Essays on Digital Technology-Enabled Mental Healthcare Delivery

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ABSTRACT

Mental health disorders are a leading cause of disability worldwide, affecting over 700 million people and incurring significant economic costs consisting of direct healthcare spending and lost earnings due to mental health-induced disabilities. The COVID-19 pandemic has exacerbated these issues, highlighting the urgent need for accessible mental health services. Traditional healthcare systems often fall short, particularly due to unique challenges in mental health care delivery, such as stigma and the reluctance of individuals to seek help, as well as a significant shortage of mental health care providers. These barriers are especially pronounced for underserved populations facing economic, geographic, and social obstacles. This dissertation examines the potential of digital technologies to address these gaps through three essays focused on different stages of the mental health help-seeking pathway: initiating care, escalating to professional care, and delivering professional care.

The first essay investigates whether mental health mobile apps (MHMAs) can mitigate the inequities seen in traditional mental health services by helping patients gain equitable self- and peer-support. Using detailed usage data from 1,688 users, the study examines the extent to which MHMAs are utilized and beneficial across different socio-demographic groups. The findings indicate that MHMA usage and benefits are statistically equivalent between underserved and better-served populations, suggesting that these apps can potentially promote equity in mental health support and encourage help-seeking behavior, especially among underserved populations.

The second essay addresses the challenge faced by patients who have already initiated help-seeking on online platforms but lack timely referrals to professional care

when needed. It adopts an abductive reasoning research design and explores the development and exploratory evaluation of an AI-enabled platform designed to improve the mental health service referral process. This platform uses advanced algorithms such as large language models to match users with appropriate mental health services based on their specific needs and socio-demographic backgrounds and deliver the personalized referral process through a chatbot. Initial testing with healthcare providers demonstrates that our proposed AI-enabled online mental health service referral platform has the potential to connect certain patients who have unmet mental health needs with professional mental health services, effectively bridging gaps in service delivery and ensuring timely escalation to professional care for those patients. However, the technology is not universally applicable; it is most effective for certain target populations. The essay also highlights that this AI solution can promote equity by encouraging patients from underserved populations to seek professional care, addressing a key issue where providers, due to long waiting lists, lack the incentive to prioritize equitable service delivery.

The third essay investigates the delivery of professional mental health care through telemental health services, focusing on the factors that influence their uptake and impact on mental health condition at the population level. Using 3-digit Zip Code Tabulation Area-level longitudinal data across 19 U.S. states, the study examines how improvements in provider-side technological infrastructure, specifically enhanced broadband access, and telehealth coverage and payment parity laws affect the adoption of telemental health services. The key finding is that these improvements have a synergistic effect: both enhanced broadband access and telehealth parity laws must work together to drive higher uptake of telemental health services and result in better population mental health condition.

This synergy is crucial for maximizing the benefits of telemental health and improving overall population mental health.

This dissertation makes significant contributions to the healthcare operations management literature, particularly in the underexplored context of mental health services. Addressing the unique challenges of mental health care delivery is vital for improving outcomes and reducing the overall burden of mental health disorders. Firstly, the dissertation underscores the importance of expanding healthcare operations management research to include the entire help-seeking pathway, not just the interaction between patients and professional care providers. By focusing on digital technologies that facilitate the initiation of care and the escalation to professional services, this research highlights how these early stages can significantly influence overall care accessibility and effectiveness, contributing to reducing inequities by ensuring that underserved populations can engage with mental health services from the outset. Secondly, the research emphasizes the need to go beyond the traditional 3A-framework of affordability, access, and awareness in healthcare service delivery. The findings suggest that patient acceptance is a critical factor in the effective delivery of mental health services. Ensuring that patients are willing to engage with the services offered, particularly through digital platforms, is essential for achieving equitable health outcomes.

In terms of practical implications, this dissertation offers valuable guidance for policymakers, healthcare providers, and technology developers. For policymakers, the research highlights the necessity of supporting telehealth infrastructure and enacting telehealth parity laws to enhance the uptake of telemental health services. Enhanced provider broadband access combined with telehealth parity laws can work synergistically to improve mental health condition. Healthcare providers can adopt AI-enabled referral platforms to improve the efficiency and accuracy of connecting patients with the appropriate services, thereby addressing a critical gap in the current healthcare system. For technology developers, the findings underscore the importance of designing digital health solutions that are not only accessible and affordable but also acceptable to the target populations. By focusing on these areas, stakeholders can leverage digital technologies to promote equity and efficiency in mental health care, ultimately leading to better population health outcomes.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

> *"[Operations management research] needs to incorporate social concerns and conditions of* ***underserved populations****, with an emphasis on* ***inclusion*** *and* ***equity****. ... [New processes or business models should] look for* ***needs of excluded population*** *that* ***emerging technology*** *can solve." (Kalkanci et al. 2019, p. 2960 & p. 2963)*

Mental health disorders are among the leading causes of disability worldwide, affecting over 700 million people and resulting in substantial economic costs (World Economic Forum, 2021). In the United States alone, mental health issues account for approximately $193.2 billion annually in lost earnings (NAMI, 2021a). The COVID-19 pandemic has exacerbated these challenges, increasing mental distress due to isolation, fear, and economic uncertainty (Moreno et al., 2020; Wang et al., 2020). Despite the growing recognition of mental health's importance and the availability of effective interventions, the global prevalence of mental illnesses continues to rise, and mental health service utilization rates remain low. For instance, only 47% of U.S. adults with a mental illness received mental health services in 2021(SAMHSA, 2019). The situation is particularly dire for underserved populations who face additional barriers such as economic, geographic, and social factors.

The mental healthcare delivery gap and disparities are complex and multifaceted issues. Studies have shown that sexual and racial minorities and low-income populations are disproportionately affected by low utilization rates of mental health services. For example, individuals from lower-income backgrounds are more likely to experience unmet mental health needs, have reduced access to care, and face poorer treatment outcomes (Alegría et al., 2002; Aneshensel, 2009). Racial and ethnic minorities often encounter barriers to accessing mental health services and receive poorer quality care, resulting in delayed diagnosis, inadequate treatment, and suboptimal outcomes (Beyer, 2020; Cooper et al., 2003). Gender disparities are also evident, with men being less likely to seek help and experiencing higher suicide rates, while women are more likely to be diagnosed with mood and anxiety disorders (Berger et al., 2005). Additionally, LGBTQ+ individuals are at a higher risk for mental health disorders and suicide yet often face barriers to accessing care, including discrimination, stigma, and a lack of culturally competent providers (Masuda et al., 2009, 2012).

Emerging digital health technologies offer promising solutions to address these gaps and reduce disparities in mental health service delivery. Mobile health applications (MHMAs), AI-enabled online platforms, and telemental health services have the potential to enhance accessibility, reduce costs, and improve the efficiency of mental health services. MHMAs, for example, provide immediate support through self-management tools and peer support communities, offering a stigma-free environment that encourages help-seeking behavior (Rickwood et al., 2007; Yan & Tan, 2014). AI-enabled platforms can streamline the referral process, ensuring that individuals receive timely and appropriate care based on their specific needs. Telemental health services can overcome geographic barriers, providing professional mental health care to individuals in remote or underserved areas (Price et al., 2014; Schaffer et al., 2020). These digital solutions can play a critical role in making mental health services more equitable and effective.

Despite the potential of digital health technologies, there is a lack of comprehensive research examining their impact on mental health service delivery across different stages of the help-seeking pathway. This dissertation aims to fill this gap by exploring how digital technologies can improve mental health service delivery at various stages: initiating care, escalating to professional care, and delivering professional care. The overarching research question guiding this dissertation is: *How can digital technologies improve the accessibility, effectiveness, and equity of mental health services?*

Here are brief summaries of the three essays:

1.1 Essay 1: Delivering Equitable Mental Health Support via Mobile Apps

The first essay is motivated by the significant inequities in mental health service utilization, particularly among underserved populations defined by socio-demographic characteristics such as race, gender, and sexual orientation. Traditional clinic-based mental health services often fail to adequately serve these groups due to barriers like stigma, accessibility, and affordability. The emergence of mental health mobile apps (MHMAs) offers a potential solution by providing accessible, affordable, and stigma-free environments for seeking help. The central question addressed in this study is: *Does the inequity in usage and benefit in the traditional channel of mental healthcare delivery also exist in the context of mental health mobile apps (MHMAs)?*

To answer this question, the study uses detailed app usage data from 1,688 users of a MHMA called "Hope" (pseudonym). The research design involves analyzing user engagement with the app's self-support and peer-support functions and assessing the impact on their mental health condition. The essay employs statistical methods to compare the app usage and benefits between underserved and better-served populations.

The findings reveal that MHMA usage is statistically equivalent between underserved and better-served populations. Furthermore, there is a positive relationship between app usage frequency and improvements in users' mental health conditions.

Notably, the benefits derived from app usage are also equivalent across different socio-demographic groups. These results suggest that MHMAs can promote equity in mental health support by encouraging help-seeking behavior and providing effective self-management and peer-support tools for underserved populations.

1.2 Essay 2: Designing an AI-Enabled Online Mental Health Service Referral Platform

The second essay addresses the challenge of escalating help-seeking patients to professional care, especially in online platforms where timely referrals are often lacking. The motivation behind this essay is the critical need to improve the referral process to ensure that patients receive the appropriate level of care when required. The central research question is*: How can an AI-enabled platform improve the efficiency and accuracy of mental health service referrals, particularly for underserved populations?*

The study involves the development and exploratory evaluation of an AI-enabled referral platform designed to match users with suitable mental health services based on their specific needs. The research design follows an abductive reasoning framework and includes initial ideation, prototype development, and review by healthcare providers. Advanced machine learning and natural language processing algorithms are utilized to enhance the referral process, ensuring timely and accurate connections to professional care.

The evaluation results demonstrate that the AI-enabled platform significantly improves referral efficiency and accuracy, effectively connecting certain online platform users who have unmet mental health needs with professional care services. However, the study also finds that this technological solution is not universally suitable and targets specific populations. By encouraging patients from underserved populations to connect with professional care, the platform addresses a critical gap where providers lack incentives to improve equity due to long waiting lists. The essay concludes that while this AI tool has the potential to enhance mental health service referrals, it must be tailored to meet the needs of specific target groups to promote equity effectively.

1.3 Essay 3: Telemental Health Service Uptake and Population Mental Health Condition

The third essay explores the delivery of professional mental health care through telemental health services, focusing on the factors influencing their uptake and impact on mental health condition. The motivation for this study stems from the increasing adoption of telehealth solutions during the COVID-19 pandemic and the ongoing need to address geographic and accessibility barriers in mental health care. The central research question is: *What are the operational drivers of telemental health uptake? How does telemental health uptake impact population mental health condition?*

Using national-level longitudinal data, the study examines the impact of improved broadband access and telehealth parity laws on the uptake of telemental health services. The research design involves a difference-in-differences as well as instrumental variable identification strategies to assess the relationship between these factors and mental health condition across various regions.

The key finding is that improvements in provider broadband access and telehealth parity laws have a synergistic effect: both must work together to drive higher uptake of telemental health services and result in better mental health condition. Improving broadband access alone is insufficient without parity laws that ensure equal reimbursement for telehealth and in-person care. This synergy is crucial for maximizing the benefits of telemental health and improving overall population mental health. The essay underscores the importance of policy support and infrastructure development in promoting the effective delivery of telemental health services.

Chapter 2: Delivering Equitable Mental Health Support via Mobile Apps

2.1 Introduction

Affecting more than 700 million people around the world (World Economic Forum, 2021), mental illnesses[1] have become a leading cause 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). The COVID-19 pandemic has further exacerbated the already-severe mental illnesses due to fear and stress related to COVID-19 death tolls, working from home, reduced social contact, and unemployment (Moreno et al., 2020; Wang et al., 2020). Recognizing that preventing mental illnesses is essential for sustainable development on a global scale, the United Nations has officially established Goal 3.4, aiming to reduce mental illness-related mortality by one third before 2030 (United Nations, 2020a). Similarly, the United Nations has responded to the mental health challenges posed by the COVID-19 pandemic by issuing comprehensive guidance (United Nations, 2020b).

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 suffer from insufficient resources (e.g., shortages of psychiatrists and mental health clinics, and limited insurance coverage) (Mnookin, 2016). Second, on the demand-

[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).

side, unlike the patients with physical health conditions (e.g., patients with flu or cancer), individuals with mental health conditions often fail to recognize or acknowledge their illnesses due to self-stigma and/or social-stigma associated with seeking professional help at mental health clinics (Eisenberg et al., 2009; Masuda et al., 2009, 2012). Collectively, these observations indicate a significant gap between the supply and demand of mental healthcare delivery, with existing resources for mental health services being constrained and underutilized.

Furthermore, it is concerning that the highlighted gap in mental health service usage varies significantly across populations. The gap widens disproportionately for the underserved population characterized by their socio-demographic characteristics of race-ethnicity and sexual orientation.[2] Individuals from this population are often concentrated in underdeveloped regions, face socio-economic disadvantages (Chow et al., 2003), and/or experience discriminations (Thornicroft, 2008). Consequently, essential services, including mental health services, are not equally provided to these groups, making them encounter difficulties in accessing these services due to the *supply-side* challenges. For instance, in 2021 in the U.S., among adults with any mental illness, 52.4% of white patients received mental health services, compared with 39.4% of African American, 36.1% of Hispanic or Latino, and 25.4% of Asian patients (NAMI, 2021a). Similarly, lesbian, gay, bisexual, and transgender (LGBT) individuals are less likely to access mental healthcare services compared to the non-LGBT population (NAMI, 2021a; Semlyen et al., 2016).

[2] According to the White House and the Department of Health and Human Services (The White House, 2021; US Department of Health and Human Services, 2019), the underserved population encompasses "*populations sharing a particular characteristic […] that have been systematically denied a full opportunity to participate in aspects of economic, social, and civil life*" and include individuals from several sub-populations such as Latinos, African Americans, LGBTQ+ individuals, and more.

These inequities extend beyond service usage and also persist in the benefits derived from such services. For instance, African-American patients are more likely to discontinue clinic-based treatments prematurely compared to White patients (Fleck et al., 2005; Mongelli et al., 2020; Satcher, 2001), suggesting that the underserved population is also less likely to benefit from mental health services even when they use them.

Interestingly, unlike other service domains, the definition of the underserved population within mental healthcare goes beyond sub-populations characterized by their race-ethnicity or sexual orientation, and also includes the male sub-population. The mental healthcare literature consistently demonstrates that males (including White males and heterosexual males) are worse off with respect to their mental health indicators, exhibiting higher rates of suicide, disorders, substance use, and violence compared to their female counterparts (Berger et al., 2005; Davis et al., 2023; Michael, 2017; Rice et al., 2018; SAMHSA, 2023; Smith, 2022; Wong et al., 2017). This arises because compared to females, males: (i) have more difficulty in recognizing emotional issues; and (ii) have greater self- and social-stigma associated with seeking mental health support as they perceive help-seeking as a threat to their masculinity (Berger et al., 2005). Subsequently, even though mental health services are equally available across gender groups, males face difficulties in utilizing these services due to the *demand-side* challenges stemming from social norms. In the U.S., for instance, among adults with any mental illness, the rate of mental health service usage is 51.2% for females but only 37.4% for males (NAMI, 2021a). Similarly, among White adults with any mental illness in the U.S., the rate of mental health service usage between 2015 and 2019 was 54.5% for White females but only 39.7% for White males (SAMHSA, 2021). Considering these empirical insights and aligning with the mental healthcare literature, this essay refers to individuals as belonging to the *underserved population* if they identify themselves with one or more of the following socio-demographic characteristics: (i) Gender (i.e., male and other non-female gender identities (Berger et al., 2005; Eisenberg et al., 2009)); (ii) Sexual orientation (i.e., homosexual and other non-heterosexual identities (Hegland & Nelson, 2002; NAMI, 2021a; Plöderl & Tremblay, 2015)); and (iii) Race-ethnicity (i.e., African American, Asian, Hispanic/Latino and other non-white identities (Masuda et al., 2009)). Conversely, the *better-served population* refers to individuals who identify as female, heterosexual, and White (Terlizzi & Norris, 2021).

Given the significant supply and demand gap, as well as the existing inequities, various stakeholders in the mental healthcare ecosystem are actively seeking solutions to ensure equitable mental health services (Agic, 2019; Kirmayer & Jarvis, 2019). One solution that has gained traction is the use of *mental health mobile apps* (MHMAs). In recent years, there has been a proliferation of MHMAs offering a range of mental health services to individuals with mental health needs (Donker et al., 2013; Moreno et al., 2020). The demand for MHMAs has been on the rise as people increasingly feel comfortable and secure seeking support for their mental health needs through mobile apps (Gray et al., 2005; Rickwood et al., 2007). Initially, early versions of MHMAs (e.g., DBT Field Coach, CBT MobilWork) were primarily developed for clinical use, empowering mental health professionals to prepare patients for treatments, deliver interventions (e.g., therapies) via the apps, and engage in follow up with patients post-treatment (Ancis, 2020; Price et al., 2014). More recent versions of MHMAs (e.g., I Am Sober, Sanvello, and Happify) were designed for non-clinical use by individuals, providing self-support and/or peer-support mental health services (Dorwart, 2023). In these MHMAs, mental health professionals do not play a direct role. Instead, app users can: (i) partake in self-support by utilizing app functions such as self-management, skill-training, and symptom tracking, which do not require interactions with other users (NIH, 2019); and/or (ii) engage in peer-support with other app users by utilizing app functions that facilitate informational support, emotional support, and companionship (Yan & Tan, 2014).[3] Consequently, unlike clinic-based mental health services that are typically accessed when patients seek treatment from professionals in clinical settings, mental health support within MHMAs is accessed as app users engage with self-support and peer-support functions available to them. Despite the emergence of such apps, to the best of our knowledge, no study has examined whether the well-documented inequity across the underserved and better-served populations in the traditional clinic-based mental healthcare setting also exists within the context of MHMAs designed for providing self-support and peer-support. Towards addressing this gap, our study aims to investigate the following research questions:

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

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

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

[3] MHMAs differ in two aspects from social media platforms that may also foster peer-support (Ancis, 2020): (i) MHMAs uniquely offer evidence-based self-support tools such as mindfulness, meditation, anxiety control, attention span improvement, self-awareness, suicide prevention, and self-reflection; (ii) MHMAs facilitate anonymous online communities where users can exchange social support in a psychologically safe environment, while social media platforms encourage disclosure of identities and sharing personal information for connection-building and upkeep.

