# Delivering Mental Healthcare to the Underserved Communities: Evaluating the Potential of Social Technologies

**Yi Tang**
University of Minnesota – Twin Cities
tangx688@umn.edu

**Kingshuk K. Sinha**
University of Minnesota – Twin Cities
ksinha@umn.edu

**Adam Moen**
Real EmPowerment Solutions
adam@reptech.io

**Necati Ertekin**
University of Minnesota – Twin Cities
nertekin@umn.edu

## Abstract

In this paper, we evaluate the potential of social technologies, in the form of mobile apps, to deliver mental healthcare to the underserved communities characterized by their socio-demographic identities of gender, sexual orientation, and race-ethnicity. Using longitudinal user-level data collected from a mental health mobile app, we empirically examine whether the inequity in clinic-based mental health services between traditionally underserved and better-served populations well-documented in the literature is also present in the context of mobile app enabled mental healthcare delivery. We find that: (i) the app usage of users from the traditionally underserved population is statistically equivalent to the app usage of users from the better-served population; (ii) there is a positive relationship between the app usage frequency and the mental health condition of app users; and (iii) users from the traditionally underserved population are at least as likely as users from the better-served population to benefit from the use of the app. These results suggest that mobile apps are likely to offer equity in both usage and the benefit from such usage. Our post-hoc analysis reveals that such social technologies are likely to offer equity for traditionally underserved population via self-management functions and for better-served population via peer-support functions. We conclude by discussing the implications of our study for social technology firms, mental healthcare providers, and public policy makers in supporting their efforts to address inequities in mental healthcare supply chains.

Key words: Mental healthcare operations, mobile app, underserved communities

## 1. Introduction

Social technologies facilitate virtual interactions between individuals and organizations, and between individuals. Applications of social technologies are rapidly growing in several sectors including retailing (Cui et al. 2018, Gao et al. 2020, Qiu and Whinston 2017), healthcare (Huang et al. 2021, Khurana et al. 2019), restaurant (Kumar et al. 2018), telecommunication (Qiu et al. 2019), and movie (Lee et al. 2018). Recent studies argue that such technologies have the potential to advance social sustainability initiatives and call for research that investigate how organizations can leverage technologies to deliver services to the underserved communities (Kalkanci et al. 2019). In response to the call, this paper investigates the potential of social technologies to deliver mental healthcare to the underserved communities.

Affecting more than 700 million people around the world (WEF 2019), mental illnesses[1] have become one of the leading causes of disability for decades (Murray et al. 2018). In the U.S. alone, mental illnesses are estimated to generate a $193.2 billion loss in annual earnings (NAMI 2021a). Recently, the COVID-19 pandemic has only exacerbated the already-severe mental illnesses due to fear and stress related to COVID-19 death tolls, working from home, lack of social contact, and unemployment (Moreno et al. 2020, Wang et al. 2020). Recognizing that preventing mental illnesses is essential to sustainable development for countries, United Nations officially set a goal (Goal 3.4) to reduce mental illness related mortality by one third by 2030 (United Nations 2020). In the same vein, as part of the COVID-19 response, World Health Organization issued a guidance to address the increasing mental illnesses during the COVID-19 pandemic (United Nations 2020).

Despite the increasing global efforts to address mental illnesses, surprisingly, only around 40% of adults with any mental illness used mental health services between 2013 and 2018 (SAMHSA 2019) mainly for two reasons. First, on the supply side, mental health services are poorly resourced (e.g., psychiatrist shortages, mental health clinic shortages, less insurance coverage) (Mnookin 2016). Second, on the demand side, unlike the physical health patients (e.g., patients with flu, cancer etc.), many mental health patients either do not recognize or do not acknowledge their mental illnesses due to the self-stigma or social-stigma associated with seeking clinic-based mental healthcare (Eisenberg et al. 2009, Masuda et al. 2009, 2012). These insights indicate that in the context of mental healthcare supply chains, there is a substantial gap between supply and demand of care, and that the existing limited mental healthcare resources are not being used effectively.

Furthermore, it is disconcerting that the highlighted gap in mental health service usage is not homogenous across communities. The gap widens disproportionately among the underserved communities characterized by their socio-demographic identities of gender, sexual orientation, and race-ethnicity. For instance, among adults with any mental illness in the U.S., mental health service usage rate is 51.2% for females but only 37.4% for males (NAMI 2021a). Similarly, due to discrimination, lesbian, gay, bisexual, and transgender individuals are more likely to be denied mental healthcare than non-LGBT individuals (NAMI 2021a, Semlyen et al. 2016). As such, it is reported that, among transgender individuals, 11% were denied equal mental healthcare and 12% were harassed or disrespected at mental health clinics (Grant et al. 2011). Such inequities go beyond the mental health service usage and also exist in the benefit from using such services. For instance, African-American patients are more likely to leave clinic-based treatments prematurely than White patients (Fleck et al. 2005, Satcher 2001), suggesting that the underserved communities are also less likely to benefit from such treatments even if they start to use mental health services. Acknowledging these empirical insights and following the mental healthcare literature, hereafter in this paper, we refer to an individual as belonging to the *traditionally*

[1] A mental illness is a mental, behavioral, or emotional disorder that can vary in impact, ranging from no impairment to mild, moderate, or severe impairment (NAMI 2021b). Our study particularly focuses on mild to moderate mental illnesses (e.g., anxiety disorder, depression, eating disorder, etc.) and does not consider serious mental illnesses (i.e., those that interfere or limit major life activities).

*underserved population* if the individual can be characterized by one or more of the following socio-demographic identities of (i) Gender (i.e., male and other gender identities except for female (Berger et al. 2005, Eisenberg et al. 2009)), (ii) Sexual orientation (i.e., homosexual and other sexual orientation identities except for heterosexual (Hegland and Nelson 2002, NAMI 2021a, Plöderl and Tremblay 2015)), and (iii) Race-ethnicity (i.e., African, Asian, Hispanic/Latino and other race-ethnicity identities except for White (Masuda et al. 2009)). In contrast, we refer to a female, heterosexual, White individual as belonging to the *better-served population* (Terlizzi and Zablotsky 2020).

Given the significance of inequity in mental health service usage and its benefits, many practitioners today seek solutions to improve the equity and inclusion of mental healthcare delivery systems (Agic 2019, Kirmayer and Eric Jarvis 2019). One particular solution that has gained increasing popularity in recent years is the use of social technologies. Social technologies such as e-Health platforms and smartphone mobile applications enable (i) mental healthcare providers to interact with patients and deliver care remotely (Li et al. 2021) and (ii) patients to find peers with similar health problems on social technology platforms and to seek social support from peers such as emotional support (Yan et al. 2015, Yan and Tan 2014). In this paper, we particularly focus on the use of mobile apps for mental healthcare delivery. The demand for care using mental health mobile apps (MHMAs) has been increasing as individuals feel more comfortable and secure to seek care using such apps (Gray et al. 2005, Rickwood et al. 2007). To meet such demand, MHMAs are increasingly becoming available to provide care to people with mental health needs (Donker et al. 2013, Moreno et al. 2020).

While the trend in expanding the delivery of mental healthcare through mobile apps is visible in practice, it is not clear whether MHMAs can enable equity in mental healthcare delivery across the underserved and better-served communities. On one hand, it is conceivable that MHMAs are likely to enable equity in mental healthcare delivery since MHMAs provide easy and cheap (sometimes free) access to online mental health services for anyone with a smartphone and internet access. Furthermore, due to the ability to remain anonymous, regardless of their gender, sexual orientation, and race-ethnicity, MHMA users from both underserved and better-served communities can freely express their emotions, seek help, and get support from peers and professionals without having the self- or social-stigma associated with clinic-based mental healthcare (Ray et al. 2017). Hence, MHMAs are likely to improve mental health conditions among their users equally while minimizing the inequity in usage present in the traditional modality of mental healthcare delivery.

On the other hand, it is also conceivable that MHMAs may contribute towards further worsening the inequity in mental healthcare delivery. Because MHMAs often require users to have knowledge about and access to Internet and smartphones, the traditionally underserved populations who are typically economically and educationally disadvantaged (Ramsetty and Adams 2020) may have less access to MHMA enabled mental health services. In addition, anonymous and less-restricted environment in MHMA platforms may lead to anti-social behaviors (such as harassment or online abuse) among users (Cheng et al. 2015, Wadden et al. 2020), which could decrease the quality of mental health support provided on those platforms and diminish the usage rate and benefits of such social technology applications. Consequently, MHMAs may also increase the inequities in usage among its users and be ineffective in delivering the benefits of care. In summary, it is not clear a priori whether there is equity in the usage of MHMAs and equity in benefits from the usage across traditionally underserved population and better-served population. In light of these mixed and inconclusive possibilities, our study aims to explore the following research questions:

*I.* **(Equity in Usage)** *Do users from the traditionally underserved population use MHMAs less than users from the better-served population?*

*II.* **(Benefit of Mobile Apps Usage)** *Does MHMA usage improve mental health condition of the users of MHMAs?*

*III.* **(Equity in Benefit)** *Do users from the traditionally underserved population benefit from MHMA usage less than the users from the better-served population?*

We address the above three research questions using data collected from a MHMA, hereafter, called Hope (pseudonym). Launched in 2015 by a social technology start-up company, Hope is free to register and use for iOS or Android smartphone users. Hope consists of two major functions: (i) the *self-reflection* function that enables users to assess their own mental health condition, and (ii) the *online community* function that allows users to freely interact with peers by sharing their feelings, asking or providing help, and offering emotional support. The self-reflection function is likely to increase awareness of a user's mental healthcare needs and can be used individually without interacting with other users. The online community function is likely to facilitate social support exchange among users and requires interaction with other users. Our data include detailed app activities related to the two functions as well as socio-demographic information from 1,843 app users between May 2015 and February 2018. 62% of the users on Hope represent the traditionally underserved population whereas the remaining 38% represent the better-served population. The average membership duration among all users is one year. The data allow us to track an individual user's app activities and the corresponding change in self-reflected mental health condition over time.

Analyzing this longitudinal data, we evaluate the equity of usage by comparing the app usage frequency between users from the traditionally underserved population and users from the better-served population. We quantify the benefit of app usage by assessing the link between the self-reflected mental health condition of a user in a given time and the app usage frequency of the same user prior to that time. We introduce the indicator of traditionally underserved vs. better-served user as a variable that moderates this link. By doing so, we examine the equity in benefit between the two groups. From a methodological standpoint, we assess equity by examining statistical equivalence in usage and benefit between the users from the traditionally underserved population and users from the better-served population.

Our analysis enables us to make the following contributions towards advancing the literature on social technologies in healthcare service operations. First, we find that the inequity in clinic-based mental health service usage repeatedly reported in the literature (Alegría et al. 2002, Aneshensel 2009, Berger et al. 2005, NAMI 2021a, Plöderl and Tremblay 2015) between the traditionally underserved and better-served populations is not likely to be present in the context of MHMA enabled mental healthcare delivery. As such, we find that the app usage of users from the traditionally underserved population is statistically equivalent to the app usage of users from the better-served population. Second, social technologies in the form of MHMAs are likely to complement mental healthcare resources as we find a positive relationship between the app usage frequency and the users' mental health condition. For instance, we find that doubling app usage frequency for a user with median mental health condition is likely to increase the self-reflected mental health condition score by 4.42% in our sample. Third, with respect to equity in benefit, we find that users from the traditionally underserved population are at least as likely as the users from the better-served population to benefit from the use of Hope, suggesting that MHMAs are likely to offer equity in not only usage but also the benefit from such usage. We find that our main results are consistent across several identification strategies and robustness checks.

We later conduct post-hoc analysis to examine: (i) the mechanism on how the two major functions – i.e., the self-reflection function and the online community function – of Hope contribute to the above study results and (ii) whether the above results are more nuanced across different underserved sub-populations. With respect to the two major functions, while our main results hold for the usage of each function, we find that users from the traditionally underserved population are marginally more likely to use the self-reflection function than the users from the better-served populations. Thus, the benefit of Hope is realized more through the use of the self-reflection function for users from the traditionally underserved population, whereas it is realized more through the use of the online community function for users from the better-served population. This suggests that app developers should consider the value proposition of each function since MHMAs are likely to create value mainly (i) by increasing the awareness of mental healthcare needs for users from the traditionally underserved population, and (ii) by facilitating social support exchange among peers for users from the better-served population. With respect to the heterogeneity across underserved sub-populations, our results indicate that MHMAs are particularly helpful for female users from the underserved sub-populations (e.g., female African-American, female homosexual, etc.). Compared to other underserved sub-populations, female users from the underserved sub-populations not only use the app more frequently but also benefit more from the app usage. This suggests that MHMAs might be particularly useful in societies where violence and discrimination against female underserved individuals are more pronounced. For other underserved sub-populations, we find that while certain sub-populations (e.g., other gender identity, other sexual orientation, White underserved) use Hope significantly more than their better-served counterparts, the equity in benefit is homogenous across all the underserved sub-populations. Taken together, our results highlight the potential of MHMAs to support healthcare providers' social sustainability efforts directed at delivering mental healthcare to the underserved communities.

