability to differentiate facts from misinformation, we first inquire about the respondent's preferred language for consuming news and then present the news snippet in the selected language. Respondents are asked to judge the accuracy of the news item on a scale of one to five, ranging from 'not at all accurate' to 'very accurate'. We will estimate the effect of treatment on the ability to gauge the veracity of a news item. The possible responses on the likert response scale will be code as 0, 0.25, 0.5, 0.75, and 1 respectively. Following Carney (2022), our outcome will be calculated as the difference between a participant's total in the accurate stories minus the total score in the false stories. To address concerns that the effects are due to decreased social media

[21] The subjective happiness scale includes two questions to measure how happy participants were over the past four weeks and how happy they were compared to their peers. The Satisfaction with Life Scale consists of five items, designed to evaluate overall assessments of one's life satisfaction. The Loneliness scale consists of three items to measure the perception of social isolation.

usage rather than the misinformation curriculum (Ventura et al., 2023), we will also include stories on topics that were in the news before the baseline period.

5.3 Secondary outcomes

Hypothesis 4: Exposure to treatment leads to greater adoption of commitment devices

We use the following measures to capture whether students used a commitment device: (i) *self-reported measure*: the endline survey includes a question on whether respondents use any commitment devices on their phones; and (ii) *objective measure*: in addition to the minutes of usage, our high-frequency Dashboard data also allows us to look at the extent to which the respondents set binding limits on specific apps.[22] Slightly adapting the definition in Allcott et al. (2022) to fit our study set-up, we define the variable limit tightness.[23] This variable quantifies the hypothetical reduction in app usage if the limits set by users were applied to their baseline use. We will estimate this both for overall phone use, as well as app-specific use for the most popular apps.

Hypothesis 5: Exposure to treatment improves academic outcomes

We hypothesize that optimal digital media consumption may lead students to develop better focus and control over their phone use, leading to better academic outcomes. We collect data on end-of-term examinations include semester scores and overall GPA from our partner universities to estimate the impact of the treatment on academic outcomes.

[22]The key limitation of this measure is that it does not provide information on the use of other commitment devices. For this reason, we will examine both the self-reported and Dashboard data.

[23]Specifically, define x_{iad1} as the average screen time of individual i on application a for day d of the week during the baseline period before any intervention, and h_{iadj} as the corresponding average screen time limit for app a on date j, which falls on day d of the week in period t. The limit tightness for that date, H_{iaj}, is calculated as:

$$H_{iaj} = \max\left\{0, x_{iad1} - h_{iadj}\right\}.$$

This formula employs the max function to assess whether the average daily usage x_{iad1} exceeds the set limit h_{iadj}. If the average usage is within the limit, the function returns 0, indicating a non-binding limit. If it exceeds the limit, the function returns the difference, thus measuring the excess screen time for that day. To compute a comprehensive measure of limit tightness for the individual across all apps and days in period t, we first calculate limit tightness for each app

$$H_{ia} = \frac{1}{N_j} \sum_{j \in T} H_{iaj},$$

where N_j is the total number of days in period t. The final measure, H_i, aggregates these across apps:

$$H_i = \sum_{a} H_{ia}.$$

Hypothesis 6: Exposure to treatment increases concentration during class hours

We will measure concentration using class hours by combining actual usage data from mobile application with administrative data on student attendance and class schedules collected from partner universities. We will generate a measure of cumulative smartphone and social media usage during class hours.

Hypothesis 7: Exposure to treatment reduces phone usage around bedtime

Digital media consumption before bedtime has been linked to delayed bedtime, poor sleep quality, increased tiredness, and pre-sleep hyperarousal (He et al., 2020). We will test whether our treatment leads to a reduction in phone usage before bedtime using the following outcomes: (i) *self-reported measure*: in the endline survey we collect data on phone usage in the hour before bedtime; and (ii) *objective measure*: we combine baseline survey data on sleep patterns with usage data from the mobile phone application to construct an actual usage measure of phone usage in the hours right before and after sleep.

Hypothesis 8: Exposure to treatment improves quality of sleep

Restricted phone usage before bedtime may lead to improved sleep quality. We test the effect on improved sleep quality using the following survey outcomes: (i) self-reported quality of sleep on a scale ranging from *very poor* to *excellent*, (ii) hours of sleep calculated from reported time of falling asleep and waking up.

Hypothesis 9: Exposure to treatment reduces proclivity towards social comparison

We measure respondents' proclivity towards social comparison using a five-item scale based on Tandoc Jr et al. (2015). The scale assesses social comparison, specifically focusing on feelings of inferiority, envy, and perceptions of others' social lives and overall life satisfaction compared to one's own. The outcome will be a variance-weighted index.

5.4 Exploratory outcomes

Additionally, we collect data on exploratory outcomes which may be impacted by the intervention.

- **Valuation of Social Media**: We will estimate the effect of treatment on the respondents' valuation of social media using multiple price lists to gauge the minimum amount respondents are willing to accept to deactivate their Instagram account for 2 weeks. The question is presented as a multiple price list task with real-stakes to ensure honest reporting of valuations. We do not have a directional prior on this outcome. The intervention may lead people to reduce their valuation of social media after developing more critical awareness about their self-control problems, platform design, and the existence and extent of misinformation. On the other hand, if the treatment leads students to regulate their usage and improve the quality of their engagement with social media, it may increase their valuation.

- **Content shared and viewed on Instagram**: Given that our treatments may induce changes in the quality of social media consumption, we will test for differences in content shared and viewed by the participants. This test is, however, conditional on being able to collect Instagram data from at least 10% of the participants.

- **Career Aspirations**: Treatment may improve aspirations as participants may apply lessons from the digital empowerment course to other aspects of their lives. Additionally, improved well-being and reduced psychological distress may enable participants to focus on their careers. In our endline survey, we include questions on aspirations about academic and job market performance and ideal age at marriage. We will generate an aggregate index for aspirations.

- **Job Search Effort**: Treatment may lead students to divert time from digital media use to other productive pursuits. We capture one dimension of effort, that is job search effort. We ask students about whether they applied for jobs and internships and how many job or internships they applied for in the last two months.

5.5 Construction of outcomes

Unless specified otherwise, we will construct our outcome indices following Anderson (2008). To construct an index variable we first recode the outcome variables so that more positive values have the same meaning within each family. We then normalize each outcome variable into standard deviation units using the control group mean and standard deviation. Finally, we calculate the average of the outcome variables, weighted by the inverse covariance matrix. Appendix D provides a detailed description of variables used for the construction of each of these measures.

5.6 Multiple hypotheses

We follow two approaches to address issues associated with testing multiple hypotheses. First, as discussed above, to reduce the number of hypotheses tested, we will construct indices for key outcomes following Anderson (2008). Second, we will compute the sharpened false discovery rate-adjusted q-values (Anderson, 2008), in addition to the p-values associated within each family of outcomes. This approach is suitable for our specifications, which include strata fixed effects and clustered standard errors. We will not adjust p-values across our primary hypotheses as these are three thematically different analyses. However, within each hypothesis, we will account for the two tests, one for the digital empowerment and one for the microlearning treatment. We will treat our secondary hypotheses as a family and report sharpened q-values for each test. We will not adjust p-values for our exploratory outcomes.

6 Empirical Framework

6.1 Empirical specifications

To estimate the effect of exposure of digital empowerment curriculum, we will estimate the following specifications using OLS:

$$Y_{ijk} = \beta_0 + \beta_1 T_{jk} + X_{ijk}\gamma + \lambda_k + \varepsilon_{ijk} \tag{1}$$

$$Y_{ijk} = \beta_0 + \beta_1 T1_{jk} + X_{ijk}\gamma + \lambda_k + \varepsilon_{ijk} \tag{2}$$

where Y_{ijk} is our outcome of interest for student i in cohort j in major-university k. T_{jk} is a treatment assignment indicator that equals one if cohort j is assigned to one of the digital empowerment treatments. Specifically, it takes the value one for the *self-control and misinformation* (T1) and the *self-control only* (T2) sub-treatments, and zero for the control group. $T1_{jk}$ is a dummy variable that takes the value one if cohort j is assigned to the *self-control and misinformation* sub-treatment. X_{ijk} denotes a vector of baseline covariates, including pre-intervention values of the outcome of interest. λ_k denotes randomization strata fixed effects. ε_{ijk} is the error term. The standard errors will be clustered at the cohort level. Our goal is to estimate $\hat{\beta}_1$, which gives the impact of being assigned to a digital empowerment (sub-)treatment cohort.

We employ equation 1 to test our hypotheses, with the exception of hypothesis 3 (*Exposure to treatment improves the ability to identify misinformation*). We use equation 2 to test hypothesis 3 by restricting to the sub-sample consisting of T1 and the control group.