We investigate our research questions using data obtained from an MHMA, hereafter called Hope (pseudonym). Launched by a mobile app start-up company in 2015, Hope is a free platform available for iOS or Android smartphone users. It offers two distinct functions for self-support and peer-support purposes:

(i) The *self-reflection function* enables users to evaluate their own mental condition, facilitating self-support by enhancing their awareness of personal mental health needs, all without the need to interact with other users.

(ii) The *online community function* enables app users to freely interact with other app users (peers) by sharing their feelings, seeking and/or providing informational and emotional support. This function fosters peer-support among users and requires active engagement with other users.[4]

Our data include extensive app activity records for the two functions, along with data on socio-demographic characteristics, covering 1,843 app users from May 2015 to February 2018. Among those users, 62% belong to the underserved population whereas the remaining 38% belong to the better-served population. With this dataset, we can monitor an individual user's app activities and observe how their mental condition evolves over time.

Using this longitudinal dataset, we evaluate the equity of usage by comparing the app usage frequency between users from the underserved population and users from the better-served population. We measure the benefit derived from app usage by examining the relationship between a user's mental condition at a specific time and their prior app usage frequency. Introducing an indicator that distinguishes users from the underserved

[4] As illustrated in Online Appendix A, with respect to the function offerings, Hope is representative of MHMAs for non-clinical use in the market.

population versus the better-served population as a variable that moderates this relationship, we evaluate the equity in benefits experienced by these two populations. From a methodological standpoint, we assess equity by examining *statistical equivalence* in usage and benefit between users from the underserved population and users from the better-served population.

Our study makes the following contributions to the literature on mental healthcare operations management. First, we find that the well-documented inequities in professional mental health service usage between the underserved and better-served populations (Alegría et al., 2002; Aneshensel, 2009; Berger et al., 2005; NAMI, 2021a; Plöderl & Tremblay, 2015) are unlikely to exist in the context of MHMA designed to provide self-support and peer-support. As such, the app usage among users from the underserved population is statistically equivalent to that of users from the better-served population. Second, MHMAs are likely to complement professional mental health services, as we find a positive association between app usage frequency and users' mental condition. For instance, doubling app usage frequency for users with the median self-reflection score (i.e., the measure we adopt for users' mental condition) in our study sample is estimated to improve their self-reflection score by 4.69%. Third, concerning equity in benefit, we find that users from the underserved population are at least as likely as users from the better-served population to benefit from using Hope. This suggests that MHMAs are likely to promote equity not only in usage but also in the benefits derived from such usage.

Next, we conduct post-hoc analysis to examine: (i) how the two major functions of Hope – i.e., the self-reflection function for self-support, and the online community function for peer-support – contribute to our main results; and (ii) whether the main results are more nuanced across users from various underserved sub-populations. Regarding the two major functions, we find that our main results hold true for the usage of each function. However, users from the underserved population are marginally more inclined to use the self-reflection function than users from the better-served population. This implies that the benefit of Hope is primarily realized through the self-reflection function for users from the underserved population, whereas for users from the better-served population, it is realized more through the online community function. This highlights the importance for app developers to consider the distinct value proposition of each function, since MHMAs can effectively cater to the awareness of mental health support needs for users from the underserved population and facilitate peer-support for users from the better-served population. Regarding heterogeneity across users from different underserved sub-populations, our results indicate that MHMAs are particularly beneficial for female users from the underserved population (e.g., female African-American, female homosexual, etc.). Compared to users from other underserved sub-populations, these female app users not only use the app more frequently but also derive greater benefits from the app usage. This suggests that MHMAs can be particularly valuable in societies where violence and discrimination against females from the underserved population are prevalent. For other underserved sub-populations, while some (e.g., users with other gender identity, other sexual orientation, and White underserved) use Hope significantly more than the better-served population, equity in benefit is present across all underserved sub-populations.

Our results highlight the potential of MHMAs designed for self-support and peer-support to offer equitable support to individuals with mental health needs from the underserved population. This contribution aligns with the calls for research in *Production* *and Operations Management* on identifying emerging technologies that prioritize inclusion and equity for the underserved population (Kalkanci et al., 2019) and social platforms that enhance healthcare operations and promote inclusive healthcare (Cohen et al., 2022; Qiu et al., 2021). The results have operational implications for stakeholders within the mental healthcare ecosystem. In particular, our findings suggest that to ensure equitable support, (i) MHMA firms should develop apps that include a variety of self-support and peer-support functions; and (ii) organizations (e.g., United Nations, World Health Organization, governments, firms) should expand the delivery of mental health services via MHMAs to "hard-to-reach" patient population.

The remainder of this chapter is organized as follows. In section 2.2 , we present a review of the relevant literature and develop the study hypotheses. In section 2.3 , we discuss the empirical setting, data, and variables. In section 2.4 , we present the econometric model specification and report the main results of the empirical analysis. In section 2.5 , we conduct several robustness checks. In section 2.6 , we present the post-hoc analysis results to delve into the more nuanced implications of MHMAs. Finally, in section 2.7 , we conclude with an overview of the key study findings, practical implications, and future research directions.

2.2 Literature Review and Hypothesis Development

Below, we review the relevant literature and develop study hypotheses pertaining to the equity of usage and benefit of MHMAs.

2.2.1 *Mental Healthcare Operations Management Literature*

In contrast to the well-established body of literature on physical healthcare operations management, the literature on mental healthcare operations management is still at a nascent stage and is comprised of only a few published studies. Among these studies, Yan and Tan (2014) find that social support exchange within a mental health online community can improve individuals' mental condition. In a follow-up study, Yan et al. (2019) demonstrate that treatment experiences shared by the online community members can influence how a member perceives her own mental health treatment. Zepeda and Sinha (2016) find that enhancing quality and affordability can particularly benefit the underserved population with socio-economic disadvantages. In a recent study, Li et al. (2021) find that eHealth platforms can enable mental health professionals to better-schedule follow-up visits for patients. Although these studies make valuable contributions to the literature on mental healthcare operations management, discussion around the inequities associated with socio-demographic characteristics of individuals with mental health needs is largely limited to the public health literature (Barnett, Gonzalez, et al., 2018; Ramos & Chavira, 2022). To advance this emerging stream of literature in the OM field, our study focuses on the inequities in usage and benefits of mental health services and examines the potential of MHMAs to provide equitable mental health services for the underserved population.

Inequities in mental health service usage and benefits can be attributed to several factors: First, there are significant variations across populations with different socio-demographic characteristics in terms of affordability, accessibility, and awareness (i.e., 3As that are strongly associated with the consumption of healthcare services (Kohnke et al., 2017; Sinha & Kohnke, 2009)) of mental health services (Berger et al., 2005; Beyer, 2020; Saxena et al., 2007; Sussman et al., 1987). For example, compared to the Whites, African-Americans and other minority race-ethnic sub-populations face challenges in affording and accessing mental health services due to lower income and education levels, limited insurance coverage, and geographical barriers (Beyer, 2020). Furthermore, African-Americans exhibit lower awareness regarding the potential need for such services, either considering symptoms of mental illness as normal aspects of their daily life (Sussman et al., 1987) or choosing their spiritual leaders and churches as resources for their mental health needs instead of professional counselors (Avent & Cashwell, 2015; Ayalon & Young, 2005). Similarly, males are less likely than females to be aware of their mental health needs, primarily due to the greater difficulties males experience in recognizing and acknowledging their emotional problems (Berger et al., 2005; Davis et al., 2023).

The second contributing factor is the presence of self-stigma and social-stigma associated with seeking care for mental health conditions, which distinguishes it from seeking care for physical health conditions (Masuda et al., 2012; Saxena et al., 2007). Self-stigma refers to the fear of self-disclosing distressing or potentially embarrassing personal information, whereas social-stigma refers to the societal stereotype that viewing individuals seeking mental health services as unpredictable, permanently damaged, incompetent, or threatening (Masuda et al., 2009, 2012). Such stigmas are particularly prominent within the underserved population. For instance, compared to the white individuals, African-American, Asian, and Hispanic/Latino individuals are less likely to acknowledge their mental health needs (Eisenberg et al., 2009; Lipson et al., 2018; Masuda et al., 2009, 2012). Additionally, even if they acknowledge their needs, they have less trust in mental health services because the mental healthcare system was historically exclusionary, hostile, as well as discriminatory towards them (Cooper et al., 2003; Diala et al., 2000; Eisenberg et al., 2009). Similarly, compared to female individuals, male individuals are more inclined to perceive mental health treatment as undermining their social power and control (Berger et al., 2005; Davis et al., 2023). Thus, they are less likely to seek mental health services and openly discuss their emotional conditions during treatment (Good et al., 1989; Good & Wood, 1995).

Third, the process of diagnosing and treating mental health conditions primarily relies on verbal communication, making seamless communication between mental health patients and professionals crucial for effective delivery of mental health services (Alegría et al., 2002; Nguyen & Reardon, 2013). Thus, mental health patients often prefer consulting with a health professional who shares similar socio-demographics characteristics such as gender, sexual orientation, or race-ethnicity in order to establish rapport and enhance understanding (Cooper et al., 2003). Otherwise, a socio-demographic mismatch between patients and mental healthcare providers can contribute to inequities in care. The underserved population is more likely to experience such mismatches than the better-served population because there are far fewer mental healthcare professionals from the underserved population than from the better-served population. For instance, in 2015, only 14% of clinical psychologists in the U.S. were Asian, Hispanic, or African-American, whereas the majority were White (Lin et al., 2018).

Finally, discriminatory practices, including denial of care or unfair diagnosis and treatment, also contribute to inequities in mental health services. For instance, despite a significantly higher mental illness rate of 44.1% among sexual minorities (i.e., lesbian, gay, bisexual, transgender, and questioning individuals) compared to the national average rate of 20.6%, they are at least twice more likely to be denied mental health services than their better-served counterparts (i.e., heterosexual individuals) due to discrimination (NAMI, 2021a). Such discrimination can foster long-term mistrust within the underserved population, which hinders their willingness to seek support. For instance, African-Americans exhibit a tendency to rely less on mental health services due to historical discrimination and mistreatment (Diala et al., 2000), opting to address their mental health issues independently rather than seeking professional help (Alegría et al., 2002).

2.2.2 *Hypothesis Development*

It is possible that MHMAs have the potential to mitigate the inequities observed in traditional modes of seeking mental health support. First, MHMAs are often free or have low-cost subscription plans. In addition, access to MHMAs is not restricted by geographical, temporal, or physical constraints (Stephens-Reicher et al., 2011), eliminating the commute time and costs for their users. These features make MHMAs more affordable and accessible than in-person mental health services delivered by professionals. Second, MHMAs offer the benefit of anonymity, creating a psychologically safe environment for app users. This allows users who are hesitant or uncomfortable discussing their mental health conditions to freely share their issues with their peers or seek mental health-related information without disclosing personal details such as gender, race-ethnicity, or sexual orientation (Ancis, 2020), thereby minimizing the self-stigma and social-stigma. Third, MHMAs can be designed to support various languages and user interfaces, facilitating effective conversations among users. This design feature allows individuals with similar socio-demographic characteristics and mental health concerns to connect with peers, reducing socio-demographic mismatches on the platform. Lastly, by implementing design features like active monitoring of online communities by human moderators or artificial intelligence algorithms to detect and address discriminatory, harassing, or abusive content, MHMAs can foster high quality interactions, while minimizing the risk of discrimination (Wadden et al., 2021) (i.e., a potentially significant downside that other online platforms such as social media entail (Ancis 2020)). On the other hand, MHMAs also carry several downside risks. Privacy concerns are paramount, as these apps often collect sensitive personal data, including emotional states and mental health conditions. This data is vulnerable to breaches and unauthorized access, potentially leading to identity theft or misuse of personal information. Additionally, the risk of data sharing without informed consent is high; many apps share user data with third parties, including advertisers and insurance companies, without transparent disclosure. This lack of regulation and oversight can result in users being unaware of how their data is being used or monetized, thereby compromising their privacy and security (Lecomte et al., 2020; Torous & Roberts, 2017). Overall, we believe that, if the privacy concerns are properly addressed, MHMAs are likely to motivate individuals, irrespective of their socio-demographic characteristics, to seek mental health support more frequently through MHMAs compared to in-person mental health services delivered by professionals. Because smartphone ownership rates are similar between the 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 with different socio-demographic characteristics show comparable interest in utilizing MHMAs (Anderson-Lewis et al., 2018; Lipschitz et al., 2020; Samarasekera, 2022), we anticipate that the opportunities for accessing mental health support via MHMAs apply equally to both populations. Therefore, we posit the following hypothesis:

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

MHMAs also offer several advantages that can contribute to improved mental condition for users. First, most MHMAs include functions that enable users to track their mental condition over time using visual trend plots. These tools can alert users to any downward trends or significant fluctuations that may indicate a deterioration in their mental condition. By receiving automated alerts, users are likely motivated to seek mental health support expeditiously. Studies have shown that individuals who seek mental health support early are more likely to benefit from the support than individuals who delay seeking support (P. D. McGorry et al., 2006; P. McGorry & van Os, 2013). Additionally, MHMAs facilitate peer-support by enabling users to connect with individuals experiencing similar mental health conditions. Specifically, through MHMAs, peers can learn from each other's experiences, offer immediate feedback, and exchange coping strategies (Yan & Tan, 2014). In conclusion, MHMA usage has the potential to help users significantly reduce loneliness, enhance stress management, and improve depression management (Ancis, 2020), leading to an improved mental condition (Donker et al., 2013). Thus, we posit the following hypothesis:

> **Hypothesis 2 (H2)**: *As the usage of a MHMA increases, users' mental condition improves.*

We infer from our review of the relevant literature that improving the affordability of mental health care within clinic-based services yields the greatest benefits in terms of improving mental condition, particularly for socio-economically disadvantaged communities (Zepeda & Sinha, 2016). Additionally, peer-support has been shown to offer greater mental health benefits to individuals facing higher levels of stress, such as minorities defined by their sexual-orientation (Meyer, 2003) or race-ethnicity (Aneshensel, 2009). Along these lines, we contend that MHMAs, by virtue of their affordability and ability to facilitate peer-support among users, are also likely to contribute towards enhanced mental health benefits, particularly for the underserved population. In fact, the positive impact of MHMAs may even be more pronounced, as certain underserved sub-populations (e.g., males or African-Americans) tend to express their mental health concerns more openly within a mobile app (virtual) environment (McCall et al., 2021; Ritterband, 2021), which is fundamental to realizing the benefits of mental health services (Pennebaker, 1999). As a result, MHMAs can enable individuals from the underserved population to benefit from app usage at least as much as individuals from the better-served population. Thus, we hypothesize:

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

2.3 Research Design

2.3.1 *Empirical Setting*

In this study, we collaborate with a mobile app startup company to understand whether MHMAs can offer equitable self-support and peer-support across populations with different socio-demographic identities. In 2015, the company launched its MHMA, Hope, for public users. Hope was not designed or marketed to target any specific population.

Rather, it was accessible by anyone with a smartphone. The Hope user community consists of users who are non-professionals (i.e., Hope is peer-based) and seek mental health support. Hope provides its users with two primary functions for self-support and peer-support:

The *self-reflection function.* This function allows users to self-assess their overall mental condition by responding to seven questions in Hope's Mental Condition Survey (refer to Appendix B for the survey questions). Once registered on Hope, users can use this function as frequently as they desire. This feature enables users to not only evaluate their current mental condition when needed, but also track the recorded results over time through a visual chart. This chart helps users understand the variations in their mental condition. Figure 2-1(a) demonstrates an example of the user interface and visual chart of this function.

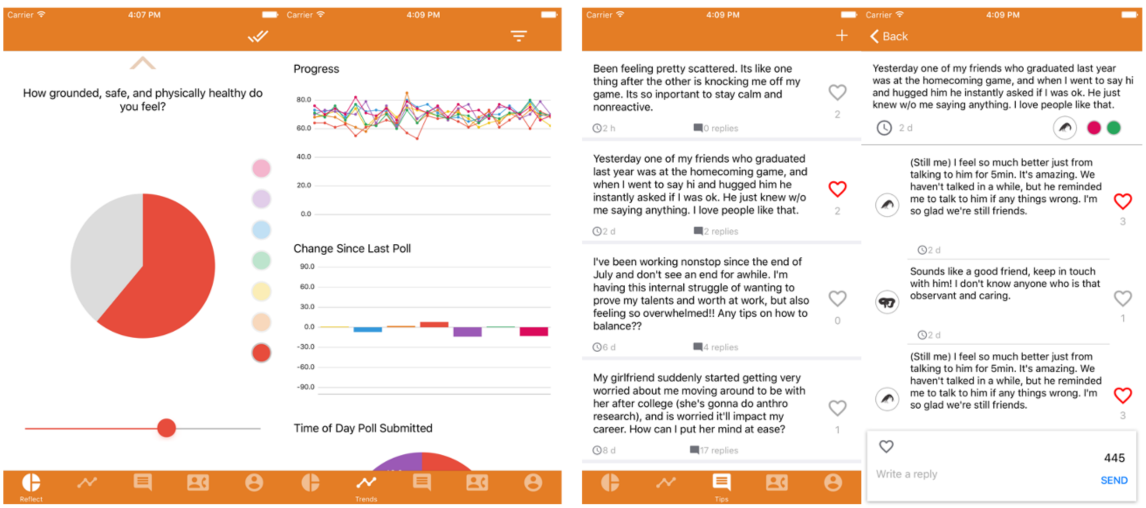
The *online community function*. This function establishes an anonymous online community within the app. Here, app users can connect and freely engage in peer-support at any time without the need to disclose their physical identities, minimizing the risk of users feeling compelled to present themselves differently for any reason. Within this online community, users can anonymously post to seek or provide help, share their feelings and personal stories, and interact with other users by responding to their posts. Figure 2-1(b) provides an example of user posts and replies within this function.

2.3.2 *Data*

Our study dataset is comprised of user-level socio-demographic and app activity data from 1,935 Hope users between May 2015 (i.e., the launch-month of the app) and February 2018. Hope records information on the socio-demographic characteristics of each user during the registration process. In addition, each time a user uses the self-reflection function or interacts with the online community function, Hope generates an activity record with detailed information such as the timestamp, 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.