The remainder of the paper is organized as follows. In section 2, we present a review of the relevant literature and then develop the study hypotheses. In section 3, we discuss the empirical setting, data, and variables. In section 4, we present the econometric model specification, report the main results of the empirical analysis, and conduct several robustness checks. In section 5, we present the post-hoc analysis results for the nuanced impacts of MHMAs. Finally, in section 6, we conclude with an overview of the key study findings, practical implications, and future research directions.

## 2. Literature Review and Hypothesis Development

Two streams of literature are foundational to our study: social technology literature and mental healthcare operations literature. Below, we review the relevant literature within these two streams and develop study hypotheses pertaining to the equity of usage and benefit of MHMAs.

### 2.1 Social Technology Literature

Social technology refers to any technology that facilitates virtual interactions among individuals or groups through a communications capability such as the Internet or a mobile device (Gartner 2021, Skaržauskienė et al. 2013). Enabling virtual interactions between individuals and organizations, social technologies offer new capabilities to collect big data and improve various aspects of organizational performance in the field of operations management (Feng and Shanthikumar 2018, Guha and Kumar 2018). For example, in the retail industry, social technologies allow retailers to collect and use detailed consumer-level data (e.g., purchase behavior, product browsing behavior, or product feedback) or social media data to improve demand forecasting (Cui et al. 2018, Feng and Shanthikumar 2018), enable a more efficient pricing strategy (Qiu and Whinston 2017), develop an effective promotion strategy (Gao et al. 2020, Mallipeddi et al. 2021, Qiu et al. 2021), or measure brand personality (Hu et al. 2019). In the service industry, social technologies enable service providers to interact with customers or use the peer reviews to improve performance (Kumar et al. 2018), build reputation (Khurana et al. 2019), mitigate biases and promote inclusiveness (Cui et al. 2020), or influence consumers' purchasing behavior (Lee et al. 2018). In the healthcare industry, social technologies allow healthcare service providers to create new channels to interact with more patients (Li et al. 2021) and to improve accessibility to healthcare resources for patients (Delana et al. 2019). Beyond allowing interaction with their own customers, social technologies also enable firms to reach out to the general public. For instance, firms can crowdsource ideas and leverage the wisdom of individuals to find solutions to various design tasks (Jiang et al. 2021) or to improve prediction market performance (Qiu et al. 2017, Qiu and Kumar 2017). In this paper, we contribute to the social technology literature by empirically evaluating the potential of social technologies, in the form of MHMAs, to deliver mental healthcare to underserved communities.

### 2.2 Mental Healthcare Operations Literature

Unlike the traditional healthcare operations literature where the research is quite developed, the mental healthcare operations literature is scant and comprised of only a few studies. Among these studies, Yan and Tan (2014) find that social support exchange among patients on a website can improve users' mental health conditions. In a follow-up study, Yan et al. (2019) demonstrate that treatment experiences shared by community members on a website can influence how a user perceives her own mental health treatment. In a clinic-based mental healthcare setting, Zepeda and Sinha (2016) find that improving quality and enhancing affordability can benefit particularly the underserved populations with disadvantaged socio-economic status. In a recent study, Li et al. (2021) find that eHealth platforms can enable mental health physicians to better-schedule patients' follow-up visits. While these studies make valuable contributions to the mental healthcare operations literature, we are not aware of any study that addresses inequity associated with socio-demographic identities in mental healthcare delivery. We contribute to this emerging literature by focusing on the inequities in usage and benefits of mental health services and examining the use of social technologies, in the form of MHMAs, as an alternative channel with the potential to deliver mental healthcare to underserved communities.

The inequities in mental health service usage and benefits are likely to arise due to four reasons. First, the affordability, accessibility, and awareness (i.e., 3As that are strongly associated with the consumption of healthcare services (Kohnke et al. 2017, Sinha and Kohnke 2009)) of mental health services are not homogenous across populations of different socio-demographic backgrounds (Berger et al. 2005, JEC 2020, Saxena et al. 2007, Sussman et al. 1987). For example, compared to the White population, African-Americans and other minority race-ethnic sub-populations are less likely to afford and access mental health services due to having lower income and education levels, limited insurance coverage, and less geographic access (JEC 2020). African-Americans also have lower awareness about the potential needs of such services as they are more likely to consider mental illness symptoms to be normal outcomes of everyday problems (Sussman et al. 1987). Similarly, males are less aware of their mental health needs than females due to having greater difficulty in acknowledging and identifying their emotional problems (Berger et al. 2005).

Second, unlike seeking physical care, seeking mental healthcare is often associated with self- and social-stigma (Masuda et al. 2012, Saxena et al. 2007). Self-stigma refers to the fear of self-disclosing any distressing or potentially embarrassing personal information, whereas social-stigma refers to the stereotype that the society perceives seeking mental healthcare as a sign of being unpredictable, permanently damaged, incompetent, or threatening (Masuda et al. 2009, 2012). Self- and social-stigma is more pronounced among the traditionally underserved populations. For instance, compared to White patients, African-American, Asian, and Hispanic/Latino patients are less likely to acknowledge their mental health needs (Eisenberg et al. 2009, Lipson et al. 2018, Masuda et al. 2009, 2012) and, even if they acknowledge, have less trust in mental health treatments (Cooper et al. 2003, Eisenberg et al. 2009). Similarly, compared to female individuals, male individuals are more likely to perceive that receiving mental health treatment undermines an individual's social power and control (Berger et al. 2005). Subsequently, they are less likely to seek mental healthcare and to openly discuss their emotional conditions during mental health treatment (Good et al. 1989, Good and Wood 1995).

Third, mental health diagnosis and treatment typically occur verbally. Thus, a seamless communication between a mental health patient and a mental healthcare provider is fundamental to seeking and providing mental healthcare effectively (Alegría et al. 2002, Nguyen and Reardon 2013). To achieve a seamless communication, mental health patients often prefer to consult a health professional with similar socio-demographics (Cooper et al. 2003). Otherwise, a socio-demographic mismatch in gender, sexual orientation, or race-ethnicity between a patient and a mental healthcare provider is likely to contribute to inequities. Patients among the traditionally underserved population are more likely to experience such a mismatch than patients among the better-served population due to the disproportional representation of both populations within the healthcare providers. For instance, with respect to race-ethnicity, in 2015, only 14% of psychologists in the U.S. were Asian, Hispanic, or African-American whereas the rest were White (Lin et al. 2018).

Finally, the potential discrimination such as denied care or unfair diagnosis and treatment can also contribute to inequities in mental health services. For instance, even though the mental illness rate among the sexual minorities (i.e., lesbian, gay, bisexual, transgender and questioning individuals) (i.e., 44.1%) is more than twice the national average mental illness rate (20.6%), those individuals are at least twice more likely to be denied mental healthcare than their better-served counterparts (i.e., heterosexual individuals) due to discrimination (NAMI 2021a). These and similar discriminations can indeed lead to a long-term trust issue among traditionally underserved patients, which can be detrimental to their wiliness to seek help. For instance, due to the historical discrimination and mistreatment faced in mental health services (Diala et al. 2000), African-Americans are found to rely less on such services. Subsequently, they ignore or try to solve their mental health-related issues by themselves rather than seeking professional mental health services (Alegría et al. 2002).

### 2.3 Hypothesis Development

We contend that social technologies, especially MHMAs, may provide several opportunities that can potentially minimize inequities observed in traditional mental healthcare delivery. First, MHMAs are often free or require a low monthly/one-time fee. In addition, since access to MHMAs is not restricted by geographical, temporal, or physical constraints (Stephens-Reicher et al. 2011), they eliminate the commute time and costs for their users, making them more affordable and accessible than the traditional mental health services. Second, the ability to stay anonymous on virtual communities (such as those on MHMAs) while interacting with peers is likely to create a psychologically safe environment for users. As such, MHMAs can enable users, particularly those with fear and discomfort to discuss their mental conditions, to freely share their mental health issues with their peers without disclosing their gender, race-ethnicity, or sexual orientation (Hegland and Nelson 2002), minimizing the self- and social-stigma. Third, because MHMAs can be easily designed to support different languages and human-computer interfaces, users are likely to have a smooth conversation among themselves. In particular, users with specific backgrounds can find peers and practitioners with similar socio-demographic identities and mental health concerns, resulting in less socio-demographic mismatch among peers on MHMAs. Finally, with appropriate application designs (e.g., actively tracking online communities to identify and eliminate conversations that include discrimination, harassment, or abuse), MHMAs can enable their users to have high quality interactions without potential discrimination towards any population (Wadden et al. 2020). Overall, these opportunities are likely to motivate individuals, regardless of their socio-demographics, to use mental health services provided by MHMAs more frequently compared to the traditional mental health services. Because the smartphone ownership rate is similar between traditionally underserved and better-served populations (e.g., 85% of whites, 83% of African-Americans, and 85% of Hispanics/Latinos own smartphones in 2021 (Pew Research Center 2021)) and people of different socio-demographic backgrounds show comparable interest in leveraging MHMAs (Lipschitz et al. 2020), we expect that the opportunities of accessing care using MHMAs apply equally to both populations. Therefore, we posit the following hypothesis:

***Hypothesis 1 (H1):*** *The usage of a MHMA is equivalent between a user from the traditionally underserved population and a user from the better-served population.*

MHMAs are also likely to serve as effective channels for mental healthcare delivery for several reasons. First, most MHMAs include functions that enable users to track mental health conditions over time through the visual trend plots. Any downward trend or high fluctuations, which might be an indication of increasing mental illness, would generate an automated alert to users and potentially motivate them to seek mental healthcare in the early stage of their illness. Patients who receive mental health treatments in the early stage are more likely to positively respond to those treatments than patients who receive such treatments in the later stage (McGorry et al. 2006, McGorry and Van Os 2013). Second, most MHMAs facilitate the exchange of social support, especially emotional support, among peers, which can improve users' mental health conditions (Yan and Tan 2014). Lastly, MHMAs can enable users to identify peers with similar mental health conditions, learn from their experiences, and get from them immediate feedback such as simple coping strategies. Overall, using several app features, MHMA users can better manage their depression and stress levels (Donker et al. 2013), leading to improved mental health conditions. Thus, we posit the following hypothesis:

***Hypothesis 2 (H2):*** *As the usage of a MHMA by a user increases, the user's mental health condition improves.*

We infer from our review of the relevant literature that improving the affordability of care in the traditional mental health supply chain translates into the greatest benefits of improving mental healthcare to socioeconomically disadvantaged communities (Zepeda and Sinha 2016). Similarly, the social support exchange in a traditional mental health service setting is likely to provide greater mental health benefits to those with higher level of stress exposure such as the sexual-orientation minorities (Meyer 2003) or race-ethnic minorities (Aneshensel 2009). Along this line, we contend that due to their affordability and facilitating social support among users, MHMAs are also likely to contribute towards greater mental health benefits particularly to the traditionally underserved population. Indeed, this positive impact might be more pronounced in MHMAs because certain traditionally underserved sub-populations (e.g., males or African-Americans) are found to express their mental health-related issues more freely in a mobile app (virtual) environment (McCall et al. 2021, Ritterband 2021), which is fundamental to realizing the benefits from mental health services (Pennebaker 1999). As a result, unlike the clinic-based mental health services in which the traditionally underserved individuals experience inequity in benefit (Alegría et al. 2008, Saxena et al. 2007), MHMAs can enable those individuals to benefit from app usage at least as much as their better-served counterparts. Thus, we posit the following hypothesis:

> ***Hypothesis 3 (H3):*** *As the usage of a MHMA increases, the mental health condition of a user from the traditionally underserved population improves at least as much as that of a user from the better-served population.*