To estimate the effect of exposure to microlearning, we will estimate the following specifications using OLS:

$$Y_{ijk} = \alpha_0 + \alpha_1 M_{ijk} + \alpha_2 T_{jk} + X_{ijk}\gamma + \lambda_k + \varepsilon_{ijk} \tag{3}$$

$$Y_{ijk} = \alpha_0 + \alpha_1 M_{ijk} + \alpha_2 T_{jk} + \alpha_3 T_{jk} \times M_{ijk} + X_{ijk}\gamma + \lambda_k + \varepsilon_{ijk} \tag{4}$$

where Y_{ijk} is our outcome of interest for student i in cohort j in major-university k. T_{jk} is a treatment assignment dummy that takes the value one if cohort j is assigned to the digital empowerment treatment. M_{ijk} is a dummy that takes the value one if the student i is assigned to receive the microlearning treatment. X_{ijk} denotes a vector of baseline covariates, including pre-intervention values of the outcome of interest. λ_k denotes randomization strata fixed effects. ε_{ijk} is the error term. The standard errors will be clustered at the cohort level. Here, $\hat{\alpha_1}$ gives the effect of being individually assigned to microlearning treatment.[24] In equation 4, $\hat{\alpha_3}$ gives the effect of being assigned to both the digital empowerment and microlearning treatment.

Our design allows us to estimate spillover effects from the microlearning treatment. We estimate treatment effects on students who were at risk of receiving the microlearning treatment but not (individually) selected for it, and who were not part of cohorts assigned to the classroom-based digital empowerment treatment. By analyzing outcomes for this subsample, we can assess whether the microlearning intervention indirectly affected students, possibly through information sharing or behavior changes within their social networks.

We will also compare the coefficients between the digital empowerment and microlearning treat-

[24]The interpretation of $\hat{\alpha_1}$ in equation 3 depends on our assumption about any interaction between the two treatments. Theoretically, the coefficients give a weighted average of treatment effects with respect to different counterfactuals in the design (Muralidharan et al., 2023). However, if one assumes no interaction effect (given the time lag between the two treatments), the coefficients give the average treatment effect of the treatment and the test is often more powered. In any case, we also estimate the model with interactions in equation 4.

ments. For example, the classroom version might be more effective because it includes activities that reinforce learning, enables students to learn from peers, and can potentially shift their perceptions of social norms. If microlearning proves to be similarly effective, it could serve as a cost-effective and scalable alternative to class-based programs.[25]

Dashboard data Data from Dashboard allows us to construct granular usage outcomes for any usage period. We will leverage this across-time variation and estimate versions of equation 1 with (i) time-varying coefficients, (ii) time fixed effects, and (iii) individual fixed effects.

Control variables For all our specifications, we will employ a Double Post Lasso (Belloni et al., 2014) to pick the relevant control variables. We will estimate specifications with and without controls. To deal with missing values, we follow Zhao and Ding (2024) and impute any missing values of baseline covariates with zero and include a dummy variable that indicates missingness of the corresponding baseline covariate.

6.2 Heterogeneous effects

Some features of our setting are unique to developing country contexts and provide interesting sources of heterogeneity in treatment effects. For example, a large share of our sample comes from rural areas and a large share acquired their first smartphone at or after 18 years of age. We will test for heterogeneity along these characteristics.

We will also test for heterogeneous effects disaggregated by baseline levels of media literacy as we posit that effects may be larger for students with lower levels of media literacy. We will also test for heterogeneous effects by baseline social media usage, given that effects may be larger for students with higher usage. Further, we will look at heterogeneity in treatment effects by gender, as males and females may use their smartphones in qualitatively different ways.

We will examine heterogeneity in treatment effects by students' propensity to give socially desirable responses to test for the presence of experimenter demand effects (Dhar et al., 2022). While recent studies have shown that experimenter demand effects may not be very prevalent in practice (Mummolo and Peterson, 2019; Dhar et al., 2022), they may be a concern in our study

[25] We are collecting cost data to conduct a cost-effectiveness analysis upon study completion.

due to the classroom setting. To measure this, we include a short validated scale based on Hays et al. (1989) in the baseline survey to evaluate the student's tendency to give socially desirable responses. We will test if treatment effects are different for people who have a high propensity to give socially desirable answers.[26]

Finally, to avoid ignoring other potentially valuable sources of heterogeneity that may only come to light during the analysis phase, we will employ machine learning methods proposed by Chernozhukov et al. (2022) to detect other potential sources of heterogeneity. The proposed method allows searching for heterogeneous treatment effects without the risk of overfitting.

6.3 Spillovers

One potential concern is that students in the treatment and control groups may interact, leading to SUTVA (Stable Unit Treatment Values Assumption) violations. Three key aspects of our setting help mitigate concerns about SUTVA violations. First, students in most universities in India do not have common classes across different years; courses are organized by year or semester of the program. Second, we collected data on student friendships at baseline to estimate the magnitude of spillovers, and found that when asked to list their top three friends, approximately 82 percent of students only listed friends in their own cohort. Furthermore, the nature of the intervention, which is intensive and high-touch in nature involving worksheets and hands-on reflection, makes it difficult for students in control groups to receive the full benefit of the curriculum through verbal interactions with students in treatment groups after the class sessions.

While the potential for spillover is limited in our setting, it cannot be fully ruled out. To the extent possible, we will document potential spillovers. We will administer a module to test for knowledge of key concepts learnt in the intervention. Within the control group, we will test whether students with higher number of friends in the treatment group (conditional on total number of friends outside their cohort) exhibit greater knowledge of concepts taught in the classroom intervention.

Given the inherently social nature of social media, students in the control group might still be influenced by the treatment indirectly if their peers in the treatment group change their social

[26]Furthermore, our main outcomes are constructed from actual usage over a long period of time, which is unlikely to driven by experimenter demand.

media behavior after receiving the curriculum. We will similarly leverage the random variation generated by the treatment assignment to look at whether having more friends assigned to the treatment group influences the social media consumption of students in the control group.

Finally, we expect any spillovers to attenuate our estimates. Under spillovers, our estimated effect size will be a lower bound for the true treatment effect.

6.4 Mechanisms

Our design enables us to test the effectiveness of main intervention components: self-control and misinformation. More specifically, we will test for (i) if the misinformation curriculum impacts social media consumption beyond the self-control module and (ii) if self-control curriculum enhances the ability to identify misinformation. To look at (i), we will compare the effects between T1 (self-control and misinformation curriculum) and T2 (self-control curriculum only). To look at (ii), we will compare T2 against control. Both these outcomes remain sufficiently powered as previous research suggests typically larger effects on social media consumption and misinformation discernment compared to digital addiction and mental health outcomes.

Furthermore, given that our content is delivered over a span of several weeks, we monitor changes in high-frequency outcomes using data from the Dashboard and through regular surveys throughout this period. These surveys are conducted at the start of each session along with a corresponding survey with the control group students. This method allows us to systematically observe how different sessions of the curriculum influence participant behavior and reported outcomes over time.

We hypothesize that by raising awareness about self-control problems and promoting the adoption of commitment devices, the curriculum might enable learners to develop a more internal locus of control, leading them to proactively control their digital media consumption. To that end, we will examine locus of control as a mechanism driving changes in behavioral outcomes, where locus of control is defined as the extent to which people believe their actions can influence outcomes. To measure locus of control, we use a seven-item scale proposed by Pearlin and Schooler (1978). The tool ask participants to evaluate their sense of control and ability to influence outcomes in their lives over the past three weeks. Respondents are asked to rate their agreement with a series of statements about personal empowerment and helplessness using a Likert scale.

We also examine if the effects stem from increased digital media literacy. However, we posit that knowledge about digital media processes alone (i.e. digital literacy) is insufficient to drive changes in outcomes. Our intervention focuses on *digital empowerment*, which also includes equipping participants with skills and tools to proactively manage their digital engagement, beyond just understanding how digital media operates. To measure digital literacy, we: (i) administer vignettes from the Youth Social Media Literacy Inventory (Purington Drake et al., 2023) covering habit formation, commitment, social comparison, and balanced use concepts taught; (ii) test subject knowledge from the curriculum. The literacy outcome is a variance-weighted average (Anderson, 2008). We hypothesize that while literacy may increase, empowerment through applied skills is the key mechanism for changing digital behavior and outcomes. We explore these potential mechanisms using Equation 1 with locus of control and digital literacy as the outcome variable.

We will perform exploratory analysis on the components of the aggregate indices to identify potential drivers of any findings related to the three primary hypotheses. For example, the composite mental health index comprises reported symptoms of depression and anxiety, subjective well-being, and perceived digital addiction. We will test the effects on these outcomes separately. However, we will treat them as a family and report adjusted q-values following the false discovery rate (FDR) procedure outlined by Anderson (2008).

Our treatment is a curriculum, which includes content on digital empowerment and encompasses a set of pedagogical techniques such as student feedback, worksheets, and audience polling. However, within the curriculum, it may also be of interest to test for some important mechanisms that have been previously identified. We will not be able to fully disentangle and decompose the effects into distinct mechanisms but we will provide some suggestive evidence. One pathway through which the digital empowerment treatment impacts students is by facilitating coordination among students to get out of the social media trap à la Bursztyn et al. (2024). This is one reason why a classroom-based curriculum delivered to a group may be a more effective tool for digital empowerment compared to individually delivered lessons. While our data does not allow us to map the entire social network in each cohort, we collect data on the top three friends from each student. We will use this information to test if the aggregate impact of the curriculum on social media usage is larger for observed friendship clusters.[27]

[27]However, such analyses will inevitably be plagued by the usual problems of estimating peer effects, such as the

For the microlearning treatment, an inherent concern is that any effect due to the text messages is likely to be a combination of increased awareness as well as a reminder effect. We will compare the impact of microlearning to that of survey text messages sent by our team. Since both types of texts are likely to remind students to consider their social media usage, any differences in their effects will provide suggestive evidence of the impact of microlearning beyond the reminder effect. We will look at short-term effects on consumption (e.g., social media use since the delivery of the last text message).