Figure 2-1: Screenshot of Hope, a Mental Health Mobile App (MHMA)

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



Using these records, we construct an unbalanced panel in which each user has one observation for every Hope's Mental Condition 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. An important consideration when analyzing mobile app data is user retention. It is likely that some users that have been on a mobile app for a long period will have more data points than others who have been in the app for a shorter period. This discrepancy can introduce sampling bias, as users with more data points will be overrepresented in the sample. To address this issue and mitigate the sampling bias, we remove 92 outliers from the dataset, resulting in a sample of 1,843 users. These outliers represent users whose cumulative self-reflection function usage exceeds the 95th percentile (i.e., users who completed more than 22 Mental Condition Surveys and thus are overrepresented in the sample). Note that in this setting, a user must complete at least one Hope's Mental Condition 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 in Section 2.5.1 , we consider all 1,843 users to evaluate the robustness of our results. Table 2-1 presents the distribution of the 1,843 users with respect to their socio-demographic identities including gender, sexual orientation, and race-ethnicity.

2.3.3 *Variable Definitions and Measurements*

2.3.3.1 Outcome Variables

Consistent with our hypotheses, we consider two outcome variables:

SRS_{ij} *(Self-Reflection Score)* represents a user's mental condition and is operationalized as the score that resulted from the Hope's Mental Condition Survey completed by user *i* at time *j*. The survey includes seven questions, each measured on a continuous scale ranging from 0 to 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 align perfectly with existing scales in the literature.

It is important to note, however, that these questions conceptually capture the same underlying constructs as the widely used *PHQ-9* (Patient Health Questionnaire with 9 items) and *GAD-7* (Generalized Anxiety Disorder scale with 7 items) scales, which are self-administered depression or anxiety disorder diagnostic instruments in mental health clinical practice.

Table 2-1: Comparison of Socio-demographic Characteristics of App Users in the Study Sample

		Gender			**Sexual Orientation**			**Race-Ethnicity**				
	Total	Female	Male	Other	Heterosexual	Homosexual	Other	White	African American	Asian	Hispanic / Latino	Other
N	1,843	1,270	487	86	1,235	153	455	1,502	67	122	131	21
%	100%	68.91%	26.42%	4.67%	67.01%	8.30%	24.69%	81.50%	3.64%	6.62%	7.11%	1.13%

To evaluate the reliability of *SRS*, we conduct an exploratory factor analysis and a confirmatory factor analysis. The results are presented in Appendix C. The factor analysis indicates that the theoretical model between the latent variable and the 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 the standardized loadings in the confirmatory factor analysis.

As an additional step, we conducted a pilot study to assess the face validity of *SRS*. In this study, we recruited 61 college students at a public research university in the mid-western United States and asked the participants to first answer both *PHQ-9* and *GAD-7* questionnaires, and then complete Hope's Mental Condition Survey. As detailed in Appendix D, we found that *SRS* is strongly correlated with both *PHQ-9* and *GAD-7* scales, providing face validity for *SRS* in measuring the mental condition of Hope users.

$\boldsymbol{AppUsage_{ij}}$ 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 Condition Survey completed at time *j* (excluding the app usage at time *t*).[5] For example, a user who completes the survey twice, writes three posts, and responds to other's posts[6] four times within the last 15 days (i.e., $AppUsage_{ij} = log(1+2+3+4)$) is considered to have a higher frequency of app usage than a user who completes the survey once, writes

[5] The average time between two consecutive Mental Condition Survey completions is 7.18 days with a minimum of 0 day, a maximum of 623 days, a standard deviation of 29.08, and the 90th percentile corresponding to 11.08 days.

[6] Following the literature that considers both giving and receiving nonprofessional, nonclinical support to be a part of peer-support (Yan & Tan, 2014), we categorize any form of online community function engagement, including responding to other peers, as part of a user's *AppUsage*.

two posts, and responds to others' posts three times within the same time-period (i.e., $AppUsage_{ij} = log(1+1+2+3)$). We measure $AppUsage_{ij}$ by strictly excluding the app usage on the day the Mental Health Condition Survey is completed to ensure that there is no simultaneity between SRS_{ij} and $AppUsage_{ij}$ (i.e., akin to using lagged variables). We select the threshold of 15 days for the following reason. The effects of a single mental healthcare session such as therapy, tend to diminish over time, necessitating multiple sessions for effective treatment (Austin, 2022; Thompson, 2022). Therefore, mental healthcare typically follows a treatment course involving weekly, bi-weekly, or monthly sessions, depending on the severity of symptoms, nature of issues, and therapy types (Solara Mental Health, 2023). By setting the *AppUsage* threshold at 15 days, we align with the bi-weekly frequency of mental healthcare delivery. Notably, this choice is consistent with our empirical mobile app setting, as 98.8% of app usages before taking a Mental Condition Survey in our panel occur within 15 days prior to taking that survey. Furthermore, we define *AppUsage* using different time-periods and validate the robustness of our findings in Section 2.5.2 .

2.3.3.2 Key Independent Variable

The key independent variable in our study is $\boldsymbol{Underserved_i}$, which indicates whether user *i* belongs to the underserved population ($Underserved_i=1$) or the better-served population ($Underserved_i=0$). Consistent with the literature documenting inequities in mental health services (Berger et al., 2005; Masuda et al., 2009; NAMI, 2021a), we define a user as belonging to the underserved population if they do not identify as a female-heterosexual-

White individual. Conversely, female-heterosexual-White users are categorized as representing the better-served population.[7]

2.3.3.3 Control Variables

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

***Age**$_{ij}$* represents the age of user *i* at time *j* and is used to control for the potential impact of technology usage patterns across different age groups on mobile app usage (Pew Research Center, 2021) and mental condition (SAMHSA, 2022).

***InitialSRS**$_{i}$* is the first *Self-reflection Score* recorded for user *i*. We use each user's *InitialSRS* as the proxy for their initial mental condition when starting using the app. Users with better initial mental condition are likely to have higher app usage frequency. We control for this variable to rule out this potential impact of users' mental condition before joining the app on their usage behavior.

***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 Condition 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.

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[7] *Underserved*$_{i}$ is constructed based on user self-reported demographic data. Using self-reported data is a common practice in similar mental health online community studies (e.g., Yan et al. 2019, Yan and Tan 2014).

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

Table 2-2 presents descriptive statistics and the correlation matrix for the variables used in the study for users from the underserved population (*Underserved=1*) and users from the better-served population (*Underserved=0*). With a variance inflation factor score mean of 1.05 and a range between 1.02 and 1.09, below the rule-of-thumb cut-off of ten, there is little evidence of multi-collinearity.

2.4 Empirical Analysis

In this section, we introduce our econometric model specification and present the estimation results.

2.4.1 *Model Specification*

In healthcare literature, the patient outcome is a pivotal outcome variable, holding equal importance for app developers who seek to establish the credibility of their apps towards improving mental condition of app users through usage. Therefore, in our study, we are particularly interested in whether there exist any differences between users from the underserved and better-served populations in: (i) *AppUsage* and (ii) *SRS* as a result of *AppUsage.*

Table 2-2: Descriptive Statistics and the Correlation Matrix

	Better-served		*Underserved*		Correlation Matrix						
Variable	Mean	SD	Mean	SD	1	2	3	4	5	6	7
1. *AppUsage*[ii]	1.21	1.09	1.38	1.10	1.00						
2. *SRS*	41.42	30.05	40.87	28.36	0.02†	1.00					
3. *Age*	23.70	8.15	23.37	7.82	-0.07***	0.12***	1.00				
4. *InitialSRS*	39.57	28.95	33.88	25.48	-0.10***	0.70***	0.19***	1.00			
5. *Tenure*[ii]	22.94	50.28	24.41	58.45	-0.02*	0.14***	0.08***	0.17***	1.00		
6. *AppRemindFrequency*	3.28	2.73	3.94	2.84	0.19***	-0.05***	-0.12***	-0.13***	-0.01	1.00	
7. *Underserved*	-	-	-	-	0.07***	-0.01	-0.02†	-0.10***	0.01	0.11***	1.00
Number of users	648		1,040								
Number of observations	2,628		4,814								

Notes: (i) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1

(ii) The *AppUsage* and *Tenure* variables in this table are repeated observations for users measured at the moment of a specific *SRS* record and are not the final app usage for users or the tenure measured at the last app activity.

This implies that *AppUsage* is expected to influence *SRS*, while *SRS* is not anticipated to affect *AppUsage*. Following this assumption[8], we specify our econometric model as a recursive system of 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]:

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

where ε_{ij} and τ_{ij} are random error terms. *UserControls* include *Age*, *InitialSRS*, *Tenure*, and *AppRemindFrequency*. *TimeControls* include year-month fixed effects. Lastly, u_i and v_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 2.5.5 , 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 α_1 in Equation 1. Similarly, the coefficients of interest to test H2 and H3 are β_1 and β_3 in Equation 2, respectively. We specify Equations 1 and 2 as linear models.

[8] We later relax this assumption in Online Appendix E.3 and find that our results hold when we allow simultaneity between *AppUsage* and *SRS*.

2.4.2 *Estimation Results*

We estimate our econometric model using maximum likelihood estimation and present the results in Table 2-3. Model 1 demonstrates the estimation of Equation 2 (the SRS equation) with only control variables. Model 2 builds on Model 1 by adding *AppUsage* into the SRS equation. Model 3 further enhances Model 2 by including the mediation model for *AppUsage*, estimating both Equation 1 and Equation 2 simultaneously without the interaction term in Equation 2. Lastly, Model 4 represents the moderated mediation model, derived from Model 3 by adding the interaction term *AppUsage* × *Underserved* into 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.

With respect to the equity in MHMA usage, the estimated coefficient of *Underserved* in the App Usage equation in Model 3 ($\alpha_1 = 0.06, p = 0.134$) is not statistically significant. Following the recent published literature that establishes racial equity in various contexts through demonstrating statistical insignificance (e.g., Cui et al. 2020, Ganju et al. 2020), this result may suggest equity in app usage between users from the underserved and better-served populations. However, the statistics literature indicates that statistical insignificance can arise due to not only statistical equivalence, but also statistical indeterminance (Tryon, 2001). Therefore, to further examine the source of

Table 2-3: Main Analysis Estimation Results

	MODEL 1	MODEL 2	MODEL 3	MODEL 4
APP USAGE EQUATION				
Underserved			0.06	0.06
			(0.04)	(0.04)
Age			-0.01**	-0.01**
			(0.00)	(0.00)
InitialSRS			-0.00	-0.00
			(0.00)	(0.00)
Tenure			-0.00	-0.00
			(0.00)	(0.00)
AppRemindFrequency			0.07***	0.07***
			(0.01)	(0.01)
SELF-REFLECTION SCORE (SRS) EQUATION				
AppUsage		2.59***	2.59***	1.91**
		(0.39)	(0.39)	(0.72)
Underserved	1.57*	1.39†	1.39†	0.57
	(0.72)	(0.72)	(0.72)	(0.60)
AppUsage × Underserved				1.01
				(0.85)
Age	0.00	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
InitialSRS	0.81***	0.81***	0.81***	0.81***
	(0.02)	(0.02)	(0.02)	(0.02)
Tenure	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
AppRemindFrequency	0.27†	0.08	0.08	0.09
	(0.14)	(0.14)	(0.14)	(0.14)
AIC	63739.42	63612.48	82825.99	82823.51
BIC	64009.1	63889.07	83372.26	83376.71
Likelihood Ratio Test	-	128.94***	-	4.47*
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.

statistical insignificance in our empirical setting, we conduct a statistical equivalence test (Schuirmann, 1987) by comparing the average app usage between users from the underserved population and the better-served population and find support for statistical equivalence ($t_1 = 5.79,\quad p_1 = 0.00;\ t_2 = 2.21, p_2 = 0.01;\quad \Delta = 0.2\sigma_{\overline{AppUsage}}$).[9]

[9] There is no universal guideline for determining the difference limit (i.e., Δ) in statistical equivalence tests. The literature often employs a standardized effect size or Cohen's d (i.e., a percentage of the standard deviation of the variable of interest) to determine Δ (e.g., $\Delta = 0.33\sigma$ in Master et al. (2016), and $\Delta = 0.45\sigma$ in Lakens et al. (2020)). Compared to the literature, we use a more conservative Δ (i.e., $\Delta = 0.2\sigma$), which

Combined with the estimated coefficient α_1 in Table 2-3, this result suggests that users from the underserved population use Hope at least as much as the users from the better-served population, supporting H1.

With respect to the benefit of MHMA usage, we find that the estimated coefficient of *AppUsage* in the SRS equation in Model 3 ($\beta_1 = 2.59, p < 0.001$) is positive and statistically significant, supporting H2. Based on the predictive margins of *SRS*, doubling app usage frequency is associated with an increase of 1.80 unit increase in *SRS.* For instance, such an increase would correspond to a 4.69% increase in self-assessed mental condition of a user with median *SRS* in our study sample, testifying the benefit of MHMA usage.

Finally, Model 4 estimation results indicate that the interaction term *AppUsage* × *Underserved* ($\beta_3 = 1.01, p = 0.237$) 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., β_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:

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

implies that two users are considered to have an equivalent usage if the difference in their number of app usage within 15 days falls within 1.16. As a sensitivity analysis, we gradually decrease Δ (i.e., making it even more conservative) and find that the support for statistical equivalence is no longer present for $\Delta < 0.16\sigma$, which is considered a trivially small Δ to rule out statistical equivalence (Maxwell et al., 2015).

where ζ_{0i} denotes the deviation of user *i*'s intercept from the mean intercept of β_0 and ζ_{1i} denotes the deviation of user *i*'s slope for *AppUsage* from the mean slope of β_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., $\chi^2(2) = 2833.47$, p=0.00) obtained from the estimated random slope model (not reported) indicates that the effect of *AppUsage* on *SRS* indeed varies between users.

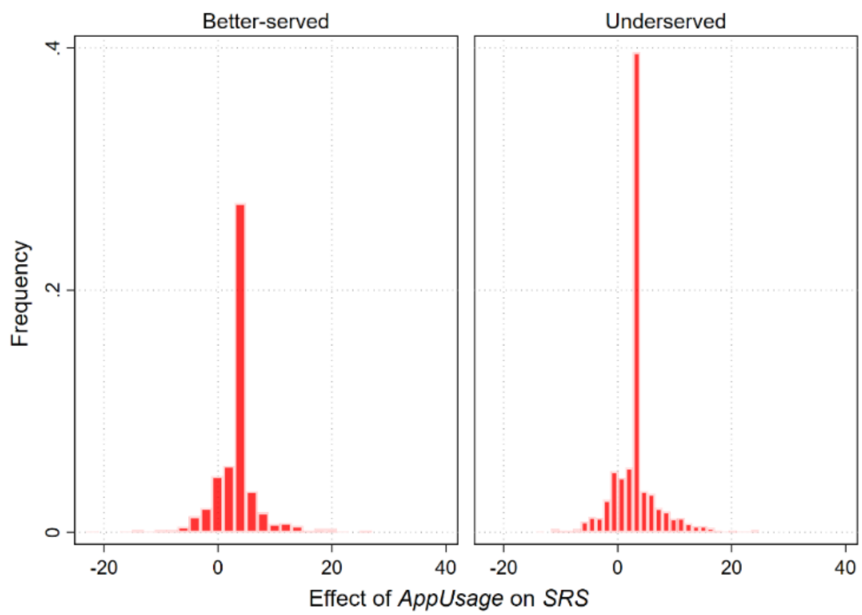
The histogram plots in Figure 2-2 summarize the estimated $\widehat{\beta_1 + \zeta_{1\iota}}$ for users from the underserved and better-served populations. Next, similarly to testing H1, we conduct a statistical equivalence test by comparing the estimated $\widehat{\beta_1 + \zeta_{1\iota}}$ between the two groups of users and find that there is statistical equivalence between them ($t_1 = 4.43,\ p_1 < 0.001;\ t_2 = 3.56,\ p_2 < 0.001;$ $\Delta = 0.2\sigma_{\widehat{\beta_1+\zeta_{1\iota}}}$[10]). Combined with the estimated coefficient β_3 in Table 2-3, this result suggests that using MHMA improves the mental condition equally for users from the underserved population and users from the better-served population, providing support for H3.

2.5 Robustness Checks

In this section, we conduct several robustness tests and demonstrate that our main results are consistent across several model specifications, variable operationalization, and alternative explanations.

[10] As with H1, we examine the sensitivity of the statistical equivalence test for H3 by gradually decreasing Δ and find that it is no longer supported when $\Delta < 0.1\sigma$, a trivially small Δ to rule out statistical equivalence (Maxwell et al., 2015).

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



2.5.1 *Endogeneity due to Sample Selection*

Sample selection bias is a potential concern for studies on mobile apps (Bateman et al., 2011; X. Li & Hitt, 2008) since registering to a mobile app is voluntary and not randomized. We use the Heckman model (Heckman, 2013; W. P. M. M. Van de Ven & 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 Condition Survey during the data period) with the assumption that those users can be seen as proxies for people who are in need for mental health support but do not register for Hope.[11] To provide face validity for this assumption, in Table 2-4, we statistically compare the 155 Hope users to the mental health

[11] 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 & Perneger, 1997; Siemiatycki & Campbell, 1984).

patient population in the U.S. with respect to gender and race/ethnicity (i.e., the two socio-demographics statistics that are publicly reported).[12] 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 χ^2 test p-value>0.14 for the two variables). We also report the sexual orientation information for the 155 Hope users.

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

Table 2-4: A Comparison of the Statistics for Socio-demographic Characteristics

	Status	**Definition**	**155 Hope users**	**U.S. Mental Health Patients %[i]**	**Pearson's χ^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%	
Sexual Orientation[ii]	Better-served	Heterosexual	69.68%	Not available	-
	Underserved	Homosexual, bisexual, other	30.32%	Not available	

Note: (i) Data source for mental health patients by gender and race-ethnicity: 2020 National Survey on Drug Use and Health (NSDUH). (ii) Sexual orientation data is not available for the U.S. mental health patients

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

[12] We are not able to compare the 155 Hope users to the mental health population with respect to sexual orientation statistic since this statistic is not available for the mental health population.