# 3. Research Design

## 3.1 Empirical Setting

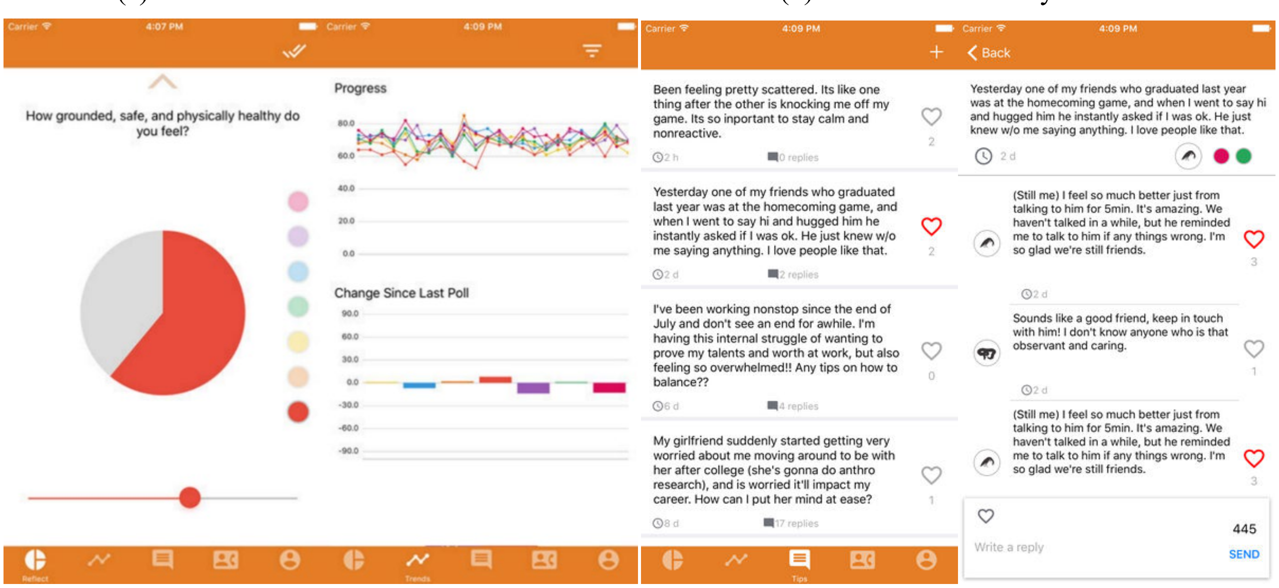
In this study, we collaborate with a social technology company to understand whether MHMAs can deliver mental healthcare across different socio-demographic groups in the population. In 2015, the company launched its MHMA, Hope, for public users. The company states that the Hope community mostly consists of users who are non-professionals and seek mental healthcare. Hope offers its users two major functions:

***(i) Self-reflection function.*** This function allows users to self-reflect their overall mental health condition by answering seven questions in the Hope's Mental Health Survey (see online Appendix A for the survey questions). Once registered on Hope, users can use this function as much as they prefer. This enables users to not only evaluate their current self-reflected mental health condition when needed, but also track the recorded results over time in a visual chart to understand the change in their mental health condition. See Figure 1(a) for an example of the user interface and visual chart of this function.

***(ii) Online community function***. This function creates an anonymous online community where users can connect and freely exchange social support at any time without being concerned about revealing their physical identities. It allows a user to post anonymously to seek or provide help, share feelings and stories, or interact with other users by responding to their posts. Figure 1(b) provides an example of user posts and replies.

**Figure 1: Screenshot of the Mental Health Mobile App, Hope**

(a) Self-reflection Function (b) Online Community Function



## 3.2 Data

Our study dataset is comprised of user-level socio-demographic and app activity data from 1,843 Hope users between May 2015 (i.e., the launch-month of the app) and February 2018. Hope records the demographics information from each user during the registration process. In addition, each time a user uses the self-reflection function or interacts with the online community, Hope generates an activity record with detailed information such as the time stamp, user id, self-reflection scores, or the post/reply texts. Our sample consists of, on average, 5.91 self-reflection records, 1.08 posts, and 7.60 replies per user.

Using these records, we construct an unbalanced panel in which each user has one observation for every Hope's Mental Health Survey completed using the self-reflection function. Hence, a row in the panel data includes variables for user *i* who uses the self-reflection function at time *j*. Note that in this setting, a user must complete at least one Hope's Mental Health Survey to be included in the panel. Among the 1,843 users, 1,688 meet this criterion. Thus, for simplicity, we initially conduct our analysis using app activity data from 1,688 users. Later, in a different specification, we consider all 1,843 users to evaluate the robustness of our results.

## 3.3 Variable Definitions and Measurements

For each observation in our panel, we construct the following variables.

### *3.3.1 Outcome Variables*

Consistent with our hypotheses, we consider two outcome variables:

***$SRS_{ij}$*** *(Self-Reflection Score)* represents a user's self-reflected mental health condition and is operationalized as the score resulted from the Hope's Mental Health Survey completed by user *i* at time *j*. The survey includes seven questions measured based on a continuous scale between 0 and 100. Therefore, we construct *SRS* as a latent variable using those questions. Since these questions are designed and implemented by the partner company, the scale items do not perfectly match existing scales in the literature. It is important to note, however, that the questions used to measure *SRS* are conceptually the same as those used to measure the *PHQ-9* (Patient Health Questionnaire with 9 items) and *GAD-7* (Generalized Anxiety Disorder scale with 7 items) scales that are widely used in mental health clinical practices as self-administered depression or anxiety disorder diagnostic measures. To evaluate the reliability of *SRS*, we conducted an exploratory factor analysis and a confirmatory factor analysis for *SRS*. The results are presented in online Appendix B. The factor analysis indicates that the theoretical model between the latent variable and seven scale items fits the data, and the scales are reliable. Thus, we operationalize the latent variable *SRS* as the weighted average of the seven survey items where the weights are estimated to be the standardized loadings in the confirmatory factor analysis.

***$AppUsage_{ij}$*** indicates the frequency of app usage and is operationalized as the natural logarithm of the number of times the app functions (i.e., both the self-reflection function and the online community function) are used by user *i* within 15 days prior to the mental health survey completed at time *j*. For example, a user who completes the survey twice, writes three posts, and responds to other's posts four times within the last 15 days (i.e., $AppUsage_{ij}=log(2+3+4)$) is considered to have a higher frequency of app usage than a user who completes the survey once, writes two posts, and responds to others' posts three times within the same time-period (i.e., $AppUsage_{ij}=log(1+2+3)$). We choose the threshold of 15 days because 98.8% of all app usages prior to taking a Mental Health Survey for any user in our panel occur within the last 15 days. Note, we also define *AppUsage* using different time-periods and confirm the robustness of our results in Section 4.3.

#### 3.3.2 Key Independent Variable

The key independent variable in our study is ***Underserved$_i$*** which indicates whether user *i* belongs to the traditionally underserved population ($Underserved_i=1$) or better-served population ($Underserved_i=0$). Consistent with the literature documenting inequities in mental healthcare delivery (Berger et al. 2005, Masuda et al. 2009, NAMI 2021a), we define a user belonging to the traditionally underserved population as long as the user is not a female-heterosexual-White individual. Consistently, female-heterosexual-White users represent the better-served population.

#### 3.3.3 Control Variables

We use several control variables that are potentially related to the outcome variables:

***Tenure$_{ij}$*** indicates a user's membership length and is measured as the number of days between user *i*'s app registration day and time *j* when the mental health survey is completed.

***AppRemindFrequency$_i$*** indicates the number of weekly notifications received by user *i*. This count variable captures the feature where users have the option to set, between 1 and 7, how many times a week Hope should send a notification to their smartphones to remind users that they can engage with the app.

***Year-month fixed effect*** controls for any common trend and seasonality that might be related to app usage or mental health condition. We operationalize this fixed effect using year-month indicators.

Table 1 presents descriptive statistics and the correlation matrix for the variables used in the study for users from the traditionally underserved population (*Underserved=1*) and users from the better-served population (*Underserved=0*). With a variance inflation factor score mean of 1.03 and a range between 1.02 and 1.05, below the rule-of-thumb cut-off of ten, there is little evidence of multicollinearity.

**Table 1: Descriptive Statistics and the Correlation Matrix**

| | *Underserved* = 0 | | *Underserved* = 1 | | Correlation Matrix | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | 1 | 2 | 3 | 4 | 5 |
| 1. *AppUsage* | 1.21 | 1.09 | 1.38 | 1.10 | 1.00 | | | | |
| 2. *SRS (Self-reflection Score)* | 41.42 | 30.05 | 40.87 | 28.36 | 0.02 | 1.00 | | | |
| 3. *Tenure* | 22.94 | 50.28 | 24.41 | 58.45 | -0.02* | 0.14* | 1.00 | | |
| 4. *AppRemindFrequency* | 3.28 | 2.73 | 3.94 | 2.84 | 0.19* | -0.05* | -0.01 | 1.00 | |
| 5. *Underserved* | - | - | - | - | 0.07* | -0.01 | 0.01 | 0.11* | 1.00 |
| Number of users | 648 | | 1,040 | | | | | | |
| Number of observations | 2,628 | | 4,814 | | | | | | |

Note: Correlations with * are significant at $p<0.05$ level

## 4. Empirical Analysis

In this section, we introduce our econometric model, present the estimation results, and conduct several analyses to verify that our findings are robust across an array of alternative specifications and explanations.

### 4.1 Model Specification

In our study, we are particularly interested in whether there exist any differences between users from the traditionally underserved and better-served populations in (i) *AppUsage* and (ii) *SRS* as a result of *AppUsage.* This suggests that the two outcome variables, namely *SRS* and *AppUsage,* are inherently related to each other. Therefore, we specify our econometric model as a system of two simultaneous equations:

[App Usage Equation]

$$AppUsage_{ij} = \alpha_0 + \alpha_1 Underserved_i + \boldsymbol{UserControls_{ij}\alpha_2} + \boldsymbol{TimeControls_{ij}\alpha_3} + u_i + \varepsilon_{ij} \quad (1)$$

[SRS (Self-Reflection Score) Equation]:

$$SRS_{ij} = \beta_0 + \beta_1 AppUsage_{ij} + \beta_2 Underserved_i + \beta_3 AppUsage_{ij} \times Underserved_i + \boldsymbol{UserControls_{ij}\beta_4} + \boldsymbol{TimeControls_{ij}\beta_5} + u'_i + \tau_{ij} \quad (2)$$

where $\varepsilon_{ij}$ and $\tau_{ij}$ are random error terms. *UserControls* include *Tenure* and *AppRemindFrequency*. *TimeControls* include year-month fixed effects. Lastly, $u_i$ and $u'_i$ denote the random effects for user *i*. Since our interest is to identify the impact of the time-invariant variable *Underserved* on outcome variables, we specify our model as a random effect model. Later in section 4.3, we estimate our model using a fixed effect specification and find that our results related to *SRS* still hold. Note that, in our specification, *AppUsage* is a mediator and *Underserved* moderates the relationship between *AppUsage* and *SRS,* making our model a moderated mediation model. The coefficient of interest to test H1 is $\alpha_1$ in Equation 1. Similarly, the coefficients of interest to test H2 and H3 are $\beta_1$ and $\beta_3$ in Equation 2, respectively. We specify Equations 1 and 2 as linear models.

### 4.2 Estimation Results

We estimate our econometric model using maximum likelihood estimation and present the results in Table 2. Model 1 represents the SRS equation with only control variables. Model 2 adds *AppUsage* variable to the SRS equation. Model 3 includes the mediation model for *AppUsage.* Lastly, Model 4 adds the interaction term *AppUsage* × *Underserved* to the SRS equation.

We examine the significance of the incremental variance due to any added variable in the SRS equation by performing a likelihood ratio test that compares the model with the added variable and the model without the added variable. We use Model 3 to test H1 and H2 because these hypotheses are related to the main effects of *Underserved* (in the App Usage equation) and *AppUsage* (in the SRS equation). We test H3 using Model 4 as it includes the interaction term.

For the equity in MHMA usage, the estimated coefficient of *Underserved* in the App Usage equation in Model 3 ($\alpha_1 = 0.068, p = 0.104$) is not statistically significant. Statistical insignificance can arise due to either statistical indeterminance or statistical equivalence (Tryon 2001). To examine the source of statistical insignificance in our empirical setting, we conduct a statistical equivalence test (Schuirmann 1987) by comparing the average app usage between traditionally underserved and better-served users and find evidence for statistical equivalence ($t_1 = 5.79, p_1 = 0.00;\ t_2 = 2.21, p_2 = 0.01;\ \Delta = 0.2\sigma_{\overline{AppUsage}}$). Combined with the estimated coefficient $\alpha_1$ in Table 2, this result suggests that users from the traditionally underserved population use Hope at least as much as the users from the better-served population, supporting H1.

For the benefit of MHMA usage, the estimated coefficient of *AppUsage* in the SRS equation in Model 3 ($\beta_1 = 2.44, p < 0.001$) is positive and statistically significant, supporting H2. Based on the predictive margins of *SRS*, we find that doubling app usage frequency is associated with an increase of 1.69 unit increase in *SRS*. For instance, such an increase would correspond to a 4.42% increase in self-reflected mental health condition of a user with median *SRS* and testifies the benefit of social technology usage in the MHMA setting.