7 Administrative information

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9 Tables and Figures

Table 1: Baseline sample characteristics based on partial data

	Mean (1)	SD (2)	Min (3)	Max (4)	N (5)
Current age (years)	20.00	1.18	17.00	24.00	940
Gender is female	0.85	0.36	0	1	940
Father attended college	0.37	0.48	0	1	940
Mother attended college	0.46	0.50	0	1	940
Reside in same city as parents	0.76	0.43	0	1	940
Lived in urban area before university	0.15	0.36	0	1	940
Has WiFi connection at home	0.58	0.49	0	1	940
Age of first phone acquisition	16.22	2.97	1	21.00	932
Self-reported social media use per day (hours)	5.15	4.77	0	24.00	929

Notes: Reports are based on the partial baseline data collected from four partner universities at the time of writing.

Table 2: Baseline balance for digital empowerment curriculum based on partial data

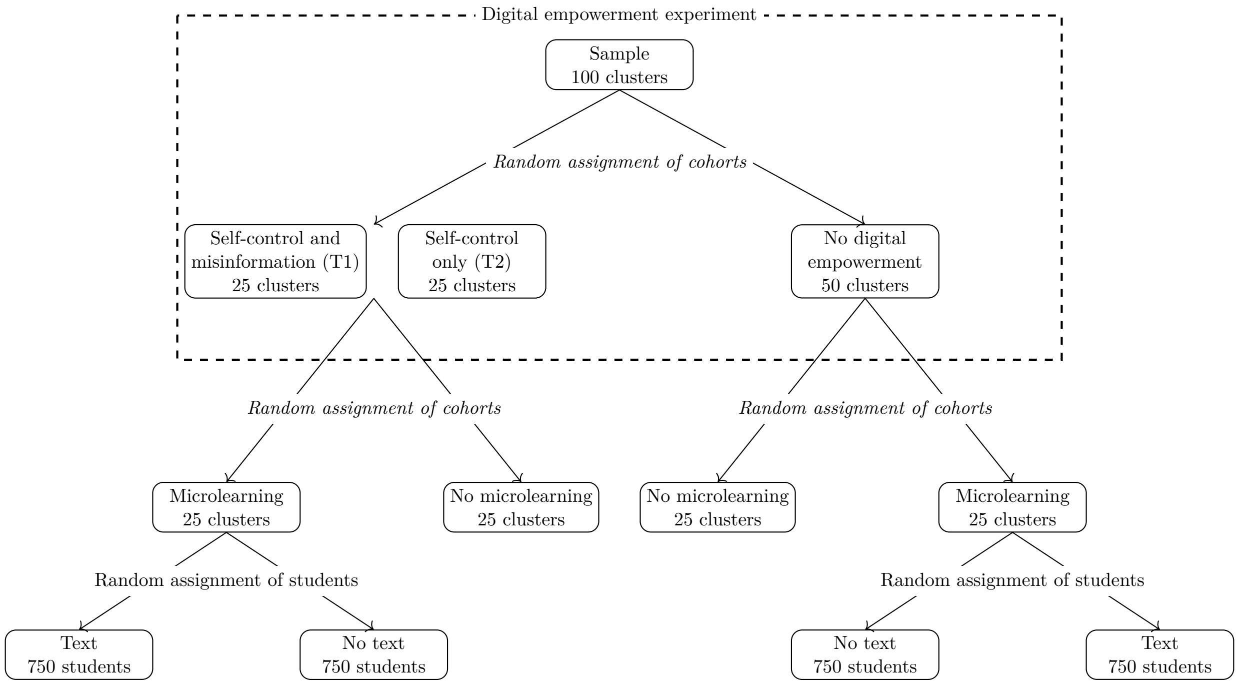
	Control mean (1)	Difference (2)	N (3)
Current age (years)	20.08	0.15	940
		(0.23)	
Gender is female	0.82	0.00	940
		(0.02)	
Father attended college	0.38	0.00	940
		(0.02)	
Mother attended college	0.45	0.03	940
		(0.02)	
Reside in same city as parents	0.76	-0.00	940
		(0.02)	
Lived in urban area before university	0.14	0.03*	940
		(0.02)	
Has WiFi connection at home	0.60	0.00	940
		(0.02)	
Socioeconomic status	0.09	0.01	940
		(0.04)	
Age of first phone acquisition	16.07	0.20	932
		(0.20)	
Self-reported social media use per day (hours)	5.24	-0.02	929
		(0.42)	

Notes: The estimates are based on the partial baseline data collected from four partner universities at the time of writing. All specifications control for randomization strata fixed effects. Standard errors are clustered at the cohort level. Socioeconomic status is calculated as a variance-weighted index of household assets. ***, **, and * indicate significance at 1%, 5%, and 10%.

Table 3: Theory of change

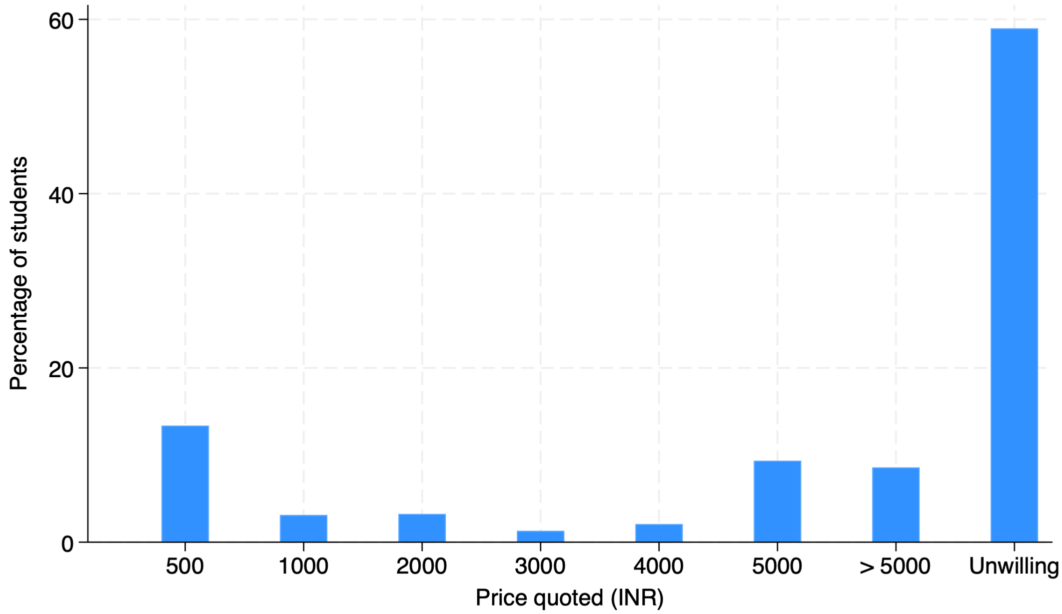
Need	Inputs	Outputs	Outcomes
• Excessive use of smartphone and social media • Vulnerability to digital addiction and misinformation • Absence of guidance in the current environment	• Three in-person sessions (and/or) series of text messages on digital empowerment • Content builds awareness and provides actionable strategies and tools for intentional and mindful use	• Attendance in sessions (implementation fidelity) • Higher awareness of self-control problems and attention to habit formation • Intentional use of digital technologies • Sense of control • Higher digital literacy	**Primary:** • Reduction in social media consumption • Improvement in mental health (anxiety, depression, perceived addiction, subjective well-being) • Better ability to identify misinformation **Secondary:** • Higher adoption of commitment devices • Improved academic outcomes • Reduced phone usage during class hours • Reduced phone usage around bedtime • Improved quality of sleep • Reduced proclivity towards social comparison **Exploratory:** • Changes in valuation of social media • Changes in content shared and viewed on Instagram • Improved career aspirations • Improved job search effort

Figure 1: Experimental design and treatment assignment



Notes: The figure illustrates the experimental design of the study. For the classroom-based digital empowerment arm, cohorts are randomly assigned to receive the digital empowerment treatment (either self-control only or self-control and misinformation curriculum with 50 % risk) or to a control. These groups are cross-randomized to cohorts with 50% risk of microlearning treatment or no risk of microlearning treatment. Individuals in cohorts assigned to 50% risk of microlearning are then individually randomized to either receive or not receive microlearning lessons through text messages.

Figure 2: Distribution of Instagram data sharing prices



Notes: The figure shows the distribution of prices at which respondents indicated willingness to share their Instagram data. Reports are based on the partial baseline data from four partner universities that was collected at the time of the registered report initial submission.