Mental Condition 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 2-5 demonstrate the estimation results for Models 3 and 4 with the probit specification. The estimated coefficients and their significance levels in models with probit specification are qualitatively similar to those in Models 3 and 4 in Table 2-3 with one noticeable difference – the coefficient of the interaction term $AppUsage' \times Underserved$ $(\beta_3 = 0.28, p = 0.025)$ is positive and statistically significant. Consistent with H3, this indicates that users from the underserved population benefit more from having any app usage than users from the better-served population. Considering that our hypotheses continue to be supported by the non-linear probit specification, we use it 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 2-5. In the first stage of the Heckman model, using all the covariates in our main 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 Mills ratios. Then, in the second stage, we estimate Equations 1 and 2 by including the inverse Mills ratios obtained from the first stage. Comparing the last two columns to the first two columns in Table 2-5, there is a negligible difference in the coefficient estimates.

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

Table 2-5: 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)
Age	-0.01**	-0.01**	-0.01*	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
InitialSRS	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Tenure	-0.00	-0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
AppRemindFrequency	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
SELF-REFLECTION SCORE (SRS) EQUATION				
AppUsage'	0.38***	0.20†	0.38***	0.20†
	(0.06)	(0.10)	(0.06)	(0.10)
Underserved	0.17*	0.01	0.17*	0.01
	(0.08)	(0.08)	(0.08)	(0.08)
AppUsage' × Underserved		0.28*		0.28*
		(0.13)		(0.13)
Age	0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
InitialSRS	0.06***	0.06***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)
Tenure	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
AppRemindFrequency	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
				-0.69
SELECTION MODEL	NO	NO	YES	(0.56)
AIC	13827.57	13815.33	13823.2	13817.11
BIC	14214.8	14181.82	14348.74	14342.64
Likelihood Ratio Test	-	-6.24	-	-6.09
ρ			-1***	-1***
ϱ			-.71	-.69
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) ρ and ϱ are the correlations between the App Usage and the Selection models, and between the Self-reflection Score and the Selection models, respectively. (v) ρ for the App Usage equations are truncated at -1.

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 2-6 reports the results from this sensitivity analysis. We find that the coefficients of interest for H1 in the *AppUsage* equation and H2 in the *SRS* equation remain the same across various correlation values and are consistent with those estimated in Table 2-5. Overall, the Heckman selection model estimation and the sensitivity analysis suggest that the potential sample selection bias has a negligible impact on our qualitative insights.

2.5.2 *Operationalization of AppUsage with Different Time Thresholds*

In the data, 98.8% of the app usages (used to operationalize *AppUsage*) before taking a Mental Condition Survey occur within 15 days prior to taking that survey. It might be possible that the remaining 1.2% not considered when operationalizing *AppUsage* can change our results. To explore this possibility, we construct two alternative *AppUsage* variables by considering two different thresholds; one month and two months corresponding to 99.3% and 99.6%, respectively, of the app usages occurred prior to taking a Mental Condition Survey. Table 2-7 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 Condition Survey, implying that missing out on significant periods of activity has a negligible impact on our results.

Table 2-6: Sensitivity Analysis for the Heckman Probit Selection Model

App Usage Equation ρ	-0.9	-0.7	-0.5	-0.3	-0.1	0.1	0.3	0.5	0.7	0.9
Underserved	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Self-Reflection Score (SRS) Equation ϱ	-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†
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
AppUsage' × *Underserved*	0.28*	0.28*	0.28*	0.28*	0.28*	0.28*	0.28*	0.29*	0.29*	0.29*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)

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.

Table 2-7: Estimation Results for Operationalization of AppUsage with Different Time Thresholds

Alternative Operationalization of *AppUsage*:	**Number of Observations**	**APP USAGE EQUATION**	**SELF-REFLECTION SCORE (SRS) EQUATION**		
		Underserved	*AppUsage*	*Underserved*	*AppUsage* × *Underserved*
1 Month	7,442	0.07	1.94**	0.31	1.17
		(0.05)	(0.70)	(0.59)	(0.82)
2 Months	7,442	0.06	1.92**	0.19	1.24
		(0.05)	(0.66)	(0.59)	(0.79)

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.

2.5.3 *Simultaneity between AppUsage and SRS*

As discussed in Section 2.4.1 , our main model assumes that *AppUsage* is expected to influence *SRS*, while *SRS* is not anticipated to affect *AppUsage*. However, it is conceivable that users with higher *SRS* (i.e., better mental conditions) may be more willing to use MHMAs as they find MHMAs helpful, which is likely to imply simultaneity between *AppUsage* and *SRS*, and thus to violate our model assumption. To address this, we relax the model assumption by including the *Lagged SRS* variable in the *AppUsage* equation (Equation 1 of our main model) to capture the potential impact of previous *SRS* on the current *AppUsage*. Note that by adding the *Lagged SRS* variable, we lose observations (5,754 vs. the original 7,442 data points) because the values for the *Lagged SRS* variable cannot be obtained for the first time a user takes the survey, and thus all the observations related to the first-time usage are dropped. Table 2-8 presents the results. The estimated coefficient of *Lagged SRS* is positive and significant ($\alpha = 0.003, p < 0.001$), confirming that the previous *SRS* does have a significant and positive association with the current app usage. Nevertheless, our hypotheses still hold after considering the simultaneity between *AppUsage* and *SRS*, suggesting a negligible impact of the simultaneity between *AppUsage* and *SRS* our results.

2.5.4 *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

Table 2-8: Estimating Results for Simultaneity between AppUsage and SRS

	MODEL 4
APP USAGE EQUATION	
Underserved	0.11*
	(0.05)
Lagged SRS	0.003***
	(0.00)
Age	-0.00
	(0.00)
InitialSRS	-0.00**
	(0.00)
Tenure	-0.00***
	(0.00)
AppRemindFrequency	0.03***
	(0.01)
SELF-REFLECTION SCORE (SRS) EQUATION	
AppUsage	1.83*
	(0.86)
Underserved	1.60
	(1.57)
AppUsage × Underserved	0.02
	(1.02)
Age	0.02
	(0.07)
InitialSRS	0.68***
	(0.03)
Tenure	0.01†
	(0.01)
AppRemindFrequency	0.08
	(0.21)
Number of users	942
Number of observations	5,754

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.

aforementioned diminishing marginal benefits vary between users from the underserved and better-served populations, 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 Condition Survey completed at time *j*) and estimate Models 3 and 4 with a quadratic term for this cumulative variable in the SRS equation. Table 2-9 presents the results. The estimated coefficient of the qudratic term *AppUsage*^{2} in the SRS equation ($\beta = -0.65, p < 0.01$) is negative and statistically significant in Model 3 and insignificant ($\beta = -0.39, p > 0.1$) in Model 4. These results suggest that the significant quadratic term coefficient in Model 3 is indeed driven by the difference in benefits from app usage between users from the underserved and better-served populations, suggesting that diminishing benefit is unlikely in our sample. Regardless, our hypotheses continue to hold with these specifications, ruling out diminishing benefit as an alternative explanation.

Table 2-9: Estimation Results for Diminishing Benefits of App Usage

Model	APP USAGE EQUATION	SELF-REFLECTION SCORE (SRS) EQUATION				
	Underserved	*AppUsage*	*Underserved*	*AppUsage* × *Underserved*	*AppUsage*^{2}	*AppUsage*^{2} × *Underserved*
Model 3	0.06	4.97***	1.38†		-0.65**	
	(0.05)	(0.72)	(0.71)		(0.21)	
Model 4	0.06	3.14**	-0.60	2.85†	-0.39	-0.41
	(0.05)	(1.14)	(0.44)	(1.46)	(0.34)	(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.

2.5.5 *Specification with Fixed Effects*

As discussed in Section 2.4.1 , 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 of Table 2-10) and compare the estimated coefficients to those in the random effect model in Table 2-3. We find that while the coefficients of interest (i.e., *AppUsage* and *AppUsage* × *Underserved*) are slightly different in magnitude between the two models, the qualitative insights remain the same.

Table 2-10: Estimation Results for Various Robustness Checks

Robustness Check	Number of Observations	APP USAGE EQUATION	SELF-REFLECTION SCORE (SRS) EQUATION		
		Underserved	*AppUsage*	*Underserved*	*AppUsage × Underserved*
Fixed Effect Model	7,442		2.32*** (0.69)		0.33 (0.83)
Negative Binomial Model	7,442	0.11 (0.09)	0.14† (0.08)	1.66* (0.68)	-0.04 (0.10)
Alternative Operationalization of *AppUsage:* Excluding Responding to Other Peers	7,442	0.06† (0.03)	2.18* (0.89)	0.25 (0.60)	1.58 (1.04)
Alternative Operationalization of *Underserved:* Excluding gender	7,442	0.09* (0.04)	2.15*** (0.55)	-0.40 (0.60)	0.88 (0.77)
Alternative Operationalization of *SRS*	7,442	0.06 (0.04)	1.74* (0.73)	0.58 (0.60)	1.01 (0.86)
Alternative Panel Structure: Fixed Time Window (1 month)	2,748	0.09† (0.04)	1.19* (0.53)	0.95† (0.57)	1.11† (0.65)

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.

2.5.6 *Specification with Negative Binomial Model*

In our data, the count variable app function usage prior to completing the Mental Condition Survey has a right-skewed distribution, which is the reason why we operationalized *AppUsage* as the natural logarithm of the number of times the app functions. 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 Condition Survey and re-specify Equation 1 as a negative binomial model. As is evident from the results presented in the second row of Table 2-10, our qualitative insights from the main analysis still hold with this alternative specification.

2.5.7 *Operationalization of AppUsage with Different Peer-support Activities*

When constructing *AppUsage*, following the literature (Yan & Tan, 2014) we consider peer-support usage activities related to both receiving support (i.e., writing original posts) and giving support (i.e., responding to other users' posts). Despite this classification in the literature, one may argue that responding to other users' posts may not necessarily benefit the user who responds, and thus should not be considered a part of the peer-support app usage activities. To examine whether our results change under this alternative classification of app usage activities, we exclude all peer-support activities related to responding to other peers, reconstruct *AppUsage* using only activities related to self-reflection function usage and writing a post, and estimate Model 4 with this alternative *AppUsage* variable. As evident in the third row of Table 2-10, we find that our insights regarding the equity in usage and benefit remain the same with this alternative *AppUsage* variable.

2.5.8 *Operationalization of Underserved without Gender*

In this robustness test, following the traditional definition of the underserved population in other service domains that consider only supply-side challenges, we operationalize *Underserved* using only socio-demographic identities of race-ethnicity and sexual orientation, ignoring the gender identity. With this alternative classification, we refer to individuals as belonging to the *underserved population* if they identify with one or more of the following socio-demographic identities: (i) Sexual orientation (i.e., homosexual, and other non-heterosexual identities); and (ii) Race-ethnicity (i.e., African American, Asian, Hispanic/Latino and other non-White identities). Conversely, the *better-served population* refers to individuals who identify as heterosexual and White. The results for Model 4 with this alternative *Underserved* variable are presented in the fourth row of Table 2-10. As is evident from the results, excluding gender when operationalizing *Underserved* does not impact our insights. In fact, we find that users from the underserved population would use MHMA more than their better-served counterparts, a desirable outcome for the underserved population. These results imply that our results are not driven by considering gender in classifying underserved users.

2.5.9 *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 fifth row of Table 2-10, our qualitative insights are also robust to this alternative operationalization.

2.5.10 *Alternative Panel Structure*

In our panel data, each observation corresponds to a completed Mental Condition Survey. Due to variations in the number of survey completions, it is possible that individuals who use the survey more frequently are overrepresented in our panel compared to those who use it less frequently. To examine the potential impact of this overrepresentation, we construct an alternative panel where the panel time intervals are set to one month (i.e., representing the 98th percentile of the distribution of the time between two consecutive SRSs). Since the average time between two consecutive Mental Condition Survey completions is 7.18 days, it is likely that individuals who use the survey more frequently may complete more than one survey within a month period. Therefore, in this panel, we operationalize *SRS* as the average score of (multiple) surveys completed by user *i* in time *t* and *AppUsage* as the total app usage of user *i* in time *t-1*. With this data, for users who complete multiple surveys within one month, obtaining the average SRS from those survey scores and creating only one observation for that month (as opposed to having multiple observations as we do in our main analysis), we ensure that individuals using the survey more frequently are not over-represented. We estimate our main model using this alternative panel and present the results in the last row of Table 2-10. We find that our insights from the original panel regarding equity in usage and benefit of MHMAs remain the same with this alternative panel. In addition, users from the traditionally underserved population use MHMA marginally more and benefit marginally more from MHMA usage than their better-served counterparts, supporting H1 and H3. Overall, this robustness test indicates that the over-representation of individuals who use the survey more frequently has a negligible effect on our results.

2.6 Post-hoc Analysis

Having established the robustness of our results, we now conduct post-hoc analysis to understand: (i) 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.

2.6.1 *Self-reflection Function vs. Online Community Function*

The two MHMA functions offer distinct types of support to app users. The self-reflection function enables users to monitor their mental condition and increase the awareness of their own mental healthcare needs without interacting with other users. In contrast, the online community function facilitates user interactions and the exchange of peer-support within Hope. It provides a platform for users to connect with one another, offering the opportunity to receive from and provide support to fellow users. Hence, the two app functions can be associated with two different user behaviors, with the self-reflection function emphasizing individual introspection and the online community function emphasizing interaction and peer-support.

To investigate whether there are differences in user behaviors between users from the underserved population and users from the better-served population, we conduct post-hoc analysis. This analysis expands on 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 Condition 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. Further, there is a potential interplay between *SRUsage* and *OCUsage.* Users who engage with the online community through the app may feel happier and more inclined to track their mental condition, leading to increased *SRUsage*. Similarly, users who frequently use the self-reflection function may be more motivated to engage and assist others, resulting in increased *OCUsage*. To account for this interdependency, we include the lagged *OCUsage* variable as a control variable in the *SRUsage* equation and the lagged *SRUsage* variable as a control variable in the *OCUsage* equation.

As is evident in column *SRUsage* Model 3 in Table 2-11, we find that users from the underserved population use the self-reflection function marginally more frequently than users from the better-served population ($\alpha_1 = 0.05, p = 0.078$). We do not find a similar difference with respect to the usage of the online community function ($\alpha_1 = -0.003, p = 0.928$ in column *OCUsage* Model 3). With respect to the impact of the usage of each function on mental condition, we find that the use of both functions is associated with an increase in *SRS* ($\beta_1 = 3.58,\ p < 0.001$ in column *SRUsage* Model 3 vs. $\beta_1 = 1.34$, p $= 0.005$ in column *OCUsage* Model 3). However, when we compare these two coefficients in a seemingly unrelated regression model, 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 ($\chi^2 = 18.18, p < 0.001$). This suggests that MHMAs are likely to offer value particularly through increasing awareness of users' mental health needs. When we examine the two functions with respect to the equity in benefit, we find no significant difference between users from the underserved and better-served populations $\beta_3 = 1.73,\ p = 0.121$ in column *SRUsage* Model 4 vs. $\beta_3 = -0.66,\ p = 0.536$ 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 model that β_3 in the *SRUsage* model is

Table 2-11: 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	0.05†	0.05†	-0.00	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)
Lagged SRUsage			0.35***	0.35***
			(0.03)	(0.03)
Lagged OCUsage	0.43***	0.43***		
	(0.02)	(0.02)		
Age	-0.00**	-0.00**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
InitialSRS	0.00	0.00	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Tenure	-0.00*	-0.00*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
AppRemindFrequency	0.05***	0.05***	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
SELF-REFLECTION SCORE (SRS) EQUATION				
SRUsage	3.58***	2.41*		
	(0.51)	(0.96)		
OCUsage			1.34**	1.79†
			(0.47)	(0.91)
Underserved	1.34†	0.22	1.54*	1.75*
	(0.71)	(0.60)	(0.72)	(0.69)
SRUsage × Underserved		1.73		
		(1.12)		
OCUsage × Underserved				-0.66
				(1.06)
Age	0.02	0.02	0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.03)
InitialSRS	0.81***	0.81***	0.81***	0.81***
	(0.02)	(0.02)	(0.02)	(0.02)
Tenure	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
AppRemindFrequency	0.04	0.04	0.24†	0.24†
	(0.14)	(0.14)	(0.14)	(0.14)
AIC	78225.29	78218.75	78130.36	78131.21
BIC	78778.48	78778.86	78683.55	78691.32
Likelihood Ratio Test	-	8.54**	-	1.15
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.

significantly greater than β_3 in the *OCUsage* ($\chi^2 = 4.77, p = 0.03$). In other words, users from the underserved population benefit more from using the self-reflection function whereas users from the better-served population benefit more from using the online community function. This suggests that MHMAs are likely to offer value to: (i) users from the underserved population mainly through increasing their awareness of mental health needs and (ii) users from the better-served population more through facilitating peer-support among app users.

In summary, our post-hoc analysis of the two app functions reveals that the variety in mental health support offerings through MHMAs is likely to be key towards ensuring equity in usage and benefits. Such variety allows users from both underserved and better-served populations to leverage each of the two MHMA functions in ways that best align with their specific mental health needs.

2.6.2 *Equity Across Users from Different Underserved Sub-populations*

In our main analysis, we treat all users belonging to the underserved population (e.g., African-American, Asian, Hispanic/Latino, etc.) as similar in terms of the inequities they may face regarding usage and benefit of mental health services, without distinguishing between different socio-demographic characteristics. However, there is evidence suggesting that the degree of inequity may vary across different underserved 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 potential variations across users from different underserved sub-populations within a MHMA setting.

To identify users from different underserved sub-populations, we use three socio-demographic variables corresponding individually to: gender (*male, female*, *other gender*), sexual orientation (*heterosexual, homosexual, other sexual orientation*), and race-ethnicity (*white, African American, Asian, Hispanic / Latino, other race-ethnicicty*). In Equations 1 and 2, we substitute the variable *Underserved* with a categorical variable indicating different underserved sub-populations and the better-served population. For instance, when identifying users from underserved sub-populations based on gender, the categorical variable indicates whether a user belongs to the better-served population (i.e., female, heterosexual, White individual), the female-underserved sub-population (e.g., a female African-American), the male-underserved sub-population, or the other-gender-underserved sub-population (e.g., Hispanic individuals who do not associate themselves with any gender). We handle sexual orientation and race-ethnicity in similar ways. We then estimate our recursive system of equations (i.e., Model 4) with each of the three categorical variables (with users from the better-served population being the reference level) and present the results in Table 2-12.