**Table 2: Estimation Results**

| | MODEL 1 | MODEL 2 | MODEL 3 | MODEL 4 |
|---|---|---|---|---|
| APP USAGE EQUATION | | | | |
| *Underserved* | | | 0.07 | 0.07 |
| | | | (0.04) | (0.04) |
| *Tenure* | | | -0.00 | -0.00 |
| | | | (0.00) | (0.00) |
| *AppRemindFrequency* | | | 0.07*** | 0.07*** |
| | | | (0.01) | (0.01) |
| SELF-REFLECTION SCORE EQUATION | | | | |
| *AppUsage* | | 2.44*** | 2.44*** | 2.08** |
| | | (0.37) | (0.37) | (0.69) |
| *Underserved* | -0.67 | -0.81 | -0.81 | -1.16 |
| | (1.18) | (1.18) | (1.18) | (1.20) |
| *AppUsage* × *Underserved* | | | | 0.53 |
| | | | | (0.82) |
| *Tenure* | 0.05*** | 0.05*** | 0.05*** | 0.05*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| *AppRemindFrequency* | -0.74*** | -0.91*** | -0.91*** | -0.91*** |
| | (0.22) | (0.21) | (0.21) | (0.21) |
| AIC | 65716.78 | 65630.05 | 84849.56 | 84850.63 |
| BIC | 65972.63 | 65892.82 | 85368.18 | 85376.16 |
| Likelihood Ratio Test | - | 88.73*** | - | 0.93 |
| Number of users | 1,688 | 1,688 | 1,688 | 1,688 |
| Number of observations | 7,442 | 7,442 | 7,442 | 7,442 |

Notes: (i) Robust standard errors clustered at the user level in parentheses. (ii) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. (iii) User random effects and year-month fixed effects are included in all models.

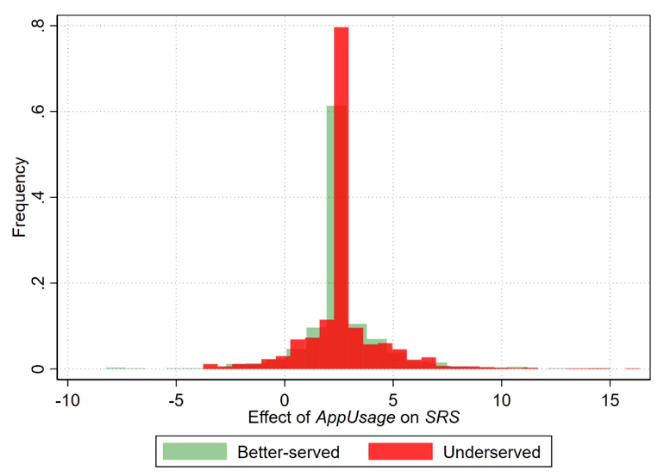
Finally, Model 4 estimation results indicate that the interaction term *AppUsage* × *Underserved* ($\beta_3 = 0.530, p = 0.518$) is positive but not statistically significant. Note that unlike with the equity in usage in which we seek statistical equivalence between the two groups with respect to the variable *AppUsage*, the equity in benefit requires statistical equivalence between the two groups with respect to the effect of *AppUsage* on *SRS* (i.e., $\beta_1$ in Model 3, which is a slope rather than a variable). Thus, to examine the source of the insignificance of the interaction term coefficient, we first re-specify Equation 2 as a random slope model in which the effect of *AppUsage* on *SRS* varies between users:

$$SRS_{ij} = \beta_0 + \beta_1 AppUsage_{ij} + \beta_2 Underserved_i + \boldsymbol{UserControls_{ij}\beta_4} + \boldsymbol{TimeControls_{ij}\beta_5}$$
$$+\zeta_{0i} + \zeta_{1i} AppUsage_{ij} + \tau_{ij} \quad (3)$$

where $\zeta_{0i}$ denotes the deviation of user *i*'s intercept from the mean intercept of $\beta_0$ and $\zeta_{1i}$ denotes the deviation of user *i*'s slope for *AppUsage* from the mean slope of $\beta_1$. With this specification, the effect of *AppUsage* on *SRS* for user *i* is estimated to be $\beta_1 + \zeta_{1i}$. The significant log-likelihood ratio test statistic (i.e., $\chi^2(2) = 4{,}419$, *p*=0.00) obtained from the estimated random slope model (not reported) indicates that the effect of *AppUsage* on *SRS* indeed varies between users.

Figure 2 summarizes the estimated $\widehat{\beta_1 + \zeta_{1\iota}}$ for the traditionally underserved and better-served users using a histogram plot for each group. Next, we conduct a statistical equivalence test by comparing the estimated $\widehat{\beta_1 + \zeta_{1\iota}}$ between traditionally underserved and better-served users and find that there is statistical equivalence between the two groups ($t_1 = 4.51, p_1 = 0.00;\ t_2 = 3.48,\ p_2 = 0.01; \Delta = 0.2\sigma_{\widehat{\beta_1+\zeta_{1\iota}}}$). Combined with the estimated coefficient $\beta_3$ in Table 2, this result suggests that using MHMA improves the mental health condition equally for traditionally underserved and better-served users, providing support for H3.

**Figure 2: Estimation Results of the User-specific Effect of *AppUsage* on *SRS* (Self-reflection Score)**




## 4.3 Robustness Checks

While our main results indicate that the inequity in mental healthcare usage and benefit between traditionally underserved and better-served populations is not likely to be present on MHMAs, it might be possible that our modeling assumptions or other alternative explanations drive those results. In this section, we conduct several robustness tests to consider alternative model specifications and explanations.

### *4.3.1 Endogeneity due to Sample Selection*

Sample selection bias is a potential concern for studies on mobile applications (Bateman et al. 2011, Li and Hitt 2008) since registering to a mobile app is voluntary and not randomized. We use the Heckman model

(Heckman 1979, Van de Ven and Van Praag 1981) to address this concern. For this model, in addition to our main sample (i.e., data from 1,688 users), we also use data from users who registered but never used Hope (i.e., 155 users who never completed Hope's Mental Health Survey during the data period) with the assumption that those users can be seen as proxies for mental health patients who do not register for Hope[2]. To provide face validity for this assumption, in Table 3, we statistically compare the 155 Hope users to the mental health patient population in the U.S. with respect to gender and race/ethnicity, the two socio-demographics statistics that are publicly reported for the U.S. mental health patient population. We find that the socio-demographic differences between underserved and better-served groups among the 155 Hope users are not statistically different from those among the U.S. mental health patient population (the Pearson's $\chi^2$ test *p-value>0.14* for both variables).

**Table 3: A Comparison of the Socio-demographic Statistics**

| | Status | Definition | 155 Hope users | U.S. Mental Health Patients %* | Pearson's $\chi^2$ test |
|---|---|---|---|---|---|
| **Gender** | Better-served | Female | 67.74% | 63.65% | *p-value = 0.278* |
| | Underserved | Male, other | 32.26% | 36.45% | |
| **Race-Ethnicity** | Better-served | White | 72.90% | 67.39% | *p-value = 0.143* |
| | Underserved | Asian, African, Hispanic/Latino, other | 27.10% | 32.61% | |

* Note: Data source for mental health patients by gender and race-ethnicity: 2020 National Survey on Drug Use and Health (NSDUH).

We explore the impact of the potential sample selection on our results in three steps. First, we re-specify our SRS equation as a non-linear model since our selection model does not include an exclusion restriction and the Heckman model can be estimated without an exclusion variable for non-linear models (Ichino et al. 2008). We achieve this by (i) dichotomizing the continuous *AppUsage* and *SRS* variables into binary variables $AppUsage'_{ij}$ (equals 1 if user $i$ has used the app at least once within 15 days prior to the mental health survey completed at time $j$, 0 otherwise) and $SRS'_{ij}$ (equals 1 if $SRS_{ij}$ is greater than the median *SRS* (i.e., high *SRS*) in our entire sample and 0 otherwise (i.e., low *SRS*)); and (ii) and estimating Equations 1 and 2 as Probit models with $AppUsage'_{ij}$ and $SRS'_{ij}$ being the outcome variables. The first two columns in Table 4 demonstrate the estimation results for Models 3 and 4 with the probit specification. Since the estimated coefficients and their significance levels in models with probit specification are qualitatively similar to those in Models 3 and 4 in Table 2, we use the non-linear specification as a benchmark to assess the potential impact of sample selection. Second, we estimate the Heckman probit selection model using data from all 1,843 users and present the results in the last two columns in Table 4. In the first stage of the Heckman model, using all the covariates in our main

[2] A similar approach is heavily used in the literature to address non-response bias in survey based research by assuming that late respondents in a survey can be seen as proxies for non-respondents (Etter and Perneger 1997, Siemiatycki and Campbell 1984).

model, we estimate whether a user is active (i.e., belongs to 1,688 users) or not (i.e., belongs to 155 users) and obtain the inverse Mill's ratios. Then in the second stage, we estimate Equations 1 and 2 by including the inverse Mill's ratios obtained from the first stage. Comparing the last two columns to the first two columns in Table 4, there is negligible difference in the coefficient estimates.

**Table 4: Heckman Probit Selection Model Estimation Results**

| | Ordinary Probit Model | | Heckman Selection Model | |
|---|---|---|---|---|
| | MODEL 3 | MODEL 4 | MODEL 3 | MODEL 4 |
| APP USAGE EQUATION | | | | |
| *Underserved* | 0.07 | 0.07 | 0.06 | 0.06 |
| | (0.06) | (0.06) | (0.06) | (0.06) |
| *Tenure* | -0.00 | -0.00 | 0.00*** | 0.00*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| *AppRemindFrequency* | 0.11*** | 0.11*** | 0.10*** | 0.10*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| SELF-REFLECTION SCORE EQUATION | | | | |
| *AppUsage'* | 0.32*** | 0.20* | 0.31*** | 0.20* |
| | (0.06) | (0.09) | (0.06) | (0.09) |
| *Underserved* | -0.02 | -0.10 | -0.02 | -0.11 |
| | (0.10) | (0.11) | (0.10) | (0.11) |
| *AppUsage' × Underserved* | | 0.18 | | 0.18 |
| | | (0.12) | | (0.12) |
| *Tenure* | 0.00*** | 0.00*** | 0.01*** | 0.00*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| *AppRemindFrequency* | -0.07*** | -0.07*** | -0.07*** | -0.07*** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| SELECTION MODEL | NO | NO | YES | YES |
| AIC | 15065.84 | 15079.26 | 15042.92 | 15044.43 |
| BIC | 15501.48 | 15570.22 | 15547.70 | 15563.05 |
| Likelihood Ratio Test | - | 2.58 | - | 2.49 |
| $\rho$ | | | -1*** | -1*** |
| $\varrho$ | | | -.61 | -.61 |
| Number of users | 1,688 | 1,688 | 1,688 | 1,688 |
| Number of observations | 7,442 | 7,442 | 7,442 | 7,442 |

Notes: (i) Robust standard errors clustered at the user level in parentheses. (ii) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. (iii) User random effects and year-month fixed effects are included in all models. (iv) $\rho$ and $\varrho$ are the correlations between the App Usage and the Selection models, and between the Self-reflection Score and the Selection models, respectively. (v) $\rho$ for the App Usage equations are truncated at -1.

Third, because the selection model does not include an exclusion restriction, following Ichino et al. (2008), we conduct a sensitivity analysis to understand whether and how including a potential exclusion restriction in the selection model could have changed our results. To do so, we estimate the Heckman probit selection model by fixing the correlations between the *AppUsage*'/*SRS*' models and the selection model at various levels between -0.9 to 0.9. The premise of this approach is that including a potential exclusion restriction in the selection model might provide different correlations and thus can change the estimated coefficients. Hence, examining the sensitivity of estimated coefficients with respect to correlations fixed at different values within a plausible range (i.e., -0.9 to 0.9) enables us to understand the maximum effect that any theoretical exclusion restriction might have on our results if included in the selection model. Table 5 reports the results from this sensitivity analysis. We find that the coefficients of interest for H1 in the *AppUsage'* model and H2 in the *SRS'* model remain the same across various correlation values and are consistent with those estimated in Table 4. Overall, the Heckman selection model estimation and the sensitivity analysis suggest that the potential sample selection bias has negligible impact on our qualitative insights.