Figure 3: Organizational structure of partner universities

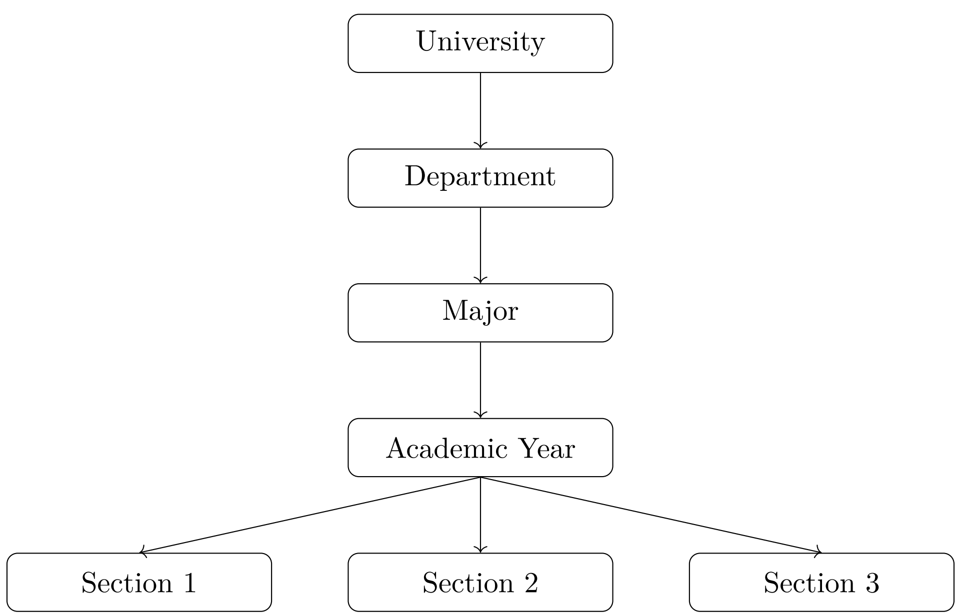
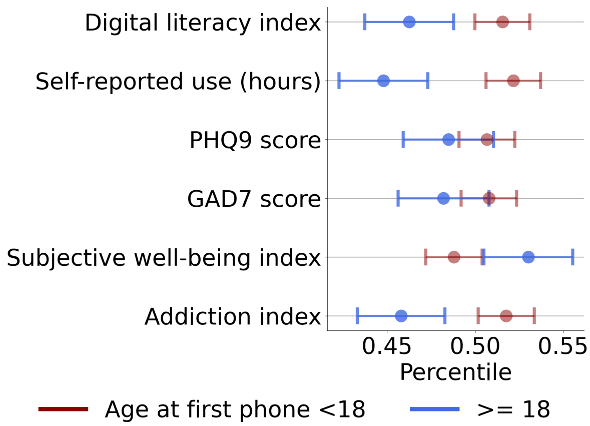
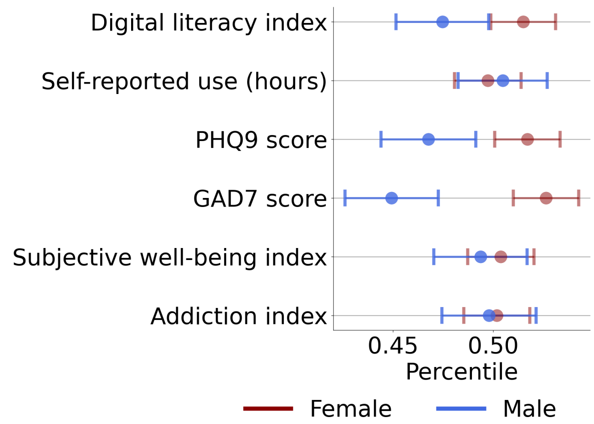


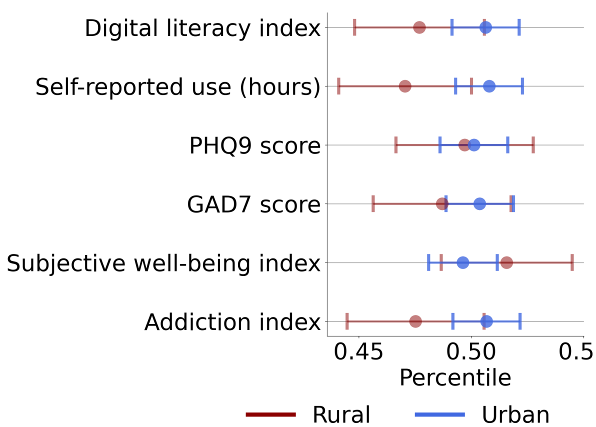
Figure 4: Associations between student characteristics and outcomes



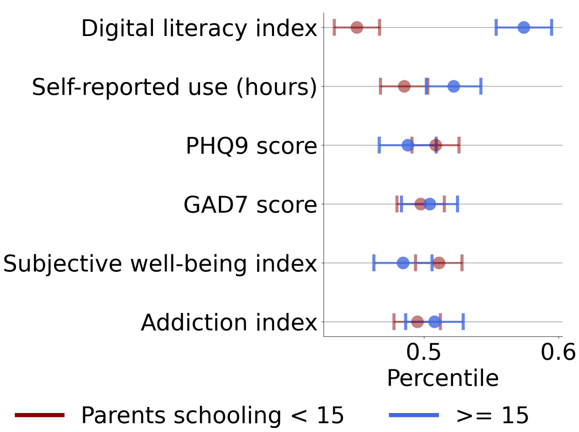
(a) Age at first phone



(b) Sex



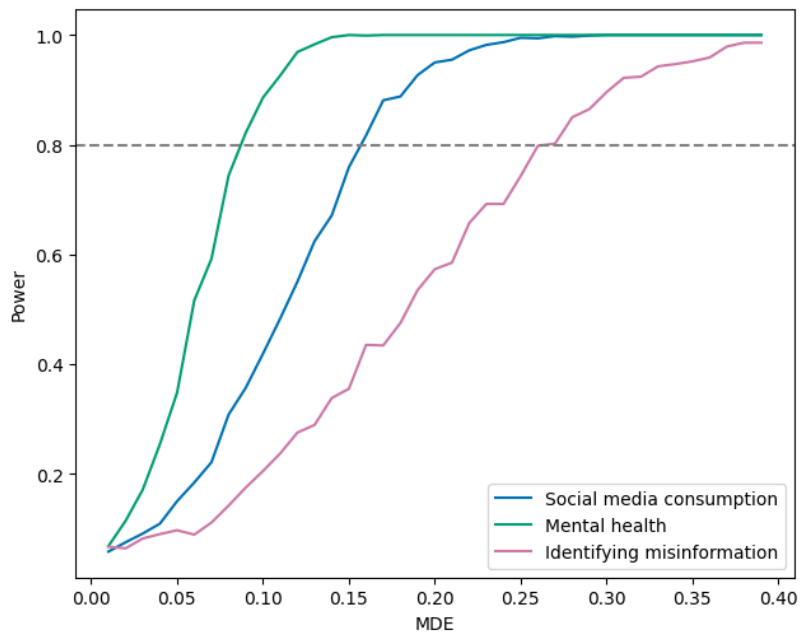
(c) Rural or urban dwelling



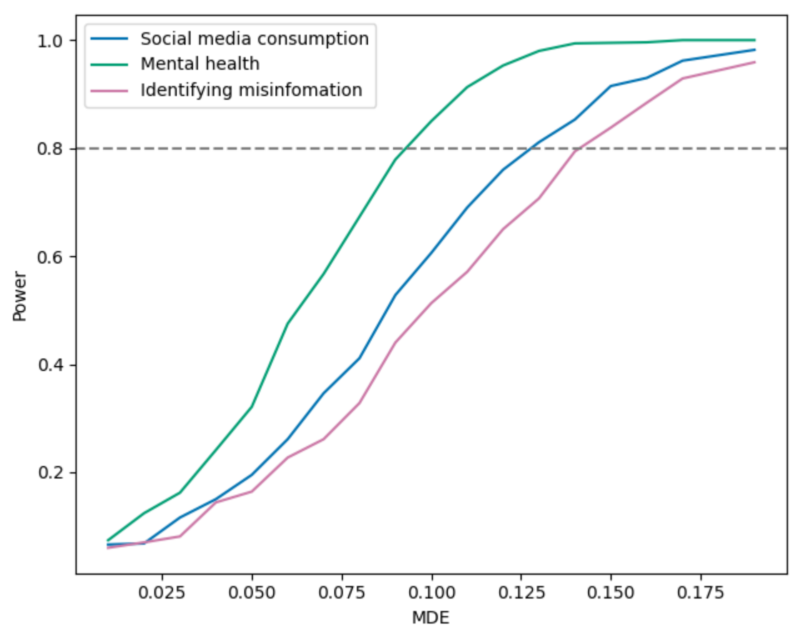
(d) Parents' schooling

Notes: The estimates are based on the partial baseline data collected from four partner universities at the time of the registered report initial submission. Figure plots mean outcomes and 95% confidence intervals for outcomes.