From these results, the following two insights stand out. First, regardless of how we identify underserved sub-populations, we consistently find across all three model estimation results that none of the users from these sub-populations use and benefit from the MHMA significantly less than users from the better-served population.[13] This suggests that the inequity against the underserved population reported in the prior literature for clinic-based mental health sevices (NAMI, 2021a; Terlizzi & Norris, 2021) is unlikely to be present in the context of MHMAs for users from any of the underserved sub-populations examined. Second, the results reported in the first column of Table 2-12 indicate that MHMAs might be particularly effective for female users within the underserved population

[13] Statistical equivalence tests comparing the average app usage and benefit between users from the underserved sub-populations (for which a statistically insignificant coefficient is estimated in Table 2-12) and the better-served population provide support for statistical equivalence between them with one exception: due to small sample size of users from the other race-ethnicity underserved population, the test is indeterminate for the Other-Underserved vs. better-served comparison in Equations 1 and 2 in Column 3.

Table 2-12: 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-demographic Characteristics:*</u>						
	Female-Underserved	0.07	*Heterosexual-Underserved*	-0.02	*White-Underserved*	0.08†
		(0.05)		(0.05)		(0.04)
	Male-Underserved	0.02	*Homosexual-Underserved*	0.06	*African-Underserved*	0.09
		(0.05)		(0.08)		(0.13)
	Other-Underserved	0.25*	*Other-Underserved*	0.15**	*Asian-Underserved*	0.03
		(0.10)		(0.05)		(0.08)
					Latino-Underserved	0.01
						(0.09)
					Other-Underserved	-0.15
						(0.18)
Age		-0.01*		-0.01*		-0.01**
		(0.00)		(0.00)		(0.00)
InitialSRS		-0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)
Tenure		0.00		0.00		-0.00
		(0.00)		(0.00)		(0.00)
AppRemindFrequency		0.07***		0.07***		0.07***
		(0.01)		(0.01)		(0.01)
SELF REFLECTION SCORE (SRS) EQUATION						
AppUsage		1.91**		1.91**		1.91**
		(0.72)		(0.72)		(0.72)
Socio-demographic Characteristic Main Effects		Estimated		Estimated		Estimated
AppUsage × Socio-demographic Characteristics:						
	Female-Underserved	1.90†	*Heterosexual-Underserved*	1.04	*White-Underserved*	1.18
		(1.00)		(0.99)		(0.90)
	Male-Underserved	0.18	*Homosexual-Underserved*	1.47	*African-Underserved*	1.91
		(0.95)		(1.67)		(1.61)
	Other-Underserved	0.35	*Other-Underserved*	0.86	*Asian-Underserved*	-0.33
		(1.62)		(0.98)		(1.83)
					Latino-Underserved	0.65
						(1.68)
					Other-Underserved	-2.49
						(2.57)
Age		0.01		0.02		0.01
		(0.03)		(0.03)		(0.03)
InitialSRS		0.81***		0.81***		0.81***
		(0.02)		(0.02)		(0.02)
Tenure		0.01		0.01		0.01
		(0.01)		(0.01)		(0.01)
AppRemindFrequency		0.10		0.09		0.09
		(0.14)		(0.14)		(0.14)
AIC		82818.76		82826.28		82838.94
BIC		83413.44		83420.96		83475.11
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.

(e.g., female African-American, female homosexual, etc.). The relationship between app usage and self-reflection score is marginally stronger for these users compared to users from the better-served population. We do not find such nuanced variation for the equity in benefit for users from other underserved sub-populations, despite some of them (i.e., users from underserved sub-populations identified by other gender identity, other sexual orientation, and White race-ethnicity) using MHMAs more frequently than users from the better-served population. In summary, our analysis reveals some variations in the usage and benefit of MHMA-enabled mental health support across users from different underserved sub-populations.[14] Nonetheless, these variations are unlikely to result in inequity in usage and benefit against users from any underserved sub-populations when compared to users from the better-served population.

2.7 Conclusion

2.7.1 *Overview*

In this essay, we evaluate the potential of MHMAs to provide equitable self-support and peer-support mental health services across users from the underserved and better-served populations. It is well-documented in the literature that the traditional clinic-based mental health services are inequitably available to patients based on their socio-demographic characteristics such as gender, sexual orientation, and race-ethnicity, leading to inequities in usage of and benefit from mental health services (NAMI, 2021a; Terlizzi & Norris, 2021). COVID-19 has further highlighted these inequities (Wang et al., 2020). Small-scale empirical evidence suggests that MHMAs that facilitate self-support and peer-support have the potential to offer equitable mental health support to the underserved population (Aziz et al., 2022; Emerson et al., 2021). Our study examines this potential using longitudinal

[14] The pairwise comparison of coefficients estimated in Table 2-12 for the underserved sub-populations (within each equation) demonstrate that at least one coefficient is statistically different (i.e., $p < 0.05$ for χ^2) from another in Equations 1 and 2 in Column 1 and Equation 1 in Column 2.

user-level data on socio-demographic characteristics and app activity data collected from a MHMA. By way of research design, we estimate a recursive system of equations to assess whether equity in MHMA usage and benefit exists between users from the underserved and better-served populations. Further, we investigate: (i) whether users from the underserved and better-served populations use the two MHMA functions – namely, the self-reflection function and the online community function – similarly or differently; and (ii) whether there exists any difference in equity in MHMA usage and benefits from such usage across users from different underserved sub-populations.

2.7.2 *Contributions to the Literature*

By way of contributions, our study provides theoretically-grounded empirical analysis that highlights the potential of MHMAs in delivering equitable self-support and peer-support to the underserved population. Specifically, we examine equity with respect to two user outcomes, namely the frequency of app usage (i.e., equity in usage) and mental condition (i.e., equity in benefit). With respect to equity in usage, we find that users from the underserved population exhibit MHMA usage frequencies statistically equivalent to those from the better-served population. This suggests that the inequity in clinic-based mental health service usage reported in the literature (Berger et al., 2005; Masuda et al., 2009; NAMI, 2021a) is unlikely in MHMAs designed particularly for self-support and peer-support. In addition, our results indicate that MHMA usage frequency has a positive impact on users' mental condition. For instance, considering users with a median self-reflection score from our sample, doubling their app usage frequency (i.e., from 0.2/day to 0.4/day) can lead to a 4.69% increase in self-reflection score. With respect to equity in benefit, we find that MHMAs are equally beneficial for users from both underserved and better-served populations, as our results indicate that the association between usage frequency and mental condition is statistically equivalent between the two populations. It is worth noting that these novel insights with regards to equity in mental health support offered by MHMAs are relevant even when 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, users from none of the underserved sub-populations experience lower usage and benefit from MHMAs compared to users from the better-served population. Conversely, users from certain underserved sub-populations (e.g., female African-American, female homosexual, etc.) tend to derive greater benefit from MHMAs compared to users from the better-served population.

To shed light on how MHMAs uphold equity in usage and benefit between users from the underserved and better-served populations, we conduct a post-hoc analysis to compare the usage of the app functions (i.e., the self-reflection and the online community functions) between the two groups of users. The results suggest that equity in MHMA usage and benefit is likely to be driven by the heterogeneity in users' preferences for different app functions. Specifically, we find that users from the underserved population use the self-reflection function marginally more than users from the better-served population. Therefore, users from the underserved population derive benefit from MHMAs more through the use of the self-reflection function, whereas users from the better-served population derive benefit from MHMAs more through the use of the online community function. The self-reflection function enables users to develop self-awareness of their mental health needs and can be used individually without the need for interaction with other users. The online community function allows users to exchange peer-support with each other and requires virtual interactions. Given the distinct nature of these two functions, it is conceivable that MHMAs will likely offer value to the underserved population primarily by enhancing their self-awareness of mental conditions and needs. In contrast, MHMAs will likely offer value to the better-served population primarily by facilitating a psychologically safe environment for peer-support interactions.

2.7.3 *Practical Implications*

A significant implication of our study findings is that MHMAs designed to deliver self-support and peer-support mental health services have the potential to address the well-documented inequity across the underserved and better-served populations in the traditional clinic-based mental healthcare settings. As detailed in Appendix E, fundamental to this implication is the identification of two types of relationship between the app users and the traditional mental health patient population. Both relationships can shed light on our results and suggest distinct implications of our study findings for stakeholders within the mental healthcare ecosystem.

First, MHMA users can inherently be different from the population seeking traditional clinic-based professional support. Hence, MHMA users can be those who do not seek traditional clinic-based professional support, yet seek peer-support and self-support help on their own in the app. This implies that MHMAs may expand the mental health support (through self-support and peer-support) to a new population segment who otherwise would not seek traditional clinic-based professional support. This explanation highlights the value of MHMAs in providing access to the "hard-to-reach" mental health patient population in the traditional clinic-based mental healthcare delivery settings, which can have several practical implications when combined with our study results. For instance, several global organizations such as United Nations and WHO consider improving access and advancing equity as the core guiding principle for achieving sustainable mental healthcare delivery (World Health Organization, 2013). Our study findings suggest that by way of supporting initiatives directed towards enhancing access and advancing equity, global organizations and local governments should consider promoting and investing in enhancing the use and access to MHMAs within the underserved population, particularly in societies where there is high level of discrimination and violence against underserved females. Next, notwithstanding the potential for significant lost earnings on account of mental health-related disabilities of employees, many organizations are still hesitant to provide mental healthcare benefits and resources to their employees due to high upfront costs (Brodey 2021). In organizations that do provide such benefits and resources, employees with most needs (e.g., those from the underserved population) tend to avoid using mental health services due to social stigma and fear of losing their jobs (Brodey 2021), resulting in significant wastage of resources. Our study suggests that MHMAs can be an alternative value-added resource for organizations due to their relatively low upfront costs and the anonymity that MHMAs can offer to employees regardless of their socio-demographic characteristics. By expanding mental health services via MHMAs to employees who might not use mental health benefits in the traditional clinic-based delivery settings otherwise, organizations can enhance employee welfare, reduce wastage of investments in providing mental health benefits, and minimize lost earnings due to mental health-related disabilities.

Second, MHMA users can inherently be the same as the population seeking traditional clinic-based professional support. This implies that the self-support and peer-support functions of MHMAs can complement the delivery of mental health services for those seeking traditional clinic-based professional support. This scenario highlights the value of MHMAs in providing an alternative channel for seeking help and potentially facilitating behavioral changes among underserved population with the following implications. Specifically, our results demonstrate that MHMAs are likely to achieve equity by providing variety in app functions such as self-support and peer-support functions, which can induce different user behaviors. Therefore, mobile app firms should design apps with a variety of functions including both self-support and peer-support. Self-support functions such as Hope's self-reflection function can enable users to track their mental condition and conduct skill-training functions (i.e., to teach users coping or thinking skills) without interacting with other users (NIH, 2019). Peer support functions such as Hope's online community function enable users to seek informational support or emotional support by virtually connecting and interacting with other app users. Next, to ensure safety and effectiveness of the app functions, governmental regulatory agencies such as the United States Food and Drug Administration have formed new divisions to develop protocols and guidelines for mobile app firms. Our study suggests that, to ensure the delivery of equitable mental healthcare services to the underserved population, in addition to safety and effectiveness, regulatory agencies should also consider developing market standards for designing MHMAs that encompass functions aligning with diverse behavioral needs.

All in all, regardless of these two likely relationships between the app users and the traditional mental health patient population, our results highlight that MHMAs may have the potential to address equity in mental healthcare delivery to the underserved population. Understanding how this potential can be realized will require further research. In particular, there is a need to investigate the interaction between MHMAs and the traditional clinic-based mental healthcare setting to shed light on questions such as: (i) how MHMAs can advance equity in mental health service delivery and (ii) whether adopting MHMAs (versus not adopting MHMAs) changes mental health patients' access to and use of the traditional clinic-based mental health services. Being the first to highlight the potential of MHMAs designed to provide self-support and peer-support services, we believe our study will motivate future inquiries addressing the above two questions that have consequential health, social, and economic implications for populations at large.

2.7.4 *Limitations and Future Research Directions*

As with any studies, our research, too, has limitations. However, notwithstanding the limitations, our essay provides the motivation and lays the groundwork for future research aimed at sustaining equitable mental health service delivery, as discussed above. First, our empirical setting consists of a MHMA operated by a mobile app firm that does not involve mental health professionals. By involving professionals, MHMAs may offer more benefits by enabling them to detect at-risk patients based on their app activities and provide timely interventions and treatments. Yet, MHMAs operated by professionals may also provide users with the feeling of close monitoring, and thus exacerbate their feelings of stigma and inequity. Therefore, future research should: (i) examine how the impact on equity in usage and benefit of MHMAs changes with or without involving professionals; and (ii) identify conditions, including detailed patient characteristics, under which MHMAs should be integrated into the traditional mental health services while continuing to improve equity in usage and benefit.

Second, while we find empirical support for a positive relationship between MHMA usage and a user's mental condition, we do not investigate how mobile app 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-support and peer-support functions.

Third, in addition to mental condition tracking and peer 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 conditions as well as advance equity and inclusion in care delivery to the underserved population.

Fourth, users from the underserved population account for more than 50% of all users in the MHMA that serves as the empirical setting of our study. This proportion is typically greater than the proportion of patients from the underserved population in the traditional clinic-based mental healthcare setting (NAMI, 2021a) potentially for the following reasons: (i) the underserved population consider MHMAs to be attractive, given their effectiveness in providing access to "hard-to-reach" mental health patients; and/or (ii) the better-served population are likely to be less interested in seeking help via MHMAs. Future research could explore why the underserved population is overrepresented in MHMA settings.

Moreover, as with many observational studies on online communities (e.g., Yan et al. 2019, Yan and Tan 2014), our study relies on self-reported data on socio-demographic characteristics. Since MHMA users do not have to disclose their physical identities because the online communities in MHMA settings are anonymous, they are likely to report their socio-demographic characteristics accurately. Despite this conjecture, future research could explore what factors (e.g., distrust in any online platform, need for role playing, etc.) may motivate (if any) MHMA users to report their socio-demographic characteristics inaccurately.

Finally, one notable limitation of this study is its lack of focus on addressing privacy concerns related to MHMAs. While the primary objective was to evaluate the how users from different populations use and benefit from MHMAs, it did not delve into the critical issue of data privacy and security, which remains a significant barrier to their widespread adoption. Future research should explore robust mechanisms for safeguarding user data, including the development of standardized privacy frameworks and encryption methods tailored to mental health applications. Additionally, studies should investigate user perceptions and trust levels concerning data privacy to better understand and mitigate the risks associated with personal data exposure. Exploring legal and ethical considerations, as well as designing user-friendly privacy policies, could further enhance the security and acceptance of mental health mobile apps (Torous & Roberts, 2017).

Chapter 3: Designing an AI-Enabled Online Mental Health Service Referral Platform

3.1 Introduction

According to the World Health Organization (WHO), around 1 in 4 people in the world will be affected by mental illnesses at some point in their lives (WHO, 2001). In addition, the COVID-19 pandemic has further pushed the prevalence of mental illnesses to a historic high point due to the stress related to the virus itself and its subsequent consequences (e.g., social distancing, job and food security, etc.) (Moreno et al., 2020; Wang et al., 2020). Despite such prevalence of mental health issues, the field of mental health is facing a significant service delivery gap between the need for mental health services and the actual usage of those services. According to the Substance Abuse and Mental Health Services Administration, only around 40% of U.S. adults with any mental illness used mental health services (SAMHSA 2019). This gap is characterized by a lack of access to appropriate and timely care for individuals with mental health needs mainly for the following reasons. First, there is a shortage of mental health professionals and inadequate funding for mental health services (Mnookin, 2016). Second, there is a lack of awareness and understanding of mental health issues in the general public – a unique challenge facing mental health service delivery compared to most physical health services. Many individuals with mental health needs do not seek help due to stigma or lack of knowledge about available services (Masuda et al., 2012). Individuals (e.g., males, African Americans, etc.) may not even recognize that they have mental health concerns that require seeking help (Berger et al., 2005; Masuda et al., 2012). These challenges can lead to delays in receiving care, making it more difficult to manage mental health conditions. In addition to the highlighted gap between the supply and demand of mental health services, access to such services remains an even more significant challenge for communities with certain socio-demographics such as gender, sexual orientation, and race-ethnicity. For example, African American individuals and Hispanic individuals are less likely to receive mental health care than non-Hispanic white individuals (SAMHSA, 2019), and when they do receive care, it is often of lower quality. Similarly, 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). Therefore, it is essential to take the severe disparities associated with socio-demographics into consideration while addressing the supply and demand gap in mental health service delivery.

To effectively narrow the gap in mental health service delivery, coordinated efforts are required on both the supply and demand sides. On the supply side, it is critical to expand mental healthcare capacities that are equitable and inclusive, catering to patients from diverse socio-demographic backgrounds (Kovandžić et al., 2011). Such expansions are often outlined in proposals by various stakeholders, including governments, private firms (Joseph et al., 2018), educational institutions (Cappella et al., 2008), and other organizations. However, simply increasing the availability of mental health services is not sufficient. Addressing demand-side challenges is equally important. These challenges include a lack of awareness about available services, stigma associated with seeking help, and cultural or gender norms that hinder access to mental health services for specific populations (Berger et al., 2005; Masuda et al., 2009, 2012). To overcome these barriers, it is essential to foster an environment that reduces stigma and to streamline the process of obtaining professional care through timely and accessible referrals.

Current online mental health service referral or search platforms, such as Psychology Today, typically require patients to actively input their mental health concerns. This direct input model assumes a level of self-awareness that many individuals may lack, often due to a general low awareness of mental health issues (Yeap & Low, 2009). This gap creates a significant barrier, preventing effective use of these platforms. Furthermore, these systems require that patients initiate care-seeking behaviors and “pull” information from the platforms, contributing to substantial delays in receiving referrals. Research indicates that the average delay between the onset of mental illness symptoms and receiving any treatment can be as long as 11 years (NAMI, 2021a). To address these shortcomings, this essay aims at exploring the design principles for online mental health platforms with the goal of more effectively and quickly connecting users with unmet mental health needs to appropriate and acceptable professional services.