**Table 5: Sensitivity Analysis for the Heckman Probit Selection Model**

| App Usage Equation $\rho$ | -0.9 | -0.7 | -0.5 | -0.3 | -0.1 | 0.1 | 0.3 | 0.5 | 0.7 | 0.9 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Underserved* | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.08 |
| | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) |
| Self-Reflection Score Equation $\varrho$ | -0.9 | -0.7 | -0.5 | -0.3 | -0.1 | 0.1 | 0.3 | 0.5 | 0.7 | 0.9 |
| *AppUsage'* | 0.20* | 0.20* | 0.20* | 0.20* | 0.20* | 0.20* | 0.20* | 0.20* | 0.20* | 0.20* |
| | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) |
| *AppUsage'* × *Underserved* | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.19 | 0.19 | 0.19 | 0.19 |
| | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) |

Notes: (i) Robust standard errors clustered at the user level in parentheses. (ii) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. (iii) For brevity, only the coefficients of interests are displayed.

### *4.3.2 Diminishing Benefits of App Usage*

One can argue that as users become more familiar with the app and learn more from other users' experiences, the benefit of the app may diminish over time (akin to the learning effect). Subsequently, a newly registered user with a certain usage frequency may benefit from the app more than a relatively old user with the same usage frequency. If the aforementioned diminishing marginal benefits vary between underserved and better-served users, our result regarding the equity in benefit might be attributed to the learning effect, rather than the app itself. Subsequently, the equity in benefit may no longer be present after controlling for the learning effect. To explore this alternative explanation, we re-operationalize $AppUsage_{ij}$ as a cumulative variable (i.e., the natural logarithm of the number of times the app functions are used since app registration by user $i$ prior to the mental health survey completed at time $j$) and estimate Models 3 and 4 with a quadratic term for this cumulative variable in the SRS equation. Table 6 presents the results. In Model 3, the estimated coefficient of the qudratic term in the SRS equation ($\beta = -0.62, p < 0.01$) is negative and statistically significant. Considering that the main effect of the cumulative *AppUsage* is positive ($\beta = 4.72, p < 0.00$), the results suggest that the benefit of the app diminishes over time. Yet, as estimated in Model 4 ($\beta = -0.19, p > 0.1$) and visualized in Figure 3, the diminishing benefit is not statistically different between underserved and better-served users, ruling out this alternative explanation. In summary, while the benefit of the app is likely to decrease over time, our insights regarding the equity in usage and benefit remain the same even after controlling for this diminishing benefit.

### *4.3.3 Specification with Fixed Effects*

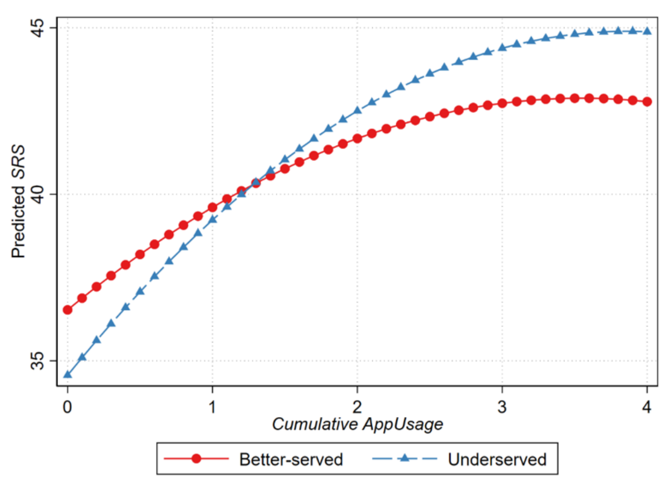
As discussed in section 4.1, our main model includes user random effects instead of fixed effects to enable the testing of H1. To examine whether a fixed effect specification would change our findings, we re-specify Equation 2 as a fixed effect model. Note that in a fixed effect model estimation, all time-invariant variables are dropped. Therefore, we estimate the fixed effect model for Equation 2 (reported in the first row in Table 7) and compare the estimated coefficients to those in the random effect model in Table 2. We find that while the coefficients of interest (i.e., the coefficients of *AppUsage* and *AppUsage* × *Underserved*) are slightly different in magnitude between the two models, the qualitative insights remain the same.

**Table 6: Estimation Results for Diminishing Benefits of *App Usage***

| Model | APP USAGE EQUATION | SELF-REFLECTION SCORE EQUATION | | | | |
|---|---|---|---|---|---|---|
| | *Underserved* | *AppUsage* | *Underserved* | *AppUsage* × *Underserved* | *AppUsage*$^2$ | *AppUsage*$^2$ × *Underserved* |
| Model 3 | 0.06<br>(0.05) | 4.72***<br>(0.72) | -0.82<br>(1.18) | | -0.62**<br>(0.21) | |
| Model 4 | 0.06<br>(0.05) | 3.58**<br>(1.12) | -1.96<br>(1.22) | 1.77<br>(1.46) | -0.51<br>(0.33) | -0.19<br>(0.42) |

Notes: (i) Robust standard errors clustered at the user level in parentheses. (ii) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. (iii) For brevity, only the coefficients of variables of interests included in the table.

**Figure 3: Quadratic Relationship between *Cumulative AppUsage* and *SRS* (Self-reflection Score)**




### *4.3.4 Specification with Negative Binomial Model*

In our data, the count variable app function usage prior to completing the mental health survey has a right-skewed distribution, the reason why we operationalized *AppUsage* as the natural logarithm of the number of times the app functions are used. For such count dependent variables, one can argue that fitting a negative binomial regression would be more appropriate. Therefore, in this robustness check, we operationalize *AppUsage* as the number of times the app functions are used within 15 days prior to completing the mental health survey and re-specify Equation 1 as a negative binomial model. As is evident from the results presented in the second row of Table 7, our qualitative insights from the main analysis still hold with this alternative specification.

#### *4.3.5 Alternative Operationalization of AppUsage*

In this test, to construct *AppUsage*, we consider two alternative time periods, namely one month and two months. 99.3% and 99.6% of all app usages prior to taking a Mental Health Survey for any user in our panel occur within the last one month and two months, respectively. The third and fourth rows in Table 7 present the estimation results for Model 4 with the two alternative operationalizations of *AppUsage*. We observe that our insights from the main analysis remain the same even when we consider longer time spans for app usage before completing the mental health survey.

#### *4.3.6 Alternative Operationalization of SRS*

In our main analysis, we operationalize *SRS* using the estimated standardized loadings in the confirmatory factor analysis. As an alternative, following Siemsen et al. (2009), we re-operationalize the dependent variable *SRS* as the scale average of the seven survey items. As is evident from the results presented in the last row of Table 7, our qualitative insights are also robust to this alternative operationalization.

**Table 7: Estimation Results for Various Robustness Checks**

| Robustness Check | APP USAGE EQUATION | SELF-REFLECTION SCORE EQUATION | | |
|---|---|---|---|---|
| | *Underserved* | *AppUsage* | *Underserved* | *AppUsage × Underserved* |
| Fixed Effects Model | | 2.37***<br>(0.69) | | 0.29<br>(0.84) |
| Negative Binomial Model | 0.11<br>(0.09) | 0.15†<br>(0.08) | -0.57<br>(1.18) | -0.05<br>(0.10) |
| Alternative Operationalization of *AppUsage*: 1 Month | 0.07<br>(0.05) | 2.14**<br>(0.68) | -1.35<br>(1.21) | 0.71<br>(0.80) |
| Alternative Operationalization of *AppUsage*: 2 Months | 0.07<br>(0.05) | 2.10**<br>(0.64) | -1.45<br>(1.21) | 0.80<br>(0.77) |
| Alternative Operationalization of *SRS* | 0.07<br>(0.04) | 1.91**<br>(0.69) | -1.19<br>(1.22) | 0.56<br>(0.81) |

Notes: (i) Robust standard errors clustered at the user level in parentheses. (ii) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. (iii) For brevity, only the coefficients of variables of interests estimated in Model 4 are included in the table.

## 5. Post-hoc Analysis

Having established the robustness of our results, we now conduct post-hoc analysis to understand: (i) the mechanism on how the two Hope (MHMA) functions (i.e., the self-reflection and online community functions) contribute to equity in usage and benefit and (ii) whether this equity holds equally across different underserved sub-populations.

## 5.1 Self-reflection Function vs. Online Community Function

The two MHMA app functions provide different services to users. The self-reflection function enables users to track the potential changes in their mental health conditions and increase the awareness of their mental healthcare needs without interacting with other users on Hope. Unlike the self-reflection function, the online community function requires users to interact with other users on Hope and serves as a peer-support tool that enables users to exchange social support and learn from each other's experiences. Hence, the two app functions can be associated with two different user behaviors.

To understand whether any of the two behaviors is more pronounced among the users from the traditionally underserved population vs. users from the better-served population, we conduct post-hoc analysis whereby we extend our main analysis by decomposing the *AppUsage* variable into two components. In particular, we operationalize $SRUsage_{ij}$ *(Self-Reflection Usage)* and $OCUsage_{ij}$ *(Online Community Usage)* as the natural logarithm of the number of times the self-reflection function and the online community function, respectively, are used by user *i* within 15 days prior to the mental health survey completed at time *j*. We then replace *AppUsage* in Equations 1 and 2 with *SRUsage* and *OCUsage*, and estimate our main model with each decomposed variable in isolation.

As is evident in column *SRUsage* Model 3 in Table 8, we find that users from the traditionally underserved population use the self-reflection function marginally more frequently than users from the better-served population ($\alpha_1 = 0.06, p < 0.1$). We do not find a similar difference with respect to the usage of the online community function ($\alpha_1 = 0.02, p > 0.1$ in column *OCUsage* Model 3). With respect to the impact of the usage of each function on self-reflection mental health condition, we find that the use of both functions is associated with an increase in *SRS* ($\beta_1 = 3.36$, $p < 0.001$ in column *SRUsage* Model 3 vs. $\beta_1 = 1.27$, $p < 0.01$ in column *OCUsage* Model 3). However, when we compare the two coefficients in a seemingly unrelated regression, we find that, for the same frequency of use, the self-reflection function is associated with significantly more increase in *SRS* than the online community function ($\chi^2 = 19.86, p < 0.001$). This suggests that MHMAs are likely to offer value particularly through increasing the awareness of users' mental healthcare needs. When we examine the two functions with respect to the equity in benefit, we find no significant difference between the traditionally underserved and better-served users ($\beta_3 = 0.96$, $p > 0.1$ in column *SRUsage* Model 4 vs. $\beta_3 = -0.76$, $p > 0.1$ in column *OCUsage* Model 4). This suggests that the equity in benefit is present for both functions. However, considering that the coefficients of the two interaction terms have opposite signs, we find in a seemingly unrelated regression that $\beta_3$ in the *SRUsage* model is significantly greater than $\beta_3$ in the *OCUsage* ($\chi^2 = 2.92, p < 0.1$). In other words, users from the traditionally underserved population benefit more from using the self-reflection function whereas users from the better-rserved population benefit more from using the online community function. This suggests that MHMAs are likely to offer value to: (i) the traditionally underserved population mainly through increasing their awareness of mental healthcare needs and (ii) to the better-served population more through facilitating social support exchange among app users on peer-support platforms.

**Table 8: Estimation Results with Decomposed *AppUsage* Variables:**
***SRUsage:* Self-reflection Function Usage; *OCUsage: Online Community Function Usage***

| | Decomposed *AppUsage* | | | |
|---|---|---|---|---|
| | ***SRUsage*** | | ***OCUsage*** | |
| | MODEL 3 | MODEL 4 | MODEL 3 | MODEL 4 |
| APP USAGE EQUATION | | | | |
| *Underserved* | 0.06† | 0.06† | 0.02 | 0.02 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| *Tenure* | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| *AppRemindFrequency* | 0.06*** | 0.06*** | 0.03*** | 0.03*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| SELF REFLECTION SCORE EQUATION | | | | |
| *SRUsage* | 3.36*** | 2.71** | | |
| | (0.48) | (0.92) | | |
| *OCUsage* | | | 1.27** | 1.81* |
| | | | (0.45) | (0.85) |
| *Underserved* | -0.83 | -1.33 | -0.70 | -0.49 |
| | (1.18) | (1.21) | (1.18) | (1.18) |
| *SRUsage × Underserved* | | 0.96 | | |
| | | (1.07) | | |
| *OCUsage × Underserved* | | | | -0.79 |
| | | | | (1.00) |
| *Tenure* | 0.05*** | 0.05*** | 0.05*** | 0.05*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| *AppRemindFrequency* | -0.94*** | -0.94*** | -0.77*** | -0.78*** |
| | (0.21) | (0.21) | (0.22) | (0.22) |
| AIC | 81632.09 | 81632.07 | 81257.88 | 81258.66 |
| BIC | 82150.7 | 82157.6 | 81776.5 | 81784.19 |
| Likelihood Ratio Test | | 2.02 | | 1.23 |
| Number of users | 1,688 | 1,688 | 1,688 | 1,688 |
| Number of observations | 7,442 | 7,442 | 7,442 | 7,442 |

Notes: (i) Robust standard errors clustered at the user level in parentheses. (ii) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.
(iii) User random effects and year-month fixed effects are included in all models.