Figure 5: Power simulations



(a) Digital empowerment



(b) Microlearning

Notes: Panel A shows power calculations for the classroom-based the digital empowerment treatment and Panel B for the text message-based microlearning treatment. Simulations assume an R^2 of 0.20 between baseline and endline values of the outcome, 100 clusters of 60 students, 10% attrition, and use equations 1, 2, and 3. The intra-cluster correlations were computed from baseline data (0.07 for social media consumption, and 0.01 for mental health). For ability to identify misinformation, we use an ICC of 0.10. The plots are based on 1000 simulations.

Appendices

Appendix A Qualitative exploration

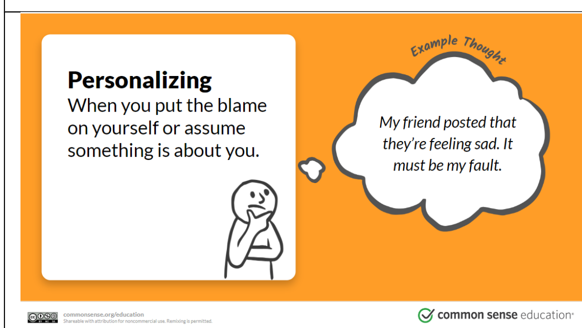
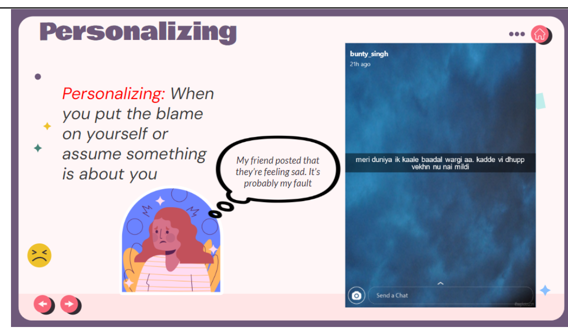
Prior to the study, we conducted focus group discussions to ensure that our intervention is relevant and applicable to the daily lives of the participants. We conducted discussions with college students below the age of 23 associated with Sukrit Trust, an NGO in Punjab, India. The sample of eight students resembled our potential study participants on observable characteristics. The discussion focused on understanding their digital engagement, particularly in relation to social media usage and its impact on their daily lives.

Three main themes emerged from the discussions. First, we found substantial use of social media among the participants. Instagram and WhatsApp were the most common platforms with screen time ranging from four to nine hours daily. Posting on social media varied, with frequencies ranging from monthly to biannually. Most reported exceeding their ideal usage and expressed feelings of regret at having spent so much time on these platforms.

Second, participants expressed a desire to regulate their smartphone use but lacked knowledge of effective strategies to do so. Smartphones were reported to be major distractions during work or study, with notifications frequently disrupting focus. Even when notifications were turned off, participants reported that the mere presence of the phone led to habitual checking. Some participants mentioned that excessive device use caused them to lose out on important things like spending quality time with family and friends. Participants also raised concerns about social comparisons and feelings of inadequacy when comparing themselves to others on social media platforms.

Third, participants generally agreed on the need for a course to develop skills for more disciplined social media use. They emphasized the need for practical strategies to reduce phone usage, suggesting engaging activities and handouts to reinforce learning. Regarding incentives for participation in a course on digital empowerment, participants preferred certificates or other forms of recognition over monetary rewards due to their lasting value.

Appendix B Exhibits of teaching material

Reference Material	Local Adaptation
	
A slide from Common Sense Media's Lesson Titled 'Clicks for Cash'. This slide introduced students to the pervasiveness of ads in everyday online and offline life.	This slide is from our first module, during which the instructor prompts students in the classroom to speculate on how the digital platforms featured on the slide generate revenue. These platforms are widely popular and commonly used in India. The aim is to encourage students to consider how advertising is typically integrated into nearly all digital platforms.
	
A slide from Common Sense Media's lesson on cognitive distortions, defining the "personalizing" thinking trap that users of digital media may frequently encounter.	Our adaptation of the same cognitive distortion involves creating a Snapchat post in the local language (Punjabi typed in Roman letters) to enhance understanding of the concept.

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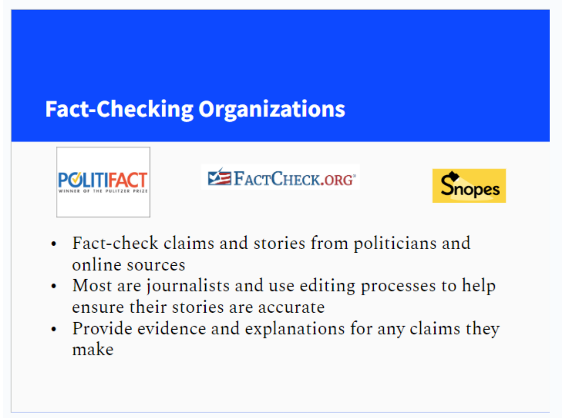
<td>
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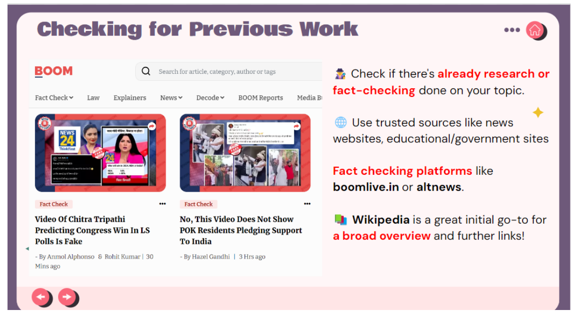
<td>
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<tr>
<td>A slide on fact-checking organizations to help evaluate information online.</td>
<td>Our adaptation to encourage students to use two nationally acknowledged fact checking websites - boomlive and altnews – for the same purpose. Boomlive is Meta’s official fact checking partner in India.</td>
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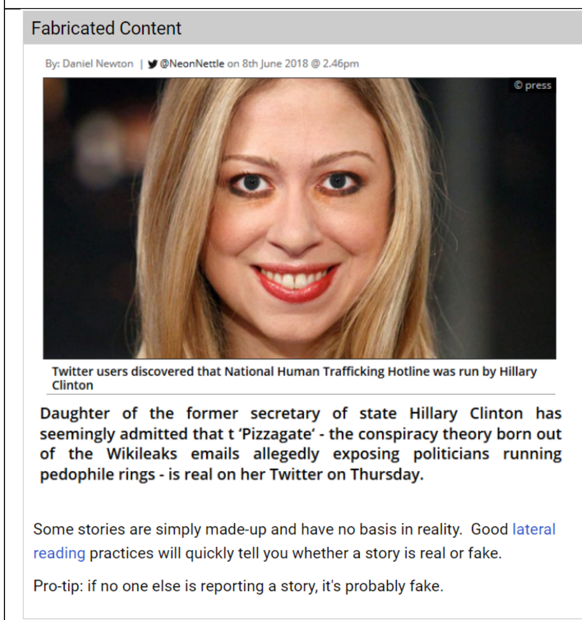
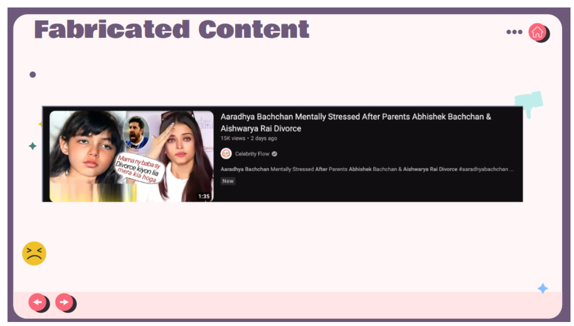
<td>
</td>
<td>
</td>
</tr>
<tr>
<td>An example of ‘fabricated content’ from University of Iowa’s online guide on evaluating online misinformation.</td>
<td>Our explanation of the same subject using an example of a disinformation item mentioning a famous celebrity.</td>
</tr>
</table>

Figure A1: Example of a slide explaining satire using an example involving a nationally famous Punjabi Singer - Diljit Dosanjh.

Figure A2: A slide from our module on social comparison using examples of hypothetical individuals with localized names.

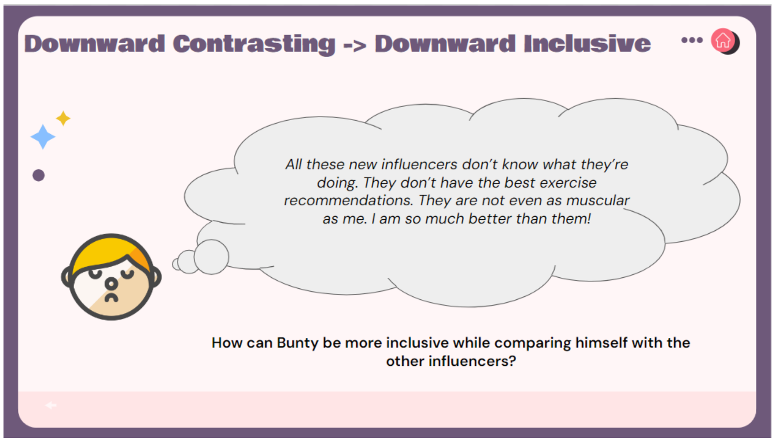


Figure A3: Example of worksheet.