In recent years, advancements in artificial intelligence (AI), particularly natural language processing (NLP) or text analytics, have promised significant potential in transforming service delivery systems, especially in mental health services where most of the data is text-based (D’Alfonso, 2020; Graham et al., 2019). Large language models (LLMs) such as GPT, BERT, XLNet, and RoBERTa, which have been developed and made publicly available over the past decade, have greatly enhanced the capabilities of NLP. These models can perform well in tasks like sentiment analysis, topic classification, question answering, text summarization, and machine translation, even without fine-tuning for specific fields (i.e., zero-shot learning) (Xian et al., 2019), although there are critics about the potential biases of such AI applications against underserved populations due to biases in training data and algorithms (Deery & Bailey, 2022). While current research has primarily focused on utilizing NLP to increase care capacity by automating tasks within existing care systems—such as triaging patients, providing information, answering frequently asked questions, and facilitating virtual therapy—there is a notable gap in research on using NLP to bridge the gap in mental health service delivery. This gap includes connecting those who have mental health needs but are not yet in the care system due to stigma and a lack of awareness, with timely and appropriate care services. Our study aims to address this gap by achieving several goals:

(i) Propose design principles for online mental health platforms that better connect users with unmet mental health needs to professional mental health services.

(ii) Develop a prototype of an online mental health service referral platform following these design principles.

(iii) Evaluate the effectiveness of this prototype and identify its boundary conditions.

(iv) Discuss how the implementation of this online mental health service referral platform could inform and enhance healthcare operations management theory.

To achieve such goals, we follow an abductive reasoning logic (A. H. Van de Ven, 2007). After setting up the study context, we start by reviewing the relevant literature and interviewing several mental health professionals (first-round interviews) to identify the design principles that guide the platform to successfully sense and respond to the personalized mental health service need of users. Next, we develop a platform prototype consisting of three inter-connected modules: (i) the core topic and context classification module; (ii) the chatbot module, and (iii) the service referral module. Finally, we create a demo of our platform and conduct a second round of interviews with 12 randomly recruited mental healthcare providers to collect exploratory evaluation of the system prototype.

The qualitative case data show that: (i) overall, the online mental health service referral platform can increase the probability that a distressed individual being connected to professional mental health services; however, (ii) the target users of the platform tend to be young adults with less family or friends available, already using digital tools extensively, and those who are not aware of available mental health services; (iii) the platform has the potential to reduce disparities in access to professional mental healthcare among the underserved populations by providing distressed individuals from such communities with culturally competent provider recommendations; (iv) even with availability of the platform, it is not likely that the provider can admit the patient without screening.

This study enriches multiple fields of research. In mental health help-seeking, we show that AI can be leveraged to support a referral system in mental health apps and online platforms, offering users tailored and immediate provider options. Unlike traditional models that require users to seek out care proactively, our AI-enabled platform identifies and meets users' specific mental health needs automatically. In the area of AI in mental healthcare, existing studies have primarily focused on early detection of mental issues or automating treatment tasks. Our work fills a crucial gap by using AI to link individuals with appropriate mental health services, aiming to increase accessibility especially for underserved populations. Lastly, in the field of healthcare operations management, our study advances this stream of literature by focusing on identifying mental health patients who are not yet in the care system and connecting them to professional care services with timely and customized referrals, highlighting the need to expand healthcare operations management research beyond healthcare facility operations. Our proposed design principles also provide refinement to the healthcare operations management theory about healthcare delivery. In particular, we expand the existing 3A-framework for healthcare delivery to the new 4A-framework consisting of *affordability, access, awareness, and acceptance*. We believe that this refined theory can better guide healthcare supply chain design especially for disease conditions where patients may be hesitant to seek care (e.g., mental illness, sexually transmitted infections, and reproductive health issues).

The rest of the essay has the following organization. Section 3.2 reviews and synthesizes several relevant streams of literature relevant to the topic of our study. Sections 3.3 and 3.4 build the theoretical underpinnings for the design of our proposed AI-enabled platform. Section 3.5 describes the process of proposing the design principles and development of the AI-enabled mental health service referral system prototype. It also documents the qualitative case data analysis for the initial evaluation of our proposed platform. Section 3.6 documents our refinement to theory based on the ideation, development, and evaluation of the referral system. Finally, Section 3.7 summarizes the research findings, discusses the theoretical and practical implications, and presents several future research directions.

3.2 Literature Review

In this section, we first review the mechanisms underlying the mental health service supply and demand gap as well as the disparities against the underserved communities. Next, we provide background information on the online platforms facilitating mental health support as well as the current Artificial Intelligence (AI) applications in mental health.

3.2.1 *Mental Health Service Delivery Gap and Disparities*

Despite the increasing recognition of the importance of mental health and the existence of effective interventions for mental illnesses, studies have consistently shown that global prevalence of mental illnesses continues to grow, and mental health service utilization rates remain low (The Lancet Digital Health, 2022).

Mental health disorders account for approximately 13% of the global burden of disease, yet only 1% of global health expenditures are allocated to mental health services (Vigo et al., 2016). Mental health disorders are estimated to cost the global economy $1 trillion in lost productivity each year due to absenteeism, presenteeism, and unemployment (Chisholm et al., 2016). Globally, an estimated 35-50% of people with severe mental health disorders and 76-85% of those with mild to moderate disorders do not receive any treatment (World Health Organization, 2022). Even in developed countries such as the U.S., only 47% of U.S. adults with a mental illness received mental health services in 2021 (SAMHSA, 2022). Sexual and racial minorities and low-income populations are particularly affected by low utilization rates of mental health services. For example, individuals from lower-income backgrounds are more likely to experience unmet mental health needs, have reduced access to care, and face poorer treatment outcomes (Lorant et al., 2003). Racial and ethnic minorities often face barriers to accessing mental health services and experience poorer quality of care (Alegria et al., 2010). This can result in delayed diagnosis, inadequate treatment, and suboptimal outcomes. Gender disparities in mental healthcare are marked by differences in the prevalence, diagnosis, and treatment of mental health disorders between men and women (Seedat et al., 2009). Men are less likely to seek help and may experience higher suicide rates, while women are more likely to be diagnosed with mood and anxiety disorders. Furthermore, LGBTQ+ individuals are at a higher risk for mental health disorders and suicide, yet they often face barriers to accessing mental health care, including discrimination, stigma, and a lack of culturally competent providers (NAMI, 2021b). In section 2.2.1 , I summarized that such underutilization and disparities of mental health services is attributed to a variety of factors, including (i) disparities in the affordability, accessibility, and awareness of mental health services; (ii) self-stigma and social-stigma associated with mental illnesses and seeking mental health services; (iii) socio-demographic mismatch between mental health patients and providers, and (iv) discrimination against underserved communities in the delivery of mental healthcare .

The mental healthcare delivery gap and disparities are complex and multifaceted issues that need to be addressed to ensure equitable access to care and improve mental health condition. These challenges are compounded by a variety of factors including stigma and discrimination based on socioeconomic status, racial and ethnic background, gender, and sexual orientation. Recognizing the complexity of these barriers is crucial in developing solutions that promote equitable utilization of mental health services. This study aims to deepen the understanding of the patient-side dynamics—specifically, the diverse needs and socio-demographic backgrounds of patients. Our objective is to design an AI-enabled technological solution that acts as an escalation mechanism in online platforms, effectively bridging the gap between the unmet demands for mental health care and the available supply of services.

3.2.2 *Online Platforms for Mental Health*

Before the Internet became prevalent, individuals with mental health needs largely depended on a network of interpersonal contacts with laypersons, such as family, friends, and religious leaders, as well as professionals to initiate professional mental healthcare (Rogler & Cortes, 1993). A significant barrier to accessing mental health care during this era was the reluctance to seek help, primarily due to the stigma associated with mental health issues and the interpersonal contacts involved in accessing care (Masuda et al., 2012). This stigma often discouraged individuals from pursuing the necessary assistance, exacerbating the challenges in effectively addressing mental health needs.

In recent years, the emergence of online platforms such as general social media, specialized online communities, and mobile apps, has presented significant potential in addressing these challenges. Platforms like these allow individuals to bypass the stigma associated with in-person interactions by offering opportunities for engagement that can be anonymous and online (Naslund et al., 2016). This shift has been crucial in reducing barriers to accessing mental health information and support, as individuals can now discreetly seek resources, share experiences, and exchange social support (Yan & Tan, 2014) without disclosing their identities, thus preserving their privacy while addressing their mental health issues. In light of such characteristics of online platforms, I confirmed the potential of such platforms on facilitating equitable mental health service delivery across historically underserved and better-served populations in Chapter 2.

While online spaces can encourage individuals experiencing distress to share their experiences, there is no certainty that they will receive the level of care they require. This concern is particularly pronounced on mental health platforms that operate without the direct supervision and regulation by mental health professionals, such as the mental health subreddit on Reddit. These platforms often lack a clear mechanism for escalating cases to professional mental health services when necessary. Users might find themselves unsure of where and how to seek professional help, potentially delaying the care they urgently need. Motivated by this critical gap, our study proposes the design principles of online mental health platforms tailored for platform users who are not in immediate crisis but require professional mental health services. While existing research primarily concentrates on detecting suicidal ideation and preventing suicide (Aladağ et al., 2018; Ji et al., 2020), it tends to overlook the needs of the broader population of mental health patients not in acute crisis situations. Our research aims to address this gap in literature by focusing on this underexplored area.

3.2.3 ***Artificial Intelligence (AI) Application in Mental Healthcare***

In recent years, AI has emerged as a promising technology to address mental health challenges by revolutionizing the way mental health services are accessed, delivered, and assessed. With the development of machine learning algorithms (e.g., unsupervised learning for explaining the variation of data, and supervised learning for predictions) and natural language processing (NLP) especially large language models (LLMs) for leveraging unstructured text-based data, AI is believed to be the "prime solution for keys issues in mental health, such as delayed, inaccurate, and inefficient care delivery" (Koutsouleris et al., 2022).

One of the main ways that AI has been applied in mental health is to leverage NLP techniques to provide classification capabilities such as sentiment analysis, emotion recognition, early detection / diagnosis of mental illnesses, and suicide ideation predictions.

NLP techniques have been used to analyze emotions and sentiments expressed in text and speech data (Al-Mosaiwi & Johnstone, 2018; Calvo & D’Mello, 2010). This can help healthcare professionals understand patients' emotional states, track treatment progress, and personalize interventions. NLP has also been employed to analyze social media content, electronic health records, and other user-generated data (e.g. gamified mobile app usage data) to identify early signs of mental health issues and suicide ideation (Birnbaum et al., 2017; Coppersmith et al., 2014; The Lancet Digital Health, 2022). By facilitating early detection and diagnosis, AI has the potential to promote timely interventions and better treatment outcomes. However, one challenge that such AI applications in mental health face is that even if early detection of emotional disorders or other mental illnesses is made possible and communicated to the patients, they may still choose not to seek help due to lack of awareness of available mental health services, stigma associated with seeking mental health-related help, and/or difficulty finding socio-demographically matched providers.

In addition, AI-powered therapeutic interventions are becoming increasingly popular in the mental healthcare domain. Treatment services such as cognitive behavioral therapy (CBT), coping strategies, mindfulness, and guided meditations are delivered to users through AI-powered chatbots and virtual therapists (D’Alfonso, 2020). In such forms of mental health service delivery, patients get accessible, cost-effective, and stigma-free mental health support (Fitzpatrick et al., 2017; Vaidyam et al., 2019). However, due to limitations such as difficulties in escalating users to clinic-based care when the symptoms are beyond the ability of virtual therapists or in emergency situations, AI agents should serve as supplements instead of replacements for human mental health providers (D'Alfonso, 2020).

Finally, AI is also augmenting the fields of computational psychiatry and precision psychiatry. More specifically, leveraging both mechanism-agnostic models (e.g., most black-box deep learning models) and mechanism-driven models (e.g., abstraction of human brain and human behaviors), AI is able to facilitate more nuanced subtyping of mental disorder diagnosis, predictions of mental health status before disorders emerge, and treatment stratification (i.e., personalized psychiatric treatments) (Hauser et al., 2022).

Such applications of AI have the potential to support efforts to narrow the gap between the supply and demand in mental health services. For example, NLP-driven mental health chatbots and virtual therapists can provide round-the-clock support, reducing waiting times and allowing more people to access mental health services (Abd-Alrazaq et al., 2019). AI can also facilitate the automation of routine tasks (e.g., progress monitoring, documentation) and enable healthcare providers to focus on delivering high-quality care (Topol, 2019). However, these existing AI applications primarily focus on automating mental healthcare tasks on the supply side when patients are already in the care system seeking professional help. As we discussed, it is crucial that we explore the application of AI to address the demand-side challenges in order to promote mental health help-seeking in the underserved communities. This study is designed to fill in this research gap where we leverage AI to connect users who are not yet in the care system with appropriate mental health services with an emphasis on enhancing equity across different socio-demographic populations.

3.3 Bridging the Gap in Mental Health Service Delivery

This study aims to propose design principles for guiding online mental health platforms to identify and address users' unmet needs for professional mental health services and connects these users with appropriate resources (e.g., therapists). The fast-growing healthcare operations management (healthcare OM) literature has made considerable progress towards optimizing patient care by ensuring that the right patients receive the right professional health services from the right providers at the right time and place at a low cost (Dai & Tayur, 2020; KC et al., 2019). While existing healthcare OM research has largely focused on the operational aspects of care delivery within healthcare facilities and its impact on service efficiency and care quality (see Dobrzykowski et al. (2014) and KC et al. (2019) for some recent reviews of this literature), it often presumes that patients are either already receiving or actively seeking care. This assumption overlooks a significant gap in mental health services, highlighted by the fact that over 50% of U.S. mental health patients did not receive any services in 2021 (SAMHSA, 2022), often due to reluctance in initiating help-seeking behaviors despite available treatments (Rogler & Cortes, 1993).

Only a few recent studies have started to address such unmet healthcare demands, especially in the context of underdeveloped countries and rural areas. For example, triangulating insights from both qualitative and quantitative data, Kohnke et al. (2017) demonstrated how an international non-profit organization's efforts improved healthcare access, affordability, and awareness in Gansu, China, leading to an increase in congenital heart disease surgeries. Similarly, in another study, leveraging a quasi-experiment in Southern India, Delana et al. (2023) observed that opening a nearby telemedicine center leads to a significant increase in the overall usage rate of ophthalmology services among the population close to the new center. Authors also concluded that such increase is primarily driven by new patients, confirming the potential of emerging technologies in identifying and fulfilling unmet healthcare demand.

Distinguishing from these studies, we situate our research in the context of mental health which has been shown to suffer from inadequate help-seeking not only in the traditionally underserved communities, but also in resource-rich countries such as the U.S., highlighting the unique patient behavioral challenges facing the delivery of mental health services. In addition, in both studies summarized above, the researchers retrospectively collected data around the efforts to promote health service usage and analyzed their impacts on health service uptake and/or health outcomes. Conversely, our research is unique in several perspectives. First, we collaborate with mental health practitioners in every step of our research to ensure the relevance of our study. Second, we apply theories to guide our ideation and development of the proposed online mental health service referral platform. Third, we assess the potential effectiveness of our proposed platform by conducting case studies with mental health practitioners and iteratively updating the design principles. Finally, based on our experience designing this platform, we offer refinements to the theories which can better guide the design of healthcare supply chain to cover the unmet health demand.

Regarding research design, our study adopts abductive reasoning logic (A. H. Van de Ven, 2007) as the guideline. Specifically, following the context-theory-context iterations that are consistent with abductive reasoning, we: (i) qualitatively analyze the current help-seeking behavior in mental health online platforms and identify the research context; (ii) apply existing theories in both healthcare operations management and medical literature to propose several design principles for online mental health platforms that address the research question; (iii) develop and iteratively update the an online mental health referral platform prototype that has the potential to nudge mental health online platform users with unmet demand to seek professional mental health services by proactively recommending matched provider(s); (iv) qualitatively assess the effectiveness of the prototype; and (v) provide refinement to the theories. In the next section, we introduce the theories guiding the ideation and development of our proposed design principles.

3.4 Conceptual Background: 3A-framework and Mental Health Help-seeking Pathway

We apply the 3A-framework (Sinha & Kohnke, 2009) from the healthcare OM literature as well as the mental health help-seeking pathway theory (Rogler & Cortes, 1993) from the medical literature to guide the ideation and development of our technological solution to promote online mental health help-seeking. We argue that the 3A-framework provides the theoretical underpinnings, from a healthcare supply chain's perspective, that guides any technology innovation aimed at bridging the gap between the unmet demand and supply for timely care. In addition, the mental health help-seeking pathway offers a critical supplement to the 3A-framework which makes it more comprehensive especially in the context of mental healthcare when patients often show unwillingness to seek care.

3.4.1 *3A-framework: Affordability, Access, and Awareness*

Sinha and Kohnke (2009) introduced the 3A-framework as a conceptual model for guiding healthcare supply chain design to "bridge the gap between demand and supply of high-quality, cost-effective, and timely care." Similar to our problem context, this framework seeks to address the persistent issue in healthcare delivery: the presence of effective treatments does not guarantee patient treatment, leaving a significant portion of the patient population untreated. The framework posits that affordability, access, and awareness (the 3As) are crucial enablers for equitable and efficient health service delivery. Specifically, affordability refers to a patient's financial capability to incur and sustain healthcare-related expenses. Access includes the physical and logistical infrastructure that enables the diagnosis and treatment of a disease condition, while awareness pertains to both patient knowledge about their treatable condition and healthcare professionals' ability to diagnose and treat it effectively. The applicability of this framework in enhancing healthcare service uptake was demonstrated in an underdeveloped province in China (Kohnke et al., 2017).

In the context of our study, applying the 3A-framework necessitates a referral function within online platforms that adeptly connects patients with unmet needs to suitable, affordable, and accessible care options, such as therapists. This mechanism inherently fulfills the awareness component by informing patients about available treatment options. To address affordability, recommendations could include therapists who accept the patient's insurance, offer payment plans, or have rates within the patient's budget. For access, the mechanism should prioritize care options that are geographically convenient or offer remote services, thereby overcoming physical barriers to treatment.

Despite the strengths of the 3A-framework in healthcare supply chain design, applying it to mental healthcare delivery presents unique challenges. Stigma, along with societal, cultural, and gender norms, may deter individuals from seeking professional mental health services, even when affordability, access, and awareness are adequately addressed. This highlights the need to extend beyond the 3A-framework and incorporate considerations specific to mental healthcare. An individual patient perspective, informed by medical literature, can uncover additional principles vital for encouraging mental health help-seeking behavior. For instance, Corrigan and Watson (2002) discuss how stigma reduction strategies can be crucial in encouraging help-seeking. Additionally, the role of social support, as discussed by Pescosolido (1992), emphasizes the importance of community support in the mental health help-seeking process. Incorporating these insights can provide a more nuanced approach to designing technological solutions that not only meet logistical and financial needs but also address the deeper social and psychological barriers to seeking mental health care. In the next section, we turn to medical literature and take an individual patient's perspective to identify the essential design principle that enables mental health help-seeking other than those related to the 3As.