In summary, our post-hoc analysis with respect to the two app functions reveals that the variety in service offerings through MHMAs is likely to be key towards ensuring equity in usage and benefits. Such variety allows users from both traditionally underserved and better-served populations to leverage each of the two MHMA functions at different levels and to effectively utilize services that are more suitable to their mental health needs.

## 5.2 Equity Across Underserved Sub-populations

In our main analysis, we do not distinguish between sub-populations characterized by their socio-demographic identities of gender, sexual orientation, and race-ethnicity. Rather, we consider all individuals belonging to the underserved population to be similar with respect to inequities in usage and benefit they may experience in the context of mental health services. Some anecdotal evidence, however, suggests that within the traditionally underserved population, the degree of inequity may vary across different sub-populations. For intance, it is reported that African-American and Asian patients experience more discriminiation in mental health services than Hispanic/Latino patients (Horowitz et al. 2019). In order to obtain nuanced insights, we now extend our analysis to examine whether such variation exists across different traditionally underserved sub-populations in a MHMA setting.

We identify different traditionally underserved sub-populations using each of the three socio-demographic variables (i.e., gender, sexual orientation, and race-ethniciy) in isolation. We substitute the variable *Underserved* in Equations 1 and 2 with the categorical variable indicating several traditionally underserved sub-populations and the better-served population. For instance, when we identify traditionally underserved sub-populations based on gender, the categorical variable indicates whether a user is from better-served population, female underserved population (e.g., a female African-American), male underserved population (e.g., a male homosexual), or other underserved population (e.g., Hispanic individuals who do not associate themselves with any gender). We then estimate our system of equations (i.e., Model 4) with each of the three categorical variables (with better-served users being the reference level) and present the results in Table 9.

From the results presented in Table 9, the following two insights stand out. First, regardless of how we identify the underserved sub-populations, we find across all three model estimation results that no traditionally underserved sub-population use and benefit from a MHMA significantly less than their better-served counterparts. This suggests that the inequity reported in the prior literature for clinic-based mental healthcare sevices (NAMI 2021a, Terlizzi and Zablotsky 2020) is not likely to be present with respect to MHMAs for any of the traditionally underserved sub-populations. Second, the results reported in the first column of Table 9 indicate that MHMAs might be particularly effective for female users from the underserved sub-populations (e.g., female African-American, female homosexual, etc.) as we find that the relationship between app usage and self-reflection score is marginally stronger for those users than users from the better-served population. We do not find such nuanced variation for the equity in benefit for other underserved sub-populations even though some of those underserved sub-populations (i.e., underserved users with reference to other gender identity, other sexual orientation, and White race-ethnicity) use MHMAs more frequently than users from the better-served population. In summary, we find that the variation in usage and benefit of MHMA enabled mental healthcare delivery exists across different traditionally underserved sub-populations. However, unlike in the traditional clinic-based mental healthcare delivery setting, this variation is not likely to result in inequities in usage and benefit for MHMA users from any underserved sub-populations compared to MHMA users from the better-served population.

**Table 9: Estimation Results for Different Underserved Sub-populations**

| | Identification of constituent underserved sub-populations | | | | | |
|---|---|---|---|---|---|---|
| | Gender (Column 1) | | Sexual Orientation (Column 2) | | Race-ethnicity (Column 3) | |
| APP USAGE EQUATION | | | | | | |
| <u>Socio-demographics:</u> | | | | | | |
| | *Female (Underserved)* | 0.09† (0.05) | *Heterosexual (Underserved)* | -0.02 (0.05) | *White (Underserved)* | 0.08† (0.04) |
| | *Male (Underserved)* | 0.00 (0.05) | *Homosexual (Underserved)* | 0.07 (0.08) | *African (Underserved)* | 0.11 (0.13) |
| | *Other (Underserved)* | 0.27** (0.10) | *Other (Underserved)* | 0.17** (0.05) | *Asian (Underserved)* | 0.04 (0.08) |
| | | | | | *Latino (Underserved)* | 0.02 (0.09) |
| | | | | | *Other (Underserved)* | -0.16 (0.19) |
| *Tenure* | | -0.00 (0.00) | | -0.00 (0.00) | | -0.00 (0.00) |
| *AppRemindFrequency* | | 0.07*** (0.01) | | 0.07*** (0.01) | | 0.07*** (0.01) |
| SELF REFLECTION SCORE EQUATION | | | | | | |
| *AppUsage* | | 2.07** (0.69) | | 2.07** (0.69) | | 2.08** (0.69) |
| *Socio-demographic Main Effects* | | Estimated | | Estimated | | Estimated |
| *AppUsage × Socio-demographic:* | | | | | | |
| | *Female (Underserved)* | 1.66† (0.94) | *Heterosexual (Underserved)* | 0.51 (0.95) | *White (Underserved)* | 0.57 (0.86) |
| | *Male (Underserved)* | -0.39 (0.91) | *Homosexual (Underserved)* | 1.05 (1.56) | *African (Underserved)* | 1.67 (1.78) |
| | *Other (Underserved)* | -0.16 (1.61) | *Other (Underserved)* | 0.58 (0.94) | *Asian (Underserved)* | -1.01 (1.72) |
| | | | | | *Latino (Underserved)* | 1.00 (1.69) |
| | | | | | *Other (Underserved)* | -1.73 (3.05) |
| *Tenure* | | 0.05*** (0.01) | | 0.05*** (0.01) | | 0.05*** (0.01) |
| *AppRemindFrequency* | | -0.81*** (0.21) | | -0.81*** (0.21) | | -0.89*** (0.21) |
| AIC | | 84764.76 | | 84823.76 | | 84858.35 |
| BIC | | 85331.79 | | 85390.78 | | 85466.86 |
| Number of users | | 1,688 | | 1,688 | | 1,688 |
| Number of observations | | 7,442 | | 7,442 | | 7,442 |

Notes: (i) Robust standard errors clustered at the user level in parentheses. (ii) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. (iii) User random effects and year-month fixed effects are included in all models.

# 6. Conclusion

## 6.1 Overview

In this paper, we evaluate the use of social technologies and their potential to deliver equitable and inclusive mental health services to traditionally underserved and better-served populations. It is well-documented in the literature that traditional clinic-based mental health services systematically fail to reach certain sub-populations characterized by their socio-demographic identities such as gender, sexual orientation, and race-ethnicity, leading to inequities in usage and benefit in mental healthcare supply chains (NAMI 2021a, Terlizzi and

Zablotsky 2020). COVID-19 has further highlighted these inequities (Wang et al. 2020). There is a growing acknowledgment, especially among practitioners, of the potential of social technologies such as e-Health platforms and mobile apps to deliver mental healthcare to underserved communities. Our study examines such potential using longitudinal user-level socio-demographic and app activity data collected from a mental health mobile app. By way of research design, we estimate a system of two simultaneous equations to assess whether equity in MHMA usage and benefit exists between users from traditionally underserved and better-served populations. Further, we investigate (i) whether the underserved and better-served populations use the two MHMA functions, namely the self-reflection function and the online community function, in a similar fashion, and (ii) whether there exists any difference in equity in MHMA usage and benefits from such usage across different underserved sub-populations.

## 6.2 Contributions

By way of contributions, our study findings provide – to the best of our knowledge – the first empirical basis that attests to the potential of social technologies to deliver mental healthcare to the traditionally underserved population. Specifically, we examine equity with respect to two user outcomes, namely the frequency of app usage (i.e., equity in usage) and the self-reflected mental health condition (i.e., equity in benefit). With respect to equity in usage, we find that users belonging to the traditionally underserved population have statistically equivalent MHMA usage frequency compared to the users from the better-served population. This suggests that the inequity in clinic-based mental health service usage reported in the literature with respect to the traditionally underserved populations (Berger et al. 2005, Masuda et al. 2009, NAMI 2021a) is unlikely to carryover to mental health services delivered through mobile apps. The equity in usage is critical to mental healthcare delivery systems because the treatment effectiveness increases as patients visit clinics more frequently (Wang et al. 2005). We find empirical support for the existence of a similar relationship for MHMAs. In particular, our results indicate that MHMA usage frequency has a positive impact on users' self-reflected mental health condition. As such, for a user with median mental health condition in our data, doubling app usage frequency (i.e., from 0.2/day to 0.4/day) can lead to a 4.42% increase in self-reflected mental health condition. With respect to equity in benefit, we find that MHMAs are likely to be equally beneficial to both underserved and better-served populations as our results indicate that the linkage between usage frequency and self-reflected mental health condition is statistically equivalent between the two populations. It is worth noting that these novel insights on equity in mental healthcare delivery enabled by MHMAs hold even if we consider specific underserved sub-populations (e.g., African-American underserved, female underserved, homosexual underserved, etc.) in isolation. As such, our post-hoc analysis demonstrates that, when considered in isolation, no users from any underserved sub-populations use and benefit from the MHMA significantly less than users from the better-served population. Conversely, we find that users from some of the underserved sub-populations (e.g., female African-American, female homosexual, etc.) benefit from MHMAs more than users from the better-served population.

To shed light on how MHMAs ensure equity in usage and benefit between the traditionally underserved and better-served populations, we conduct post-hoc analysis to examine whether users from the two populations use the app functions (i.e., the online community and the self-reflection functions) similarly. The results indicate that equity with respect to MHMA enabled mental healthcare delivery is likely to be driven by the heterogeneity in users' preferences for different app functions. As such, we find that users from the traditionally underserved population use the self-reflection function marginally more than users from the better-served population. Therefore, users from the traditionally underserved population benefit from MHMAs more through the use of the self-reflection function, whereas users from the better-served population benefit from MHMAs more through the use of the online community function. The self-reflection function enables users to be aware of their mental healthcare needs and can be used individually without interacting with other users. The online community function enables users to exchange social support among each other and requires virtual interactions. Given the nature of these two functions, it is conceivable that MHMAs will offer value to the traditionally underserved population mainly by increasing the awareness of their mental healthcare needs. In contrast, they are likely to offer value to the better-served population mainly by creating a psychologically safe platform to exchange social support.

### 6.3 Practical Implications

Our results have significant implications for different stakeholders in the mental healthcare supply chain such as social technology firms, mental health service providers, public policy makers, and organizations with a large number of employees. First, although MHMAs are not developed with an explicit goal of delivering mental health services to sub-populations with specific socio-demographic characteristics, our study shows that MHMAs are likely to have the potential to fulfill the demand for mental healthcare from the traditionally underserved population. Our results demonstrate that MHMAs are likely to achieve such equity by providing variety in app functions. We categorize MHMA functions as a self-management function or a peer-support function. Therefore, the immediate practical implication of our study would be that, to ensure equity, social technology firms should design apps with a variety of functions including both self-management function and peer support function. Self-management functions such as self-reflection and passive symptom tracking functions can enable users to track their mental wellbeing, and to conduct skill-training functions (i.e., to teach users coping or thinking skills) without interacting with other users (NIH 2019). Peer support function such as online communities can enable users to seek either social or professional support from others by virtually connecting and interacting with peers with a similar mental health condition.

Second, traditional clinic-based mental healthcare providers have long been challenged with limited resources, significant unmet demand, and inequities in service offerings. Given the empirical findings and insights gained from our study, the traditional clinic-based mental health service providers should consider using MHMAs as a complementary mental healthcare delivery technology with added features. For instance, they can use MHMAs for cognitive training (i.e., a mental health treatment procedure) that is traditionally performed in clinical settings, yet can be performed by patients at home. Subsequently, the time spent on each patient could be reduced, leading to the fulfillment of more demand for mental health services. Similarly, mental healthcare providers can use MHMAs to remotely create notifications for patients to follow treatment instructions. Such remote nudging could potentially be useful particularly for patients from the traditionally underserved population as they are more likely to leave clinic-based treatments prematurely than patients from the better-served population (Fleck et al. 2005, Satcher 2001), thereby ensuring equity in benefit from clinic-based mental health services.

Third, several global organizations such as United Nations and World Health Organization consider equity as the core guiding principle for achieving sustainable mental healthcare delivery (World Health Organization 2013). Similarly, governmental regulatory agencies such as the United States Food and Drug Administration have formed new divisions to develop protocols and guidelines for social technology firms to ensure the safety and effectiveness of digital health products such as MHMAs. Our study findings suggest that by way of supporting initiatives directed towards the delivery of mental healthcare to underserved communities, global organizations and regulatory agencies should consider: (i) promoting and investing in enhancing the use and access to MHMAs, particularly in societies where there is high level of discrimination and violence against underserved females, and (ii) improving market standards by requiring social technology firms to also include both self-management functions and peer-support functions when developing MHMAs.