Digital Media & Our Mind – Reflection Worksheet

1) One social media app I use very often: __________________________ (Enter any)

2 Good/ Positive feelings I sometimes get from using this app	Reasons why this app might be making me feel this way
1)	
2)	

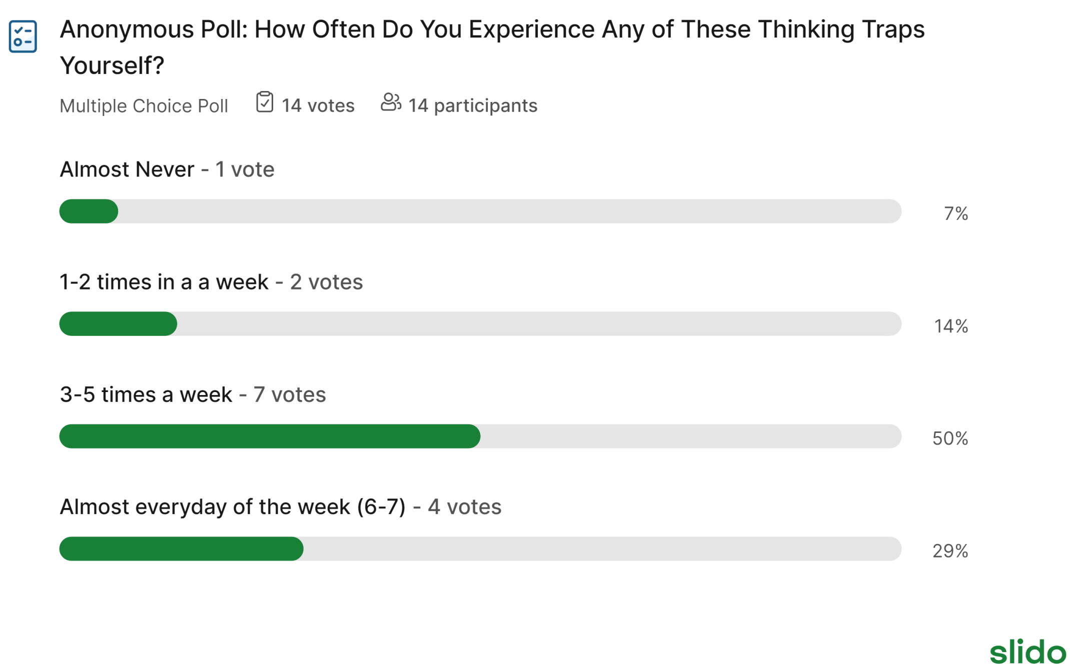
2 Bad/ Negative Feelings I sometimes get from using this app	Reasons why this app might be making me feel this way
1)	
2)	

Name: _________________ College/ University: _______________ Degree: _____________

Year: 1st/ 2nd /3rd/4th/5th [Tick the appropriate answer]

Roll no: _____________________

Figure A4: Example of an in-class live poll (anonymous).



Appendix C Microlearning text messages

Session 1 lessons

Text 1

🌟 **This week's lesson: The Hook Model & Digital Media Design Features** 📱⏳

Hey there! Let's dive into understanding why we often find it hard to put our phones down. It's not just about willpower; it's about the design features that keep us hooked. 📱🧠

Digital media platforms use various tactics to maximize user engagement. One popular model that explains this is the **Hook Model**. This model includes four main steps: Trigger, Action, Variable Reward, and Investment. These steps are designed to keep you coming back for more. 🎣✨

- **Triggers:** External cues like notifications and internal triggers like boredom or loneliness prompt you to engage with your device. 🔔📤
- **Action:** The simplest behavior in anticipation of a reward, like scrolling through a feed. ☝📜
- **Variable Reward:** The unpredictable nature of rewards, such as likes, comments, or new content, makes the experience more engaging. 🎁❓
- **Investment:** The more you engage, the more you invest your time and data, making it harder to stop. ⌛📊

These steps create a cycle that reinforces continuous usage and engagement with digital media. 🌟🧠

🔍 **Now, here's a question for you:**

Imagine you are using a social media app. Sometimes, when you open the app, you see many new likes and comments on your posts, and other times there are none. This unpredictability makes you check the app more frequently, hoping for new notifications.

Which element of the Hook Model does this scenario best illustrate?

(A) Trigger

(B) Action

(C) Variable Reward

(D) Investment

Reply with your answer below! Stay tuned for more insights on navigating the digital world with confidence. 🕵️🌐

Text 2

🌟 **This week's lesson: Navigating Social Comparison in the Digital Age** 🤳💭

Let's talk social comparison! It's a natural human thing, but social media cranks it up to eleven. We're constantly peeking into others' highlight reels and sizing ourselves up. The catch? It can be pretty toxic. When we compare ourselves to others, focusing on differences often leads to envy and feeling down. 📉 On the flip side, embracing similarities and inspiration (assimilative comparison) can pump us up and push us towards growth. 💪

In 2000, psychologist Susan Smith divided social comparison into two types: assimilative and contrasting. 🤔

Contrasting Comparison 🔄

- **Focus:** Differences.
- **Effect:** Can lead to feelings of inadequacy and jealousy.
- **Example:** Seeing someone who seems more successful and thinking, "They're better than me because they're so different."

Assimilative Comparison ✔️

- **Focus:** Similarities.
- **Effect:** Can inspire and motivate.
- **Example:** Looking up to someone's achievements and thinking, "They were once in my shoes. If they can do it, so can I!"

Engaging in this type of comparison can boost self-confidence, encourage goal-setting, and foster a sense of connection and possibility. It helps us see that success is attainable and can drive personal growth and improvement. 🌟

🔍 **Which approach do you think is more beneficial in the digital age?**

(A) Contrasting comparison 🔄

(B) Assimilative comparison ✔️

Drop your answer below! Get ready for more tips on mastering social media sanity. 🧘✨

Session 2 Lessons

Text 1

🌟 **This week's lesson: Understanding Commitment Devices and Taming Screen-Time** 📱

Hey there! This week, we're diving into commitment devices and how they can help us take control of our screen-time habits.

🛡️ **What are commitment devices?** Commitment devices are strategies or tools we use to help us stick to our goals or commitments, especially in the context of managing our digital devices.

💪 **How they can help us and why do we need them:** In today's world filled with digital distractions, commitment devices are crucial for maintaining focus, boosting productivity, and improving overall well-being. They empower us to make intentional choices about how we engage with technology.

> 📉 **Consider this study from the University of Texas in 2017:**
>
> - 📉 Participants who kept their phones on their desks performed the worst.
> - 🚪 Those who kept their phones in pockets or bags fared better but still not as well as they could have.
> - 📊 The top performers were those who left their phones in another room.

🧠 **To optimize your focus, create some distance between you and your phone during tasks that require your full attention. Remember, even the 'Phone Proximity Effect' can drain your cognitive resources without you realizing it!**

🧘 **Let's revise!: What are commitment devices in the context of managing digital devices?**

(A) Strategies for keeping your devices charged

(B) Tools to help you stick to your digital usage goals

(C) Apps that enhance your social media experience

(D) Techniques for improving your phone's performance

Reply with your answer below! Stay tuned for more tips on using commitment devices to enhance your digital well-being. 🧘

Text 2

🌟 **This week's lesson: Understanding Commitment Devices and Taming Screen-Time (Part 2)** 📱

Hey again! Today, we're delving into two other important commitment devices: DND (Do Not Disturb) mode and disabling notifications for addictive apps.

🛡️ **Defining the functions:** We begin by presenting one of the most straightforward and profoundly effective tools at our disposal - the 'Do Not Disturb' mode (DND). DND is like your digital bouncer, giving you the power to decide when your digital world can interrupt your real-world focus. Whether you're studying, working, or spending quality time, DND mode ensures that your device stays respectfully silent. 📵

Moving on, let's discuss another simple yet powerful strategy: disabling notifications for addictive apps. Different apps may be addictive for different people, and managing notifications for such apps is about taking charge, minimizing distractions, and ensuring that your digital experience aligns with your priorities. 📵📱

💪 **How to use these?**

- **DND mode:**
  - iPhone: Go to Settings > Do Not Disturb > Schedule.
  - Android: Settings > Sound > Do Not Disturb > Schedule.
- **Disabling notifications for addictive apps: Break the cycle of distraction:**
  - iPhone: Settings > Notifications > Select App > Allow Notifications > Off.
  - Android: Settings > Notifications > Select App > Toggle Off.

🌟 **Enhance your focus and productivity with these simple steps!** 🚀

🧠 **Let's revise!: Which of the following is a benefit of using DND mode or disabling notifications for addictive apps?**

(A) Increasing distractions

(B) Minimizing interruptions

(C) Decreasing productivity

(D) Enhancing focus and well-being

Reply with your answer below! Stay tuned for more tips on using commitment devices to enhance your digital well-being. 🧘

Text 3

🌟 **This week's lesson: Empowering Your Goals and Digital Well-Being** 🚀

Hey there! Following our discussions on commitment devices and managing screen-time, let's delve deeper into goal setting and how our digital devices can either aid or hinder us in achieving them.