3.4.2 *Mental Health Help-seeking Pathway*

Taking a patient-centric approach, the concept of mental health help-seeking pathways developed by Rogler and Cortes (1993) is a unifying framework that explains the process between the onset of a mental health patient's distress and their subsequent help-seeking behaviors. Such a framework can help us understand the barriers that prevent mental health patients from accessing professional help and identify research opportunities towards alleviating such barriers. Specifically, the authors define the mental health help-seeking pathways as the sequence of contacts with individuals (e.g., family, friends, religious or spiritual leaders, etc.) and organizations (e.g., primary care facilities, emergency rooms, mental health clinics, or other non-clinical organizations) initiated by the distressed individual. Two primary characteristics of such help-seeking pathways that determine whether and when the patient would access professional mental health services are the *direction* (i.e., the sequential ordering) and *duration* (i.e., time lapses) of the pathway. Right from the onset of distress to the contacts with professional care and finally to treatments in the mental health facilities, cultural norms (broadly defined, including spiritual beliefs, race/ethnic norms, gender norms etc.) and the socio-economic status of mental health patients have decisive impacts on their help-seeking pathways through influencing the direction and duration (Kleinman, 1988). Such cultural norms and socio-economic status, varying significantly across different genders, sexual orientations, race-ethnicities, nationalities, and/or other socio-demographic identities, lead to the observed low utilization of mental health services (despite they are increasingly available, affordable, and accessible) as well as the disparities across different populations. Therefore, to achieve our goal of nudging more mental health patients towards accessing professional mental health services, our solution should have the capabilities to: (i) guide the patient in the right direction of the help-seeking pathway towards professional mental healthcare through effective referrals; (ii) shorten the help-seeking pathway and thus reduce the delay between the onset of distress and getting professional help; (iii) make sure the referrals are culturally competent, i.e., the referrals should take into consideration the socio-demographic backgrounds of the patients.

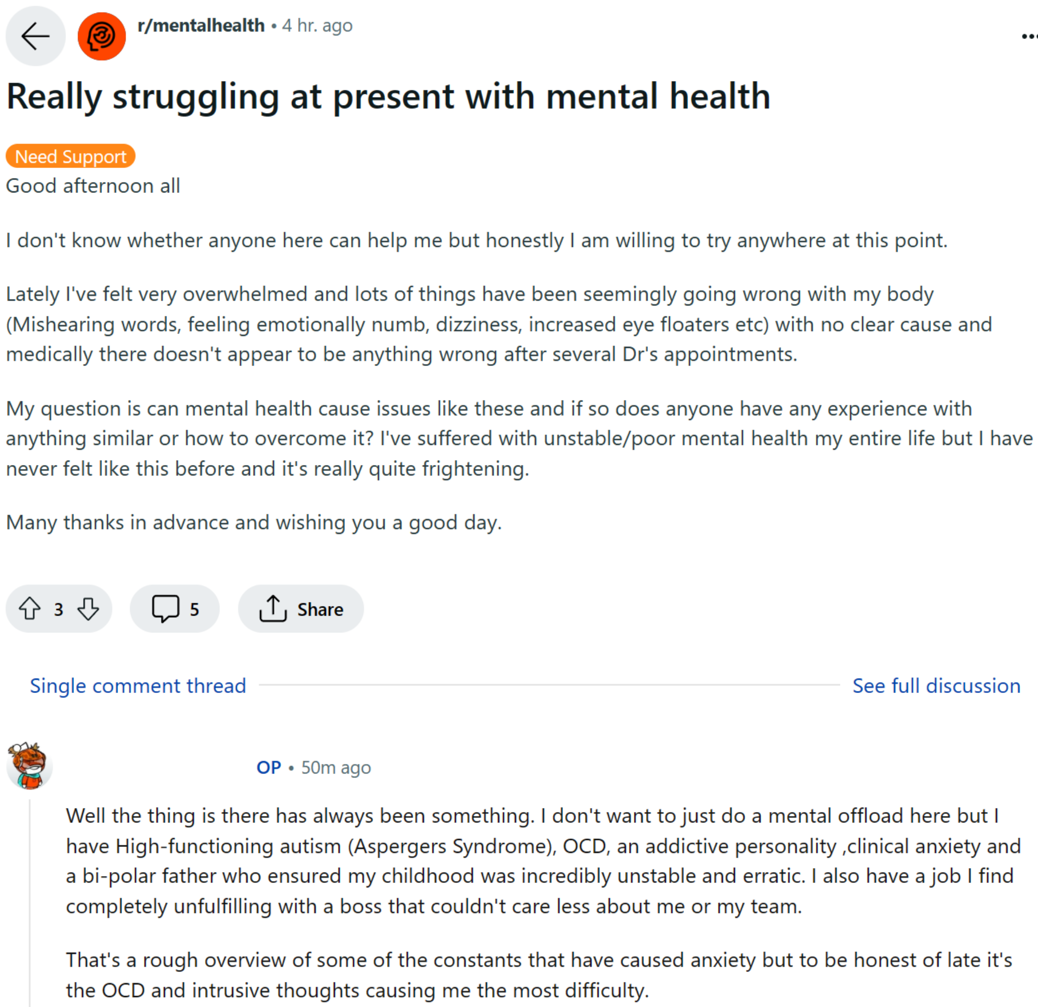
3.5 Ideation, Development, and Exploratory Evaluation of the Online Mental Health Service Referral Platform

In this section, we describe the process of the ideation as well as development of our proposed design principles for online mental health platform by adopting the abductive reasoning logic (Chandrasekaran et al., 2020; A. H. Van de Ven, 2007). Specifically, we propose the design principles that takes advantage of linked ideas in a theoretical framework to improve a situation (Checkland, 1985). While assessing the effectiveness of our proposed design principles, we reveal the shortcomings of existing theories and provide refinement to them. Our problem situation is bridging online mental health platform users with unmet mental health needs with professional care options. We apply the 3A-framework for healthcare supply chain design to guide our initial ideation for the design principles that address the problem situation. During this process, we reveal the shortcomings of the 3A-framework, and introduce the mental health help-seeking pathway theory from medical literature which inspires our refinement to the 3A-framework, making it the new 4A-framework (*affordability*, *access*, *awareness*, *acceptance*), which better captures the complexities of any healthcare situation where patients might suffer from resistance to seeking care that is affordable and accessible. With the refined theory, we iteratively update our design principles, resulting in an AI-enabled online mental health service referral platform powered by a chatbot. We describe this process in the following subsections.

3.5.1 *Initial Ideation of the Design Principles*

This research starts with an observation that while online platforms become more popular for individuals with mental health needs to seek social support (J. Song & Xu, 2023; Yan & Tan, 2014), many such online platform users fail to find the appropriate level of care they need. For example, Figure 3-1 shows a post from a mental health online platform (Menal Health Subreddit) where a user is asking for help. While this user got replies with relevant informational support and emotional support (not shown in the figure), a

Figure 3-1: Screenshot of a Post from Mental Health Subreddit (Username Deidentified)

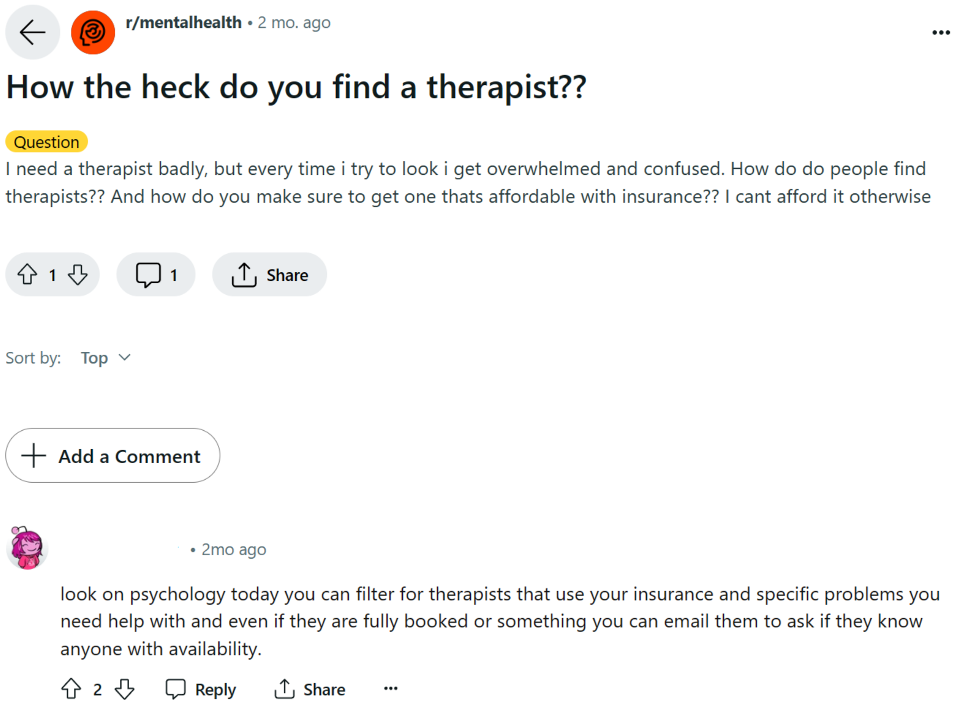


subsequent reply by the original poster (shown in the figure) reveals that this user should seek professional mental health services given the conditions they described. However, the current platform design does not have any escalation mechanism to refer this user to professional services, leading to delay in treatment or leaving the user untreated. In other words, online platform users like the one we show in Figure 3-1 represent a mental health population who already initiated the help-seeking process (i.e., seeking help in online platforms) but have not gotten professional care. This creates an opportunity to significantly improve the rate of mental health service usage if we can connect these unmet demands of mental health services with professional care services through novel technology.

To start designing such technologies, we first need to understand the goals of our intervention. Drawing from the theories (3A-framework and mental health help-seeking pathway) discussed in Section 3.4 , the proposed technology should have the capability to address the demand side challenges such as (i) the lack of awareness of available mental health services that are affordable and accessible; (ii) stigma associated with seeking help; (iii) gender, cultural, or other norms that prevent certain populations from seeking help. To convert such goals into a novel technological solution, we conduct a first round of interviews of several mental health professionals to brainstorm the necessary capabilities of our solutions and come up with a concrete plan for designing the system. We follow the purposive sampling method when selecting the interviewees (Patton, 2023). Our sample for the 1st round interview includes a combination of mental health practitioners (clinical psychologists), entrepreneurs (CTO of a large mental health clinic network), and scholars (university psychiatry professors).

During the early discussion, several professionals mentioned that there are already successful mental health demand and supply matching services or public directories of mental health providers, such as FastTracker MN and Psychology Today. These website-based services host provider information either at the national level (Psychology Today) or the state level (FastTracker MN for Minnesota). Providers such as mental health clinics or independent practitioners will post their information and real-time availability on those

Figure 3-2: A Post with Mentioning of Psychology Today



websites. Information includes the name, picture, license, expertise, contact information, the mode of care delivery (in-person or online), address, hourly rate, accepted insurance, experience treating certain sub-populations such as the LGBTQ+ community or certain race-ethnicities, among others. One professional noted, "You can simply tell the online platform users to use Psychology Today. They can search for available therapists near them who match their care needs". An example of this approach is shown in Figure 3-2. This existing intervention is particularly attractive if we assess it using the 3A-framework. Here, we list the filters which Psychology Today users can apply corresponding to each "A" (1) *Affordability*: accepted insurance and maximum hourly rate; (2) *Access*: immediate availability, zip code, the mode of care delivery, types of therapy; (3) *Awareness*: issues (i.e., conditions). In addition, as the professional noted, informing the online platform users of such demand-supply matching services is also promoting awareness. While leveraging existing technologies in this way may sound promising, a quick search of the keyword “Psychology Today” in the mental health Subreddit returns only a few posts that are months, if not years, old, suggesting that very few online platform users with unmet mental health needs got such suggestions and it is evident that most of such posts are specifically asking where to find therapists. Two practitioners who oversee the FastTracker MN program noted that while they make every effort to make sure the information about providers on their website is up to date, the traffic to the website and utilization rate are very low. Further discussion suggests the following reasons for the low utilization rate of such websites.

First, users must become aware of the websites and overcome any hesitancy towards seeking professional assistance. In other words, even when users of mental health online platforms are directed to explore resources like Psychology Today, a lack of willingness to pursue treatment can hinder their engagement, deterring them from even visiting the site. This scenario represents a "pull" model of service recommendation, where the default action for users is inaction (Halpern et al., 2007). It requires the individuals with unmet mental health needs to have the capability and motivation to actively seek out care options.

Furthermore, upon accessing such websites, individuals are required to filter providers based on criteria including issues, insurance coverage, gender, therapy types, and age group. Many, however, may only recognize their emotional states, such as feeling lonely or sad, without the ability to pinpoint a specific mental health condition like depression. The process of entering these specifics to find appropriate providers can be daunting and complex. Additionally, even after identifying a potential provider, the prospect of initiating contact through phone or email can be intimidating. Consequently, there's a critical need to enhance these service-matching platforms to simplify the process of connecting patients with the right providers and facilitating the initial step of reaching out to them. Here are some direct quotes from the professionals to support these arguments:

> *"Generally, people I see have limited resources and are looking for any guidance that they can find, any quick way to find help. They don't have capacity or motivation to do a lot of legwork, or even google searching."*

> *"There's a lot of [concerns] like: 'Well, how do I find the right person?' I think that's a huge barrier, many people say like 'I don't even want to start'."*

> *"Something that people are all often asking is like, 'Well, where do I find somebody to do that, how do I find the help, or how do I narrow it down to who would see me for eating disorders?"*

Given the challenges identified, we conclude that merely utilizing existing technologies, such as therapist search websites, falls short of the objectives outlined for this study. A critical step in bridging the service gap involves a deeper understanding of the demand aspect. When information on the supply side is publicly available, the intervention must concentrate on collecting precise data about the demand side to ensure more effective matching with available services. Furthermore, the effectiveness of the matching service itself is paramount in connecting patients with suitable providers. A superior matching service should be user-friendly and intuitive, offering clear and concise details about potential providers to empower patients with the information needed for informed decision-making. Additionally, integrating nudging strategies—subtle prompts based on behavioral economics principles that encourage decisions aligning with one's well-being—could significantly enhance the matching service. Such strategies, such as setting better default options, could assist patients in overcoming hurdles to seeking professional assistance, thereby streamlining the process of initiating contact with providers and engaging in mental health services.

These observations highlight limitations within the 3A-framework, which assumes that existing technologies like Psychology Today can comprehensively bridge the gap between unmet mental health needs and available resources by addressing issues of *availability, access, and awareness*. Later, we will explore how these insights informed the refinement of the 3A-framework in the context of designing our online mental health service referral platform.

We posit that an AI-enabled online mental health service referral platform is promising in achieving the capabilities that would help mental health patients quickly find the professional care they need. First of all, existing mental health online platforms greatly empower distressed individuals to share their concerns and seek help mainly through text-based communication such as posts. With the advancement of NLP techniques, user-generated text data can be leveraged to understand the patients better. Second, while mental health patients are generally reluctant to share their socio-demographic identities, doing so in an anonymous environment or with a virtual agent (such as chatbots) is more acceptable, making it possible to generate personalized recommendations to professional care which are more culturally competent. Finally, the AI-powered tool can be triggered immediately after the distressed individual posts mental health-related contents, providing timely responses to their mental health needs (thus shortening the help-seeking pathway) by giving personalized care recommendations (thus ensuring an appropriate direction of the pathway). This also facilitates a novel "push" model by setting the default option (Halpern et al., 2007) as following the referrals to acquire personalized recommendations unless the user chooses to opt out by quitting the referral platform.

3.5.2 *Designing the AI-enabled Online Mental Health Service Referral Platform*

The insights we generate from discussing the limitations of existing technologies have been instrumental in shaping design principles for online mental health platforms. Through the interview, we identify that, in order to timely connect mental health online platform users who have personalized support needs with matched professional services, the referral platform needs to be guided by the following design principles:

First, it should accurately **discern users' primary mental health concerns**. This requires the system's ability to analyze user-generated content across two dimensions: the core topic (or primary symptom) and the context (or underlying cause of such symptom). Specifically, for core topic categorization, we acknowledge the vast spectrum of potential mental health issues. Yet, prioritizing the most prevalent ones—such as depression, anxiety, eating disorders, substance use, and bipolar disorder—offers multiple benefits. Primarily, targeting a concise list of common mental health issues ensures we cater to the majority of users on platforms designed for individuals experiencing mild to moderate symptoms. Additionally, this approach simplifies the training process for a Natural Language Processing (NLP) classifier by reducing the number of categories, thereby requiring a smaller dataset of labeled data. This capability adequately addresses the *awareness* issue by becoming aware of users' core concerns. We provide several direct quotes from the interviews to support this first design principle:

> *"Patients present to the hospital for many different mental health issues, but there are a few more common ones like depression, anxiety, and suicidal ideas. Any [automated system] would want to clarify the main reason an individual is coming to the app to*

be able to ask more informed questions and make a better assessment of who's a good potential candidate for a referral."

"Many patients are shy to explain what's contributing to their mental health challenges. It's important to understand what they've already done to try and address their mental health problems and gauge openness to new approaches so that you can make informed recommendations about what might be possible next."

"Some of the core things we encounter in the hospital are depression, anxiety, gender and sexual identity, ethnic/racial identity, substance use, relationships, and addiction."

Second, the system must **proactively interact with users to gather health-related and socio-demographic data**. It should facilitate a structured conversation, guiding users smoothly through the information collection process. We provider several direct quotes from the interviews to guide the second design principle:

"Posing a question or a challenge can be helpful in motivating patients."

"If you can challenge a belief that is inhibiting progress, it can lead to conversation or thoughts about if those beliefs are true and working for the patient."

"People will have a really specific need. And the language identity piece matters. I think that people will have a specific thing that they're looking for, and that can be something that really limits [their ability to find services]"

"Try and help a patient bring their attention to the reasons that their mental health is inhibiting their life, if they are not able to remove themselves from their suffering and understand the impact, it will be difficult to get them to see anything they can impact to make their lives better."

"People with a lot of mental health challenges in general have a hard time doing a lot of that connection and in engagement with social people, and for them it's hard to call doctors. It's really scary."