Lastly, notwithstanding the potential for significant lost earnings on account of mental illness-induced disabilities of employees, many large organizations are still hesitant to provide mental healthcare benefits and resources to their employees due to high upfront costs (Brodey 2021). Also, in organizations that do provide such benefits and resources, employees with most needs (e.g., those traditionally underserved) tend to avoid using mental health services due to social stigma and fear of losing their jobs (Brodey 2021). Our study suggests that MHMAs can be an alternative value-added resource for both types of organizations due to their relatively low upfront costs and the anonymity that MHMAs can offer to employees regardless of their socio-demographic characteristics.

## 6.4 Directions for Future Research

Notwithstanding the limitations of our study, the paper both provides the motivation and lays the groundwork for future research aimed at designing and sustaining equitable and inclusive mental healthcare supply chains. First, in this study, we are not able to quantify the level of inequity between the traditionally underserved and better-served populations without MHMA enabled mental health services. Therefore, a logical direction for future research would be to quantify whether and how much MHMAs can advance equity in mental healthcare delivery. In particular, future research should be conducted in the form of a field study to understand how access to and use of mental health services change between users from traditionally underserved and better-served populations with the adoption of MHMAs compared to those who do not adopt MHMAs. Second, our empirical setting consists of a peer-based MHMA operated by a social technology firm. When operated by mental health professionals, MHMAs may offer more benefits by enabling those professionals to detect high-risk patients based on their app activities and provide timely treatments. Yet, MHMAs operated by professionals may also give users the feeling of close monitoring, and thus increase the feeling of stigma and inequity among the users. Future research can (i) examine how the impact on equity of usage and benefit for MHMA enabled care delivery changes when MHMA is operated by mental health professionals vs. by social technology firms, and (ii) identify conditions, including detailed patient characteristics, under which MHMAs should be integrated into traditional mental healthcare delivery while continuing to improve equity in usage and benefit. Third, while we find empirical support for a positive relationship between MHMA usage and a user's mental health condition, we do not investigate how social technology firms can increase MHMA usage. A direction of future research could be to explore the effectiveness of different strategies (e.g., monthly subscription, sending notifications, using certain incentives) to improve usage of both the self-management and peer-support functions. Lastly, in addition to well-being tracking and peer-patient engagement, it is conceivable that MHMAs can be leveraged to offer proven therapies such as cognitive behavioral therapy or acceptance commitment therapy to treat mental health disorders. A direction for future research could be to investigate whether these MHMA enabled therapies improve mental health conditions as well as advance equity and inclusion in care delivery to the traditionally underserved sub-populations.

## References

Agic B (2019) Promising practices in equity in mental healthcare: Health equity impact assessment. *Healthcare Papers* 18(2):42–47.

Alegría M, Canino G, Ríos R, Vera M, Calderón J, Rusch D, Ortega AN (2002) Inequalities in use of specialty mental health services among Latinos, African Americans, and non-Latino whites. *Psychiatric Services* 53(12):1547–1555.

Alegría M, Chatterji P, Wells K, Cao Z, Chen CN, Takeuchi D, Jackson J, Meng XL (2008) Disparity in depression treatment among racial and ethnic minority populations in the United States. *Psychiatric Services* 59(11):1264–1272.

Aneshensel CS (2009) Toward explaining mental health disparities. *Journal of Health and Social Behavior* 50(4):377–394.

Bateman PJ, Gray PH, Butler BS (2011) The impact of community commitment on participation in online communities. *Information Systems Research* 22(4):841–854.

Berger JM, Levant R, McMillan KK, Kelleher W, Sellers A (2005) Impact of Gender Role Conflict, Traditional Masculinity Ideology, Alexithymia, and Age on Men's Attitudes Toward Psychological Help Seeking. *Psychology of Men & Masculinity* 6(1):73–78.

Brodey D (2021) Why Is It So Difficult To Invest In Employees' Mental Health? *Forbes*. Retrieved (October 15, 2021), https://www.forbes.com/sites/denisebrodey/2021/05/04/why-is-it-so-difficult-to-invest-in-employees-mental-health/?sh=13968c088397.

Cheng J, Danescu-Niculescu-Mizil C, Leskovec J (2015) Antisocial behavior in online discussion communities. *Proceedings of the 9th International Conference on Web and Social Media, ICWSM 2015*:61–70.

Cooper LA, Gonzales JJ, Gallo JJ, Rost KM, Meredith LS, Rubenstein L V., Wang NY, Ford DE (2003) The acceptability of treatment for depression among African-American, Hispanic, and white primary care patients. *Medical Care* 41(4):479–489.

Cui R, Gallino S, Moreno A, Zhang DJ (2018) The Operational Value of Social Media Information. *Production and Operations Management* 27(10):1749–1769.

Cui R, Li J, Zhang DJ (2020) Reducing Discrimination with Reviews in the Sharing Economy: Evidence from Field Experiments on Airbnb. *Management Science* 66(3):1071–1094.

Delana K, Deo S, Ramdas K, Babu G, Ravilla T (2019) Multichannel Delivery in Healthcare: The Impact of Telemedicine Centers in Southern India. *Indian School of Business Working Paper*. Retrieved (October 15, 2021), http://dx.doi.org/10.2139/ssrn.3505318.

Diala C, Muntaner C, Walrath C, Nickerson KJ, LaVeist TA, Leaf PJ (2000) Racial differences in attitudes toward professional mental health care and in the use of services. *American Journal of Orthopsychiatry* 70(4):455–464.

Donker T, Petrie K, Proudfoot J, Clarke J, Birch MR, Christensen H (2013) Smartphones for smarter delivery of mental health programs: A systematic review. *Journal of Medical Internet Research* 15(11):1–13.

Eisenberg D, Downs MF, Golberstein E, Zivin K (2009) Stigma and help seeking for mental health among college students. *Medical Care Research and Review* 66(5):522–541.

Etter JF, Perneger T V. (1997) Analysis of non-response bias in a mailed health survey. *Journal of Clinical Epidemiology* 50(10):1123–1128.

Feng Q, Shanthikumar JG (2018) How Research in Production and Operations Management May Evolve in the Era of Big Data. *Production and Operations Management* 27(9):1670–1684.

Fleck DE, Keck PE, Corey KB, Strakowski SM (2005) Factors associated with medication adherence in African American and white patients with bipolar disorder. *Journal of Clinical Psychiatry* 66(5):646–652.

Gao H, Zhao H, Tan Y, Lin Y, Wei L (2020) Social Promotion: A Creative Promotional Framework on Consumers' Social Network Value. *Production and Operations Management* 29(12):2661–2678.

Gartner (2021) Information Technology Gartner Glossary: Social Technologies. Retrieved (September 1, 2021), https://www.gartner.com/en/information-technology/glossary/social-technologies.

Good GE, Dell DM, Mintz LB (1989) Male Role and Gender Role Conflict: Relations to Help Seeking in Men. *Journal of Counseling Psychology* 36(3):295–300.

Good GE, Wood PK (1995) Male Gender Role Conflict, Depression, and Help Seeking: Do College Men Face Double Jeopardy? *Journal of Counseling & Development* 74(1):70–75.

Grant JM, Mottet LA, Tanis J, Harrison J, Herman JL, Keisling M (2011) Injustice at every turn: A report of the national transgender discrimination survey. *Washington: National Center for Transgender Equality and National Gay and Lesbian Task Force*. Retrieved (October 15, 2021), https://www.thetaskforce.org/wp-content/uploads/2019/07/ntds_full.pdf.

Gray NJ, Klein JD, Noyce PR, Sesselberg TS, Cantrill JA (2005) Health information-seeking behaviour in adolescence: The place of the internet. *Social Science and Medicine* 60(7):1467–1478.

Guha S, Kumar S (2018) Emergence of Big Data Research in Operations Management, Information Systems, and Healthcare: Past Contributions and Future Roadmap. *Production and Operations Management* 27(9):1724–1735.

Heckman JJ (1979) Sample Selection Bias as a Specification Error. *Econometrica* 47(1):153–161.

Hegland J, Nelson N (2002) Cross-Dressers in Cyber-Space: Exploring the Internet as a Tool for Expressing Gendered Identity. *International Journal of Sexuality and Gender Studies* 7(2/3):139–161.

Horowitz J, Brown A, Cox K (2019) Race in America 2019. Retrieved (October 1, 2021), https://www.pewresearch.org/social-trends/wp-content/uploads/sites/3/2019/04/Race-report_updated-4.29.19.pdf.

Hu Y, Xu A, Hong Y, Gal D, Sinha V, Akkiraju R (2019) Generating Business Intelligence Through Social Media Analytics: Measuring Brand Personality with Consumer-, Employee-, and Firm-Generated Content. *Journal of Management Information Systems* 36(3):893–930.

Huang N, Yan Z, Yin H (2021) Effects of Online–Offline Service Integration on e-Healthcare Providers: A Quasi-Natural Experiment. *Production and Operations Management* 30(8):2359–2378.

Ichino A, Mealli F, Nannicini T (2008) From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity? *Journal of Applied Econometrics* 23(3):305–327.

JEC (2020) *The Economic State of Black America in 2020.* United States Congress Joint Economic Committee, ed.

Jiang ZZ, Huang Y, Beil DR (2021) The Role of Problem Specification in Crowdsourcing Contests for Design Problems: A Theoretical and Empirical Analysis. *Manufacturing and Service Operations Management* 23(3):637–656.

Kalkanci B, Rahmani M, Toktay LB (2019) The Role of Inclusive Innovation in Promoting Social Sustainability. *Production and Operations Management* 28(12):2960–2982.

Khurana S, Qiu L, Kumar S (2019) When a doctor knows, it shows: An empirical analysis of doctors' responses in a Q&A forum of an online healthcare portal. *Information Systems Research* 30(3):872–891.

Kirmayer LJ, Eric Jarvis G (2019) Culturally responsive services as a path to equity in mental healthcare. *Healthcare Papers* 18(2):11–23.

Kohnke EJ, Mukherjee UK, Sinha KK (2017) Delivering Long-term Surgical Care in Underserved Communities: The Enabling Role of International NPOs as Partners. *Production and Operations Management* 26(6):1092–1119.

Kumar N, Qiu L, Kumar S (2018) Exit, voice, and response on digital platforms: An empirical investigation of online management response strategies. *Information Systems Research* 29(4):849–870.

Lee SY, Qiu L, Whinston A (2018) Sentiment Manipulation in Online Platforms: An Analysis of Movie Tweets. *Production and Operations Management* 27(3):393–416.

Li M (Manqi), Nassiri S, Liu X, Ellimoottil C (2021) How Does Telemedicine Shape Physician's Practice in Mental Health? *Working Paper*. Retrieved (June 28, 2021), https://papers.ssrn.com/abstract=3766619.

Li X, Hitt LM (2008) Self-selection and information role of online product reviews. *Information Systems Research* 19(4):456–474.

Lin L, Stamm K, Christidis P (2018) How diverse is the psychology workforce? Retrieved (September 1, 2021), https://www.apa.org/monitor/2018/02/datapoint.

Lipschitz JM, Connolly SL, Miller CJ, Hogan TP, Simon SR, Burdick KE (2020) Patient interest in mental health mobile app interventions: Demographic and symptom-level differences. *Journal of Affective Disorders* 263:216–220.

Lipson SK, Kern A, Eisenberg D, Breland-Noble AM (2018) Mental Health Disparities Among College Students of Color. *Journal of Adolescent Health* 63(3):348–356.

Mallipeddi RR, Kumar S, Sriskandarajah C, Zhu Y (2021) A Framework for Analyzing Influencer Marketing in Social Networks: Selection and Scheduling of Influencers. *Management Science*:1–30.

Masuda A, Anderson PL, Edmonds J (2012) Help-Seeking Attitudes, Mental Health Stigma, and Self-Concealment Among African American College Students. *Journal of Black Studies* 43(7):773–786.

Masuda A, Anderson PL, Twohig MP, Feinstein AB, Chou YY, Wendell JW, Stormo AR (2009) Help-seeking experiences and attitudes among African American, Asian American, and European American college students. *International Journal for the Advancement of Counselling* 31(3):168–180.

McCall T, Ali MO, Yu F, Fontelo P, Khairat S (2021) Development of a Mobile App to Support Self-management of Anxiety and Depression in African American Women: Usability Study. *JMIR Formative Research* 5(8):e24393.

McGorry P, Van Os J (2013) Redeeming diagnosis in psychiatry: Timing versus specifi city. *The Lancet* 381(9863):343–345.