🤔 **Why should someone set goals?** Setting goals gives us direction, motivation, and a sense of purpose. They provide a roadmap for what we want to achieve and help us stay focused on what's important.

📱 **However, our digital devices can both help and hinder us in reaching our goals.** On one hand, they can serve as valuable tools for organizing, tracking progress, and providing reminders. On the other hand, they can also be sources of distraction, leading us away from our goals if not managed effectively. Remember - commitment devices such as DND and turning off notifications will help us in managing our screen-time!

🧠 **Set SMART goals!**

SMART goals are Specific, Measurable, Achievable, Relevant, and Time-bound. They help us set clear objectives and create a plan of action to achieve them effectively. Setting SMART goals ensures that our efforts are focused, our progress is measurable, and our actions are aligned with our overall vision.

❓ **Now, can you tell us what the 'A' in SMART stands for?**

(A) Achievable

(B) Adaptive

(C) Active

(D) Attainable

Reply with your answer below! Stay tuned for more tips on using commitment devices to enhance your digital well-being. 🌱

Session 3 Lessons

Text 1

This week's lesson: Navigating Misinformation in the Digital Age 🛡️

Hey there! This week, we're delving into the complex world of misinformation and disinformation and why understanding them is crucial in today's digital landscape.

What is misinformation? What is disinformation? The key difference lies in intent:

Misinformation refers to false or inaccurate information spread without the intention to deceive. Disinformation, on the other hand, is deliberately false or misleading information spread with the intent to deceive or manipulate.

Why might someone want to deliberately mislead you?

- 💰 To make money: Misleading content can attract clicks and views, generating ad revenue for creators.

- 📢 To build reputation: Spreading false information can be used to boost one's image or credibility in certain circles.
- 😈 To cause trouble: Some individuals or groups may spread misinformation to create chaos or sow discord.
- 📊 Political gain: Misinformation can be used as a tool for political manipulation, influencing public opinion or election outcomes.

Understanding the motives behind misinformation and disinformation is the first step in becoming a savvy digital consumer.

❓ Now, here's a question for you: Imagine your uncle sends you a WhatsApp forward claiming that barley seeds are a cure for diabetes, but you know this has been disproven. Is this an example of misinformation or disinformation?

(A) Misinformation

(B) Disinformation

Reply with your answer below! Stay tuned for strategies on how to spot and combat misinformation effectively!

Text 2

This week's lesson: Navigating Misinformation: Facebook's 10 General Tips 📚

Hey there! This week, we're diving into Facebook's 10 general tips for discerning misinformation, helping you become a more critical consumer of online content.

FB's 10 General Tips for Discerning Misinformation:

- Sensationalist Language/ Headlines? 📰 Be wary of exaggerated or dramatic language in headlines or content.
- Phony Source Names/ Websites? 🎭 Check the credibility of the source by verifying the website and its authenticity.
- Untrustworthy Source? ❌ Verify the reliability and trustworthiness of the source providing the information.

- Manipulated/ Out of context pictures? 🖼️ 💫 Ensure that images are not manipulated or taken out of context to mislead viewers.
- Unusual Formatting and Spelling Errors? ✏️ ❓ Look out for irregular formatting or frequent spelling errors, which can indicate potential misinformation.
- Nonsensical Dates/ Timelines? 📅 🌀 Scrutinize the timeline or date provided in the content to verify its accuracy and relevance.
- Is the story a joke? 😂 Consider if the content is meant as satire or humor rather than factual information.
- Is it Intentionally false? 🤥 Assess if the information is intentionally misleading or fabricated to deceive.
- Check the evidence 🔍 Look for supporting evidence or credible sources cited within the content.
- Look at other resources 📚 Cross-check the information with other reputable sources to confirm its accuracy.

❓ **Now, here's a question for you: Which of the following is NOT a recommended step to discern misinformation?**

(A) Ask your parents if the information is true

(B) Look at other resources

(C) Is the story a joke?

(D) Is it Intentionally false?

Reply with your answer below! Stay tuned for more strategies on navigating the digital world with confidence.

Text 3

This week's lesson: Fact-Checking Like a Pro: 4 Moves and a Habit 🕵️

Hey there! In an age of rampant misinformation and fake news, it's more crucial than ever to hone our fact-checking skills. This week, we're diving into the art of fact-checking like a pro, equipping you with four essential moves and a habit to navigate information with confidence.

4 Moves to Fact-Check Like a Pro:

- **CHECK FOR PREVIOUS WORK:** Has someone already done research or "fact-checked" this information? Look for existing credible sources.
- **GO UP TO THE ORIGINAL SOURCE:** Go "upstream" to the original source of the information to determine its trustworthiness and accuracy.
- **READ LATERALLY:** "Read laterally" across other trustworthy sites to see what others have said about the information, gaining broader context.
- **CIRCLE BACK:** If still confused or uncertain, circle back and start the fact-checking process again from the beginning.

The Habit: Check your emotions 💡: If information triggers strong emotions like anger or validation, pause and reflect on why before accepting it as fact.

❓ Now, here's a question for you: Which move involves going "upstream" to the original source of information to determine its trustworthiness?

(A) CHECK FOR PREVIOUS WORK

(B) GO UP TO THE ORIGINAL SOURCE

(C) READ LATERALLY

(D) CIRCLE BACK

Reply with your answer below! Stay tuned for more.

Appendix D Construction of outcomes

Social media consumption

1. Think about the past three weeks. On average, how much time did you spend on social media per day?

2. You mentioned you used social media for [ ] hours per day during the last three weeks. By how much would you like to reduce (increase) your time spent on social media?

Psychological distress

1. GAD-7 (Spitzer et al., 2006)

2. PHQ-9 (Kroenke et al., 2001)

Subjective well-being

1. Over the last 3 weeks, I think I was [Very unhappy / Unhappy / Neutral / Happy / Very happy]

2. Over the last 3 weeks, compared to most of my friends, I think I was [Much less happy / Less happy / About the same/ More happy / Much more happy

3. In most ways, my life over the past 3 weeks was close to ideal [Strongly disagree / Disagree / Neither agree nor disagree/ Agree Strongly agree]

4. The conditions of my life over the past 3 weeks were excellent [Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree]

5. Over the past 3 weeks, I was satisfied with my life [Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree]

6. Felt you lacked companionship or close friendships [Never / Rarely / Sometimes / Often / Always]

7. Felt left out [Never / Rarely / Sometimes / Often / Always]

8. Felt isolated from others [Never / Rarely / Sometimes / Often / Always]

Digital addiction

For this question, we would like you to think back over the past 3 weeks and indicate how frequently you...[Never / Rarely / Sometimes / Often / Always]:

1. Worried about missing out on things online when not checking your phone?
2. Checked social media, text messages, or email immediately after waking up?
3. Used your phone longer than planned/ wanted?
4. Found yourself saying “just a few more minutes” when using your phone?
5. Used your phone to distract yourself from personal problems?
6. Used your phone to distract yourself from feelings of guilt, anxiety, helplessness, or depression?
7. Used your phone to relax in order to go to sleep?
8. Tried to reduce your phone use without success?
9. Experienced that people close to you are concerned about the amount of time you use your phone?
10. Felt anxious when you don’t have your phone?
11. Found it difficult to switch off or put down your phone?
12. Been annoyed or bothered when people interrupt you while you use your phone?
13. Felt your performance in school or at work suffers because of the amount of time you use your phone?
14. Lost sleep due to using your phone late at night?
15. Preferred to use your phone rather than interacting with your partner, friends, or family?
16. Delayed tasks by spending time on your phone?

Ability to identify misinformation

The following items are examples of what will be shown to respondents. The items will be updated based on latest viral news.

Now, you will be shown a series of news items that were published recently. Please tell us whether each headline is very accurate, somewhat accurate, not very accurate, or not at all accurate in how it describes what happened. If you are not sure, you can just select "I am not sure". Based on my reading of the item above, I think the information is...[Not at all accurate / Not very accurate / Somewhat accurate / Very accurate / I am not sure]

Figure A5: Example of an accurate news item

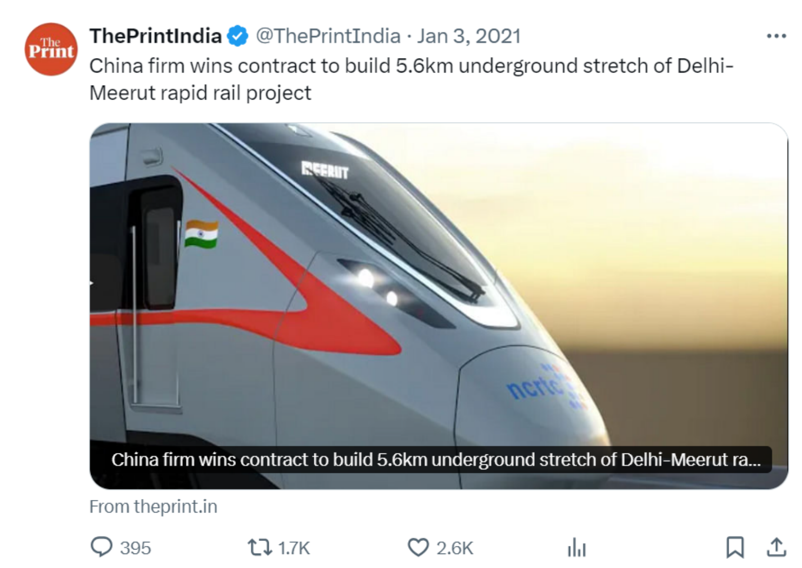
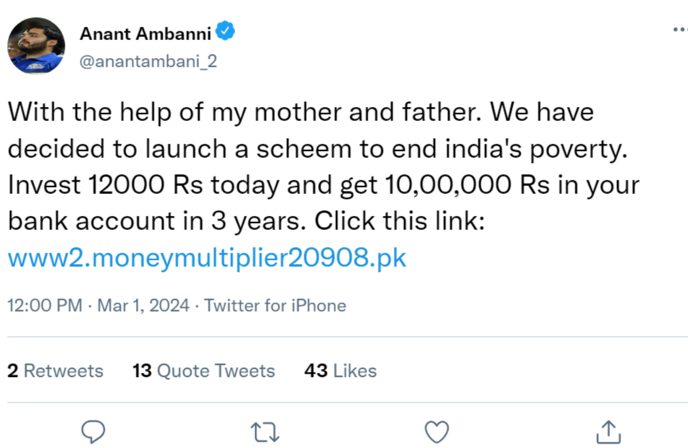


Figure A6: Example of misinformation



Use of commitment devices

1. Do you currently use any apps or in-built reminder features on your phone to limit or manage your social media use?

Phone usage around bedtime

1. Think about each night as you went to sleep over the past three weeks. On average, how much time went by between the moment you put your phone down for the last time and the moment you tried to fall asleep?Please give your answer in minutes.
2. Think about each morning as you woke up over the past three weeks. On average, how much time went by between the moment you woke up and the moment you first checked your phone? Please give your answer in minutes.
3. Think about the times over the past three weeks when you happened to wake up in the middle of the night. What percent of those times did you check your phone?

Quality of sleep

1. Rate your quality of sleep in the past week on a scale of 1-5.
2. What time did you usually fall asleep?
3. What time did you usually wake up?
4. Do you wake up in the middle of the night?

Digital media literacy

1. Your friend Ravi loves using his smartphone all the time. He uses apps like Snapchat, Instagram, Whatsapp, and Youtube very frequently on his phone. You recently noticed that he pulls out his phone while he's talking with you in-person, even without receiving any notification. He pulls it out for 1-2 minutes, checks one or two of his most-used apps, and puts the phone back in his pocket. He does it automatically, no matter if he's really interested in what's on the phone or not. Why do you think he does this? [Ravi is not a good friend and

likely doesn't care about you / Ravi has likely formed a habit, which leads him to check his phone frequently / Ravi might be awaiting important updates every time the two of you talk to each other / Ravi is using Instagram as a means of procrastination, avoiding other tasks or responsibilities that he finds less appealing]

2. Another friend of yours, Tanya, tells you about her excessive smartphone usage. She says that she often checks her phone without thinking while doing other things and spends more time on it than she wants to. She expresses difficulty in controlling, or reducing her smartphone usage and asks for your help. What would you recommend as a first step? [Tell her to have more will-power and resist using her phone / Encourage her to use tools such as setting screen-time limits on her phone / Tell her to seek medical help and ask her doctor for medicines which help conditions like this / Encourage her to try to practice meditation daily]

3. Your friend Neha tells you that when she looks at famous models and influencers on Instagram, she often compares herself to them. This makes her feel like she's not as good, leading to negative feelings about herself. On hearing this, what action would you take? [Encourage her to go to the gym, so that she feels better about her body. Help her come up with an exercise plan / Recommend that she delete all social media apps from her phone, since they have no benefits and only lead to negative feelings / Remind her that influencers and models post highly edited pictures of themselves, and comparing oneself to their online pictures would be unfair / Disregard the situation, assuming that she will manage these feelings independently]

4. Arjun posted a photo on Instagram and keeps checking his phone to see how many people have "liked" it. Which of the following statements is the most accurate reflection of a balanced approach to social media use? [Arjun is oversharing on social media, risking his online privacy, and potentially attracting negative attention / It is okay for Arjun to check frequently as he is engaging with his friends and social circle on the platform / Arjun should completely avoid using Instagram to stay focused on other tasks / Arjun should turn off his notifications to avoid the constant urge to check his phone]

5. Roopan is working hard on her fitness page but isn't getting many followers. She often looks at other fitness pages that are doing really well and feels both happy for them and a bit

jealous. What's a good way for Roopan to turn her feelings into something positive, seeing those successful pages as a kind of encouragement? [Think their success is impossible for her and try less on her page / See their success as inspiring, knowing they also started small, and make a plan to improve her own page / Stop looking at other pages to avoid feeling bad / Copy exactly what the successful pages do to mimic their success]

6. Jonty is scrolling through his social media feed and finds a news piece claiming that a popular brand he regularly uses is engaged in unethical practices. The article, filled with shocking details, instantly makes him feel angry and disappointed. How should Jonty react? [Immediately share the article to spread awareness / Write a comment expressing his anger / Check his emotions before taking any action., and then try to verify the news from other sources / Boycott the brand and encourage others to do the same / Check other sources to see if the news is true]

7. Which psychological model is designed to build customer habits and product loyalty and involves four key steps: Trigger, Action, Variable Reward, and Investment? [The Habit Loop / The Hook Model / The Fogg Behavior Model / The Five Forces Framework / I'm not sure][28]

8. You set a daily limit of 1 hour for using social media to help you study more. What is this strategy of making it harder to use apps called? [Setting goals / Creating friction / Making a schedule Building a routine / I'm not sure]

9. In the context of social media use, what term describes the cognitive distortions or patterns of negative thinking that can lead to feelings of inadequacy, jealousy, or dissatisfaction after browsing through posts and profiles? [Echo Chambers / Confirmation Bias / Thinking Traps / Social Comparison / Framing effect / I'm not sure]

10. What method should you use to check if information on social media is accurate? It involves searching for more details from various sources, not just taking the initial post at face value. [Deep Reading / Asking friends and family / Lateral Reading / Critical Thinking / I'm not sure]

[28] Questions 7-10 test subject matter knowledge based on the Digital Empowerment curriculum.

Social comparison

Now think back over the past three weeks and tell us to what extent do you agree or disagree with each of the following statements:[Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree]

1. I generally felt inferior to others
2. I felt like other people have more friends than me
3. Many of my friends had a better life than me
4. It was frustrating to see some other people always having a good time
5. My life has been more fun than those of my friends

Political views

1. How much do you think your closest friends and family agree with the government providing caste-based reservations? [Definitely should provide / Probably should provide / Probably should not provide / Definitely should not provide / Refuse to answer]
2. How much do you think your closest friends believe that women should have a say in the choice of their marriage partner? [Definitely should have a say / Probably should have a say / Probably should not have a say / Definitely should not have a say / No opinion]
3. How much do you think your closest friends feel India should be ready to use military power to deal with problems with other countries? [Extremely willing / Very willing / Moderately willing / A little willing / Not at all willing / No opinion]

Social media valuation

1. In this section, we will ask you to choose between deactivating your Instagram account in return for a payment versus keeping it. We are trying to understand what is the minimum amount you are willing to accept to deactivate your Instagram for 2 weeks. Please choose the option that best represents your preferences. At the beginning of this survey, the computer randomly determined an amount to offer you to participate in this deactivation challenge.

After we finish collecting responses from students in your university, the computer will independently choose one student to participate. If you are chosen by the computer to participate and your minimum amount for deactivation is less than or equal to the random amount already chosen by the computer, you will be eligible for this challenge. It is in your best interest to report your values honestly and accurately, as this will ensure the most beneficial outcome for you. Would you rather: [Deactivate Instagram for Rs 500, 1000, 2000, 3000, 4000, 5000 / Keep Instagram].

Aspirations

1. What is the highest level of education you would like to attain? [Bachelor / Masters / MPhil / Ph.D / Other certificate]
2. What is your aspired level of monthly salary once you graduate and start working (INR)? [5 - 15k / 15- 30k / 30k-45k / 45k - 60k / 60k - 75k / 75k to 90k /More than 90k]
3. At what age do you plan to marry?

Job Search Effort

1. Have you applied to any jobs/ internships in the last 2 months?
2. How many jobs/ internships did you apply to?

Locus of Control Think back over the past three weeks and tell us to what extent you agree or disagree with each of the following statements. Respond on the following scale: Strongly Disagree/ Disagree/ Somewhat Disagree/ Neither Agree Nor Disagree/ Somewhat Agree/ Agree/ Strongly Agree

1. I have little control over the things that happen to me.
2. There is really no way I can solve some of the problems I have.
3. There is little I can do to change many of the important things in my life.
4. I often feel helpless in dealing with the problems of life.

5. Sometimes I feel that I'm being pushed around in life.

6. What happens to me in the future mostly depends on me.

7. I can do just about anything I really set my mind to do.