McGorry PD, Hickie IB, Yung AR, Pantelis C, Jackson HJ (2006) Clinical staging of psychiatric disorders: A heuristic framework for choosing earlier, safer and more effective interventions. *Australian and New Zealand Journal of Psychiatry* 40(8):616–622.

Meyer IH (2003) Prejudice, Social Stress, and Mental Health in Lesbian, Gay, and Bisexual Populations: Conceptual Issues and Research Evidence. *Psychological bulletin* 129(5):674.

Mnookin S (2016) *Out of The Shadows: Making Mental Health a Global Development Priority*

Moreno C, Wykes T, Galderisi S, Nordentoft M, Crossley N, Jones N, Cannon M, et al. (2020) How mental health care should change as a consequence of the COVID-19 pandemic. *The Lancet Psychiatry* 7(9):813–824.

Muoio D (2020) FDA: Devs can release digital products for psychiatric disorders without 510(k) submission during COVID-19 crisis. Retrieved (August 28, 2021), https://www.mobihealthnews.com/news/fda-devs-can-release-digital-products-psychiatric-disorders-without-510k-submission-during.

Murray CJL, Mokdad AH, Ballestros K, Echko M, Glenn S, Olsen HE, Mullany E, et al. (2018) The state of US health, 1990-2016: Burden of diseases, injuries, and risk factors among US states. *JAMA - Journal of the American Medical Association* 319(14):1444–1472.

NAMI (2021a) Mental Health By the Numbers. National Alliance on Mental Illness, ed. Retrieved (August 28, 2021), https://www.nami.org/mhstats.

NAMI (2021b) Mental Health Information. Retrieved (December 1, 2021), https://www.nimh.nih.gov/health/statistics/mental-illness.

Nguyen D, Reardon LJ (2013) The Role of Race and English Proficiency on the Health of Older Immigrants. *Social Work in Health Care* 52(6):599–617.

NIH (2019) Technology and the Future of Mental Health Treatment. Retrieved (October 1, 2021), https://www.nimh.nih.gov/health/topics/technology-and-the-future-of-mental-health-treatment.

Pennebaker JW (1999) The effects of traumatic disclosure on physical and mental health: the values of writing and talking about upsetting events. *International journal of emergency mental health* 1(1):9–18. Retrieved (September 27, 2021), https://psycnet.apa.org/record/2000-16016-005.

Pew Research Center (2021) Mobile Fact Sheet. Retrieved (September 1, 2021), http://www.pewinternet.org/fact-sheet/mobile/.

Plöderl M, Tremblay P (2015) Mental health of sexual minorities. A systematic review. *International Review of Psychiatry* 27(5):367–385.

Qiu L, Cheng HK, Pu J (2017) Hidden profiles in corporate prediction markets: The impact of public information precision and social interactions. *MIS Quarterly: Management Information Systems* 41(4):1249–1273.

Qiu L, Chhikara A, Vakharia A (2021) Multidimensional Observational Learning in Social Networks: Theory and Experimental Evidence. *Information Systems Research*:1–19.

Qiu L, Kumar S (2017) Understanding voluntary knowledge provision and content contribution through a social-media-based prediction market: A field experiment. *Information Systems Research* 28(3):529–546.

Qiu L, Rui H, Whinston A (2019) Optimal auction design for wi-fi procurement. *Information Systems Research* 30(1):1–14.

Qiu L, Whinston AB (2017) Pricing Strategies under Behavioral Observational Learning in Social Networks. *Production and Operations Management* 26(7):1249–1267.

Ramsetty A, Adams C (2020) Impact of the digital divide in the age of COVID-19. *Journal of the American Medical Informatics Association* 27(7):1147–1148.

Ray R, Sewell AA, Gilbert KL, Roberts JD (2017) Missed opportunity? Leveraging mobile technology to reduce racial health disparities. *Journal of Health Politics, Policy and Law* 42(5):901–924.

Rickwood DJ, Deane FP, Wilson CJ (2007) When and how do young people seek professional help for mental health problems? *The Medical journal of Australia* 187(7 Suppl):S35.

Ritterband V (2021) How Men Are Finding Mental Health Support With Digital Tools. *Harvard Pilgrim Health Care*. Retrieved (September 1, 2021), https://www.harvardpilgrim.org/hapiguide/how-men-are-finding-mental-health-support-with-digital-tools/.

SAMHSA (2019) *Key substance use and mental health indicators in the United States: Results from the 2018 National Survey on Drug Use and Health.* Substance Abuse and Mental Health Services Administration, ed. (Rockville, MD).

Satcher D (2001) Mental health: Culture, race, and ethnicity—A supplement to mental health: A report of the surgeon general. *US Department of Health and Human Services*. Retrieved (October 15, 2021), https://pubmed.ncbi.nlm.nih.gov/20669516/.

Saxena S, Thornicroft G, Knapp M, Whiteford H (2007) Resources for mental health: scarcity, inequity, and inefficiency. *Lancet* 370(9590):878–889.

Schuirmann DJ (1987) A comparison of the two one-sided tests procedure and the power approach for assessing the equivalence of average bioavailability. *Journal of pharmacokinetics and biopharmaceutics* 15(6):657–680.

Semlyen J, King M, Varney J, Hagger-Johnson G (2016) Sexual orientation and symptoms of common mental disorder or low wellbeing: Combined meta-analysis of 12 UK population health surveys. *BMC Psychiatry* 16(1).

Siemiatycki J, Campbell S (1984) Nonresponse bias and early versus all responders in mail and telephone surveys. *American Journal of Epidemiology* 120(2):291–301.

Siemsen E, Roth A V., Balasubramanian S, Anand G (2009) The influence of psychological safety and confidence in knowledge on employee knowledge sharing. *Manufacturing and Service Operations Management* 11(3):429–447.

Sinha KK, Kohnke EJ (2009) Health care supply chain design: Toward linking the development and delivery of care globally. *Decision Sciences* 40(2):197–212.

Skaržauskiené A, Tamosiûnaitè R, Žaléniené I (2013) Defining Social Technologies: evaluation of social collaboration tools and technologies. *Electronic Journal of Information Systems Evaluation* 16(3):232–241.

Stephens-Reicher J, Metcalf A, Blanchard M, Mangan C, Burns J (2011) Reaching the hard-to-reach: How information communication technologies can reach young people at greater risk of mental health difficulties. *Australasian Psychiatry* 19(SUPPL. 1):S58--S61.

Sussman LK, Robins LN, Earls F (1987) Treatment-seeking for depression by black and white Americans. *Social Science and Medicine* 24(3):187–196.

Terlizzi E, Zablotsky B (2020) Mental Health Treatment Among Adults: United States, 2019. *NCHS Data Brief*. Retrieved (October 15, 2021), https://www.cdc.gov/nchs/data/databriefs/db380-H.pdf.

Tryon WW (2001) Evaluating statistical difference, equivalence, and indeterminacy using inferential confidence intervals: An integrated alternative method of conducting null hypothesis statistical tests. *Psychological methods* 6(4):371.

United Nations (2020) Goal 3: Ensure healthy lives and promote well-being for all at all ages. Retrieved (August 28, 2021), https://www.un.org/sustainabledevelopment/health/.

Van de Ven WPMM, Van Praag BMS (1981) The demand for deductibles in private health insurance. A probit model with sample selection. *Journal of Econometrics* 17(2):229–252.

Wadden D, August T, Li Q, Althoff T (2020) The Effect of Moderation on Online Mental Health Conversations.

Wang C, Pan R, Wan X, Tan Y, Xu L, Ho CS, Ho RC (2020) Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. *International Journal of Environmental Research and Public Health* 17(5):1729.

Wang PS, Lane M, Olfson M, Pincus HA, Wells KB, Kessler RC (2005) Twelve-Month Use of Mental Health Services in the United States: Results From the National Comorbidity Survey Replication. *Archives of General Psychiatry* 62(6):629–640.

WEF (2019) The Global Risks Report. *World Economic Forum*. Retrieved (August 28, 2021), http://www3.weforum.org/docs/WEF_Global_Risks_Report_2019.pdf.

World Health Organization (2013) Mental health action plan 2013-2020. Retrieved (October 1, 2021), https://apps.who.int/iris/handle/10665/89966.

Yan L (Lucy), Yan X, Tan Y, Sun SX (2019) Shared Minds: How Patients Use Collaborative Information Sharing via Social Media Platforms. *Production and Operations Management* 28(1):9–26.

Yan L, Peng J, Tan Y (2015) Network dynamics: How can we find patients like us? *Information Systems Research* 26(3):496–512.

Yan L, Tan Y (2014) Feeling blue? Go online: An empirical study of social support among patients. *Information Systems Research* 25(4):690–709.

Zepeda ED, Sinha KK (2016) Toward an effective design of behavioral health care delivery: An empirical analysis of care for depression. *Production and Operations Management* 25(5):952–967.

# Appendices

## Appendix A: Hope's Mental Health Survey Items

| Question | Scale |
|---|---|
| S1. (Sense of Self & Belonging) How connected, supported, comfortable, and included do you feel? | |
| S2. (Purpose & Emotional Clarity) How clear, purposeful, intentional, and intuitive do you feel? | |
| S3. (Decisions, Commitment & Reliability) How trusting, reliable, decisive, and committed do you feel? | |
| S4. (Relationships & Contentment) How open, accepting, and content do you feel? | **0-100**[a] |
| S5. (Work, Academics & Motivation) How influential, valuable, and capable do you feel? | |
| S6. (Stress & Emotional Well-being) How sparked, energized, and inspired do you feel? | |
| S7. (Sleep, Exercise & Nutrition) How grounded, safe, and physically healthy do you feel? | |

[a] Larger number stands for a better self-evaluation on the corresponding question

## Appendix B: Factor Analysis for *SRS* (Self-reflection Score)

Based on the *PHQ-9* and *GAD-7* questionnaires, the social technology firm that developed the mental health mobile app, Hope, developed the seven-question Mental Health Survey presented in Appendix A. We measure the latent variable *SRS* using those seven questions. We first perform an exploratory factor analysis using 10% of the sample and present the results in Table B1. We use principal axis factoring. All seven standardized loadings are above 0.7. The eigenvalue (5.38) and the Cronbach's α (0.9667) indicate one clear factor with high reliability, providing support for uni-dimensionality and convergent validity.

**Table B1: Exploratory Factor Analysis for *SRS* (Self-reflection Score) Scale**

| Latent variable | Measurements | Standardized Loading | Eigenvalue | Cronbach's α |
|---|---|---|---|---|
| *SRS* | S1 | 0.7949 | 5.38442 | 0.9667 |
| | S2 | 0.9871 | | |
| | S3 | 0.8924 | | |
| | S4 | 0.8262 | | |
| | S5 | 0.8573 | | |
| | S6 | 0.9290 | | |
| | S7 | 0.8375 | | |

Note: Sample size = 742

Then, to examine the fit of the theoretical model, we perform a confirmatory factor analysis using the remaining data and present the results in Table B2. All goodness-of-fit statistics (*RMSEA=0.083, CFI=0.988, TLI=0.083 SRMR=0.027*) indicate good fit. The construct reliability (0.9665) for the latent variable SRS is greater than the cutoff value of 0.7. Average variance extracted (0.8048) is greater than 0.5, indicating reliability. The Cronbach's α (0.9663) suggests high scale reliability. All seven standardized loadings are above 0.8 and statistically significant at $p=0.000$, indicating convergent validity. In conclusion, the measures are reliable, valid, and support the theoretical model.

**Table B2: Confirmatory Factor Analysis for the *SRS* (Self-reflection Score) Scale**

| Latent variable | Measurements | Standardized Loading | *z*-values | Cronbach's a | CR | AVE |
|---|---|---|---|---|---|---|
| *SRS* | S1 | 0.8271 | 282.23 | 0.9663 | 0.9665 | 0.8048 |
| | S2 | 0.9112 | 544.74 | | | |
| | S3 | 0.9278 | 655.51 | | | |
| | S4 | 0.8944 | 463.38 | | | |
| | S5 | 0.9028 | 500.3 | | | |
| | S6 | 0.9240 | 627.92 | | | |
| | S7 | 0.8888 | 411.44 | | | |

Notes: Sample size = 6,698. All loadings are significant at $p=0.000$. Goodness-of-fit measurements: *RMSEA=0.083, CFI=0.988, TLI=0.083 SRMR=0.027. CR:* construct reliability (suggested cutoff value 0.7); *AVE:* average variance extracted (suggested cutoff value 0.5); *RMSEA:* root mean squared error of approximation; *CFI:* confirmatory fit index; *TLI:* Tucker-Lewis index; *SRMR:* standardized root mean squared residual