Finally, it's crucial that the system provides **personalized mental health service recommendations**. Utilizing both the insights derived from user-generated content and the information collected during the chat, the system must be adept at scouring the internet to suggest mental health services tailored to the users' unique needs, such as online therapy programs, therapists, and clinics. For instance, an ideal therapist recommendation would account for proximity to the user or the availability of online services, ensuring the therapist's experience aligns with the user's socio-demographic profile and language preferences. This approach shifts from the conventional "pull" model, where users are tasked with actively searching for care options, to a "push" model. In this model, customized recommendations are directly delivered to users, significantly reducing search frictions and nudges users to pursue professional mental health services. The following are several direct quotes from the interview to support the third design principle:

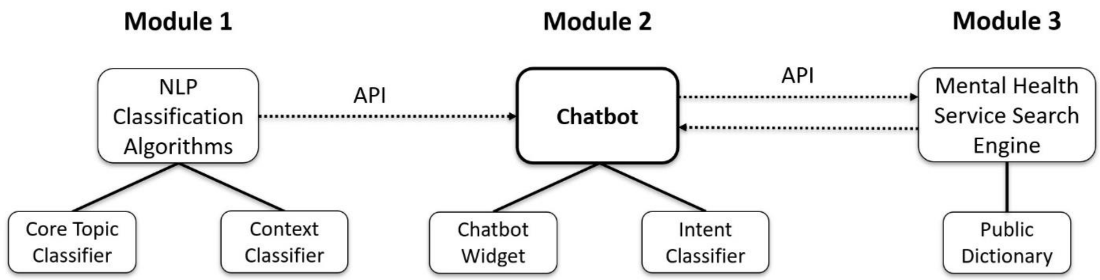
> *"I'm always looking for resources [for my clients], and how to help people find services that are specific to their needs."*
>
> *"Finance, race & racism, lack of providers, education & awareness, stigma, no time, not accepted by a person's culture or community, insurance won't cover it, paid sick leave, availability, access can be limited in many different realms and prevent patients from accessing care."*
>
> *"Justification, hesitation, defensiveness, avoidance, deflection, perseverating, their body language, how someone is orienting towards the person asking questions, engage vs. disengagement, emotions to match what's being discussed, all of these are important context clues when trying to evaluate someone."*

Based on these three capabilities identified through our interviews, we propose a mental health service referral platform prototype with the following three inter-connected modules: (i) the core topic and context classification module; (ii) the chatbot module, and (iii) the service recommender module. Figure 3-3 gives an overview of the prototype architecture. In this section, we introduce these three modules and compare the performances of different machine learning models in achieving the designed capabilities.

3.5.2.1 Classification Module

The classification module is designed to capture users' primary mental health concerns. This module serves as the foundation for the referral platform. The referral platform prototype assumes that users generate mental health-related text contents (i.e., user-generated-contents) in the online communities of the focal service referral platform. Such

Figure 3-3: Online Mental Health Service Referral Platform Architecture



text contents primarily include posts that users write in an online mental health platform (e.g., mental health mobile app) to seek or provide mental health social support such as informational support, emotional support, or companionship (Yan & Tan, 2014). Users share their mental health conditions (e.g., mood, feeling, or related physical conditions) and often describe the contexts of their mental health concerns (e.g., schooling, work, relationship, meaning of life etc.). Thus, the classification module of the referral platform should take these user-generated-contents as input and output the classification by way of: (i) the core topic (e.g., depression, anxiety); and (ii) the context around the core topic. Note that while we use core topic classifications such as *depression / anxiety*, we do not intend to conduct clinical diagnosis. The core topic classification is only indicating that a specific user post is likely to be related to a mental illness.

Since the input data for the classification module is text, we apply NLP techniques to develop this module. The module employs classic NLP models to conduct text classification. Such models include *logistic regression*, *naïve bayes*, *basic neural network*, and the *encoder model* of the *transformer model* family. In particular for the *transformer models*, there are two ways to fit such a model: (i) leverage LLMs in a *zero-shot* manner (i.e., without any fine-tuning); and (ii) use LLMs with transfer learning (i.e., fine-tune the LLMs with labeled data).

The data for this study is collected from a mental health mobile app, which consists of text-based user posts discussing their mental health experiences, concerns, and providing anonymous peer support to each other. Using the app's API, we collect a dataset of user posts while ensuring user privacy by anonymizing the data and removing any personally identifiable information. The data collection results in an input data of sample size 3,413. We further augment this input data with 620 random tweets as control data, resulting in a final sample of 4,033 text data points. The raw text data is cleaned to remove any irrelevant content, such as special characters, URLs, and excessive whitespace. We then apply techniques, such as tokenization, stemming, and stopword removal, to preprocess the text data. This step helps to improve the quality of the data for further analysis. We leverage a pre-trained GPT model, i.e., *GPT-3.5-turbo*, to conduct zero-shot classification on the user posts. Zero-shot classification involves using the model to predict the core mental health topic and context of each post without requiring any prior training on labeled data specific to the task. The tokenized text is fed into the GPT model along with a list of predefined core mental health topics, such as depression, anxiety, substance use, eating disorder, bipolar disorder, and its associated context, such as meaning of life, physical health, relationships, and work. The GPT model generates probability scores for each topic and context, indicating its confidence in the classification. The highest-scoring topic and context for each post are selected as the preliminary classifications.

To test the performance of the GPT model zero-shot classification and to further fine-tune the classification model, we hire two research assistants to label the user posts based on a coding manual (see Appendix G for the detailed manual). The manual provides guidelines on how to classify the posts into specific core mental health topics and contexts. The research assistants are trained using a small subset of the data to ensure consistency and reliability in their annotations. The research assistants independently label the dataset, assigning each user post a core mental health topic and context based on their judgment. The annotations made by the two research assistants are compared to measure inter-rater reliability using metrics like Cohen's Kappa. This helps to assess the consistency and agreement between the annotators. The human annotations are used as the ground truth to evaluate the performance of the GPT model's zero-shot classification.

This data collection and labeling process combines the power of large language models, such as GPT, with the expertise of human annotators to accurately classify user posts from a mental health mobile app into core mental health topics and contexts using human-in-the-loop machine learning or active learning. By cross validating the annotations and comparing them with the NLP classification, we can ensure the quality and reliability of the labeled data for further analysis and model development.

In addition to the zero-shot classification algorithm based on the GPT model, we further train other text classification algorithms in order to select the best model for the two classification tasks of our classification module. We use a 70:20:10 split of the labeled data into training, validation, and test sets. The training set is used to estimate the model parameters within a model class, the validation set is used to tune the hyperparameters, and the test set is used to test the model accuracy and select the overall best model from all model classes. To compare the performance of different models, we use several measures: accuracy, recall, precision, and F1 score.

In the first set of comparisons, we compare the performances of several basic NLP models - including *logistic regression, naïve bayes, basic neural networks* – and the two LLM models on a simple classification task to categorize whether a post is about *depression* or not. Table 3-1 presents the model details and performance.

Table 3-1: NLP Classification Model Comparison: "Depression" Classification Task

Model Class	**Model Name and Notes**	**Accuracy**	**Recall**	**Precision**	**F1**
		Core Topic: *Depression*	**Core Topic: *Depression***	**Core Topic: *Depression***	**Core Topic: *Depression***
Logistic Regression		0.5858	0.9940	0.5371	0.6973
Naïve Bayes		0.7649	0.8351	0.7199	0.7733
Basic Neural Networks		0.7067	0.9615	0.6369	0.7663
Transformer 1: LLM Zero-shot Classification	GPT-3.5-turbo	0.8138	0.6569	0.9152	0.7649
Transformer 2: LLM with fine-tuning	Hugging Face AutoTrain	0.9806	0.9687	0.9920	0.9802

Note: The *Depression* classification task predicts whether a post is relevant to *depression* or not

Table 3-1 indicates that *Transformer 2 (LLM with fine-tuning)* model has the best overall classification performance for the *depression* classification task with an accuracy of 98.06%, recall of 96.87%, precision of 99.20%, and F1 score of 98.02%. For other models, *Transformer 1 (LLM Zero-shot Classification)* has impressive performance with an accuracy of 81.38%, recall of 65.69%, precision of 91.52%, and F1 score of 76.49%. Compared to the transformer model with fine-tuning, the LLM Zero-shot Classification model seems to be conservative in predicting that a post is about depression, but when it gives such a prediction, it tends to be correct. This is different from the other three basic models. In particular, *logistic regression, naïve bayes,* and *basic neural networks* all have higher recall than precision, indicating these models tend to predict too many ones (that a post is related to depression).

In the second set of comparisons, we focus on the better-performing LLM models and perform a comprehensive comparison for the two target classification tasks: the core topic and context classification tasks. Specifically, we compare the performances of the following four models: (i) *Transformer 1: bart-large-mnli*, a model pre-trained for zero-shot classification with 407 million parameters; (ii) *Transformer 2: GPT-3.5-turbo* used for zero-shot classification with temperature = 0.2 (relatively low creativity). The GPT 3.5 model contains around 175 billion parameters; (iii) *Transformer 3: distilbert-base-uncased*, a pre-trained LLM with 67 million parameters fine-tuned with our input dataset; (iv) *Transformer 4: roberta-base*, a larger pre-trained LLM with 125 million parameters fined-tuned with our input dataset. The accuracy, macro average recall, weighted average precision, and weighted average F1 score of these four models for both the core topic and context classification tasks are reported in Table 3-2.

The results show that in general, as expected, the two fine-tuned LLMs outperform the two zero-shot classification models despite the two zero-shot classification LLMs have much more parameters. This is because the fine-tuned LLMs can leverage the human-labeled input data. However, the *GPT-3.5-turbo* model has a performance not much worse than the two LLMs with fine tuning (e.g., the accuracy of the *GPT-3.5-turbo* model is 0.67, while the accuracies for fine-tuned *distilbert-base-uncased* and *roberta-base* are 0.79 and 0.80). Within the two fine-tuned LLMs, the performances are similar to each other. Within the two zero-shot classification LLMs, the *GPT-3.5-turbo* model has better performance because it is a much larger language model than the *bart-large-mnli* model. These results confirm that: (i) the most recent LLMs such as the GPT models – with billions even trillions of parameters - have reasonably good zero-shot classification performances; (ii) with high

Table 3-2: NLP Classification Model Comparison

Model Class	Model Name and Notes	Accuracy		Recall (macro average[i])		Precision (weighted average)		F1 (weighted average)	
		Core Topic	Context	Core Topic	Context	Core Topic	Context	Core Topic	Context
Transformer 1: LLM Zero-shot Classification 1	bart-large-mnli	0.42	0.2	0.53	0.4	0.5	0.55	0.4	0.22
Transformer 2: LLM Zero-shot Classification 2	GPT-3.5-turbo (temperature = 0.2, low creativity)	0.67	0.56	0.73	0.58	0.71	0.67	0.68	0.55
Transformer 3: LLM with fine-tuning	distilbert-base-uncased (67M parameters)	0.79	0.70	0.68	0.40	0.78	0.69	0.78	0.69
Transformer 4: LLM with fine-tuning	roberta-base (125M parameters)	0.80	0.75	0.76	0.53	0.79	0.75	0.79	0.75

Note: (i) We use macro average for the recall measure because weighted average recall is by definition equal to accuracy; (ii) Core Topic classification task has 8 categories: *Anxiety, Bipolar disorder, Depression, Eating disorder, Substance use, Other, Positive, Not applicable*; (iii) Context classification task has 12 categories: *Emotional well-being, Gender identity, Meaning of life, Not feeling seen or heard, Physical health, Racial / ethnic identity, Relationships, Sexual orientation, Therapy, Work and/or school, Other, No context*; (iv) training sample size: 2823, validation sample size: 810, test sample size: 400

quality input data, some of the earlier and thus smaller LLMs such as *distilbert* or *roberta* can be fine-tuned to have good classification performances in the mental health context. Because the fine-tuned *distilbert-base-uncased* has fewer parameters (which result in faster training and classification) and also performs similarly to the larger fine-tuned *roberta-base* model, we implemented the fine-tuned *distilbert-base-uncased* model in the classification module of our mental health service referral platform prototype. The output of this module – the predicted core topic and context – will be fed into the chatbot module as input. Next, we discuss the chatbot module.

3.5.2.2 Chatbot Module

The chatbot module is at the center of the prototype. The chatbot is an AI-powered bot which facilitates text-based conversations with the users. It takes the classification module output as the starting point to customize the chat session with the user. The chatbot is designed to chat with the users and (i) collect additional user information; and (ii) present the customized service recommendations returned from the recommender module. Different from a general chatbot (e.g., ChatGPT) where users can feed any prompt to get a response, our chatbot has pre-defined tasks. For such bots, an interaction model with a set of questions is needed. To facilitate a conversation, the chatbot should also understand what the users type as the answers to certain questions, and thus an AI-powered intent classifier is also needed. *Intent* is the classification of user responses. For example, when users type "yes" or "sure", their intents are both "yes". Open source chatbot platforms such as the Cisco MindMeld provide solutions to train and run such intent classifiers.

To create an interaction model to prompt the users to provide more personal information, we conduct additional interviews with mental health professionals and practitioners. The final interaction model is presented in Appendix F. Question 1 asks the user to provide consent to use the referral platform. Questions 2-4 are customized using the output of the Classification Module and ask the users to confirm their core topic and context. Questions 5-7 are additional questions to ask users for consent and also a sense of empowerment by nudging the users to think "yes, I want to do something to change the current situation". Questions 8-15 collects voluntary socio-demographic information of the users as well as their preferences for a service provider. After the first 15 questions, the Chatbot Module will send the information collected through the chat session to the Service

Recommender Module, and finally, present the recommendations returned by the Service Recommender Module. At this stage, the user has several options to proceed. They can accept the recommendation and contact the service provider themselves. The app then tracks if they are clicking “call”, “email”, or “website” buttons to connect with a service provider. Finally, if the user still chooses to deny the recommendations, we ask for their reasons. Note that the Chatbot Module also educates the user about their mental health issues and offers emotional support while maintaining a non-judgmental and empathetic tone. All chatbot questions were reviewed by mental health professionals to ensure an appropriate tone and choice of words. Next, we discuss the Service Recommender Module.

3.5.2.3 Service Recommender Module

The final module is responsible for searching and recommending mental health services based on the user's personalized needs, as determined by the previous modules. The service recommender module leverages the most commonly used and publicly available free mental health service matching website PsychologyToday.com. Utilizing the classifications from the core topic and context Classification Module and the additional information from the Chatbot Module, the Service Recommender Module employs collaborative filtering or content-based recommendation techniques to identify the most suitable services for the user. The module considers the following factors when searching the public dictionary: (i) the primary mental health concern based on the core topic and context classifications; (ii) proximity based on the Zip code; (iii) affordability based on user’s insurance information; (iv) user’s preferred language; (v) user preference on the provider (e.g., gender, experience serving certain race/ethnicity, experience serving

LGBTQ+ community etc.). Once the recommendations are presented to the user through the Chatbot Module, the users are nudged to make an appointment via phone or website.

In summary, the mental health service referral platform prototype consists of three interconnected modules that work together to analyze user-generated content, engage with the user, and recommend personalized mental health services. This AI-powered system has the potential to revolutionize the way people find and access mental health support, making it more accessible, effective, and tailored to individual needs.

3.5.3 *Exploratory Evaluation of the Prototype*

To provide initial evaluations of our mental health service referral platform prototype, we follow the case study methodology and conduct a second round of interviews with 12 randomly recruited mental health professionals. Before the interviews, we make a live demo of the prototype by creating a hypothetical scenario where a distressed individual writes posts in a mental health mobile app and experiences the mental health service referral platform. In this scenario, the hypothetical user represents a type of users who only recently discover their mental health issues and sign up for the mental health mobile app. They are in need of mental health services but are not aware of any available resources (refer to Appendix H for a detailed description of the hypothetical scenario). We then conduct our second round of interviews with mental health professionals.

Before each interview, the participating professional is required to take a pre-interview survey to understand their background and their current status of client engagement, ideal client population, client screening, marketing, and their opinions around client/provider matching. During the interview, the hypothetical scenario is read, and a live demo of the prototype is shown followed by a semi-structured interviews with questions regarding whether they believe the proposed mental health service referral platform would increase the likelihood of a patient finding and subsequently accessing a better-matched provider. We also ask for their opinions on the limitations of the current system and their recommendations. The pre-interview survey and interview guide is presented in Appendix I.

All interviews lasted about an hour via video conference software and were recorded, automatically transcribed by the software, and assembled into manuscripts for the qualitative data analysis. Following the interviews, two researchers conducted post-interview discussions to summarize and cross-validate their observations derived from the interview transcripts. In this round of interviews, a total of 12 interviews were completed in 2023.

The qualitative data analysis was conducted by two researchers. Each researcher first read the interview transcripts and independently coded the participating mental health professionals' opinions around the effectiveness of our proposed mental health service referral platform in connecting individuals with mental health needs with professional mental health services. Subsequent discussions between the two researchers resolved any disagreements during the coding process. This resulted in the first-order coding of the exploratory evaluations of our proposed referral platform prototype. At this stage, relevant literature such as the mental health help-seeking pathways and supply-demand matching was incorporated to provide theoretical foundations to interpret the qualitative data. The research team then identified four themes from the first-order coding of the qualitative data and relevant literature streams.

3.5.3.1 Service Referral Platform and Mental Health Help-seeking

Enhancing mental health patients' help-seeking experience requires the mitigation of barriers that prevent them from accessing professional mental healthcare. The interviews confirm several such barriers documented in mental health literature. First, *insurance network enrollment* (i.e., the affordability of mental health services) and *provider availability* (i.e., awareness of available resources) are the most cited factors in determining mental health patients' access to professional services.

> *"I think probably the main search terms that are probably going to connect you with somebody who can see you is zip code and insurance."*

> *"The biggest barrier is insurance, and if they don't have insurance that matches who I'm credential with, they have to go to somebody else. People are not willing to not use insurance."*

> *"[What's the percentage of clients who pay with insurance] 100%."*

Second, there is a consensus that the mental health provider dictionary website Psychology Today is the primary tool used by independent providers to promote their services and get new clients. However, there is a big variation in the number of referrals from Psychology Today and from a patient's perspective, it can be overwhelming to use it because selecting a mental healthcare provider is complex. The fact that a mental health patient with little knowledge about mental illness has to select all the criteria such as their primary concern (e.g., "I have depression", "I have anxiety and eating disorder" etc.) before getting a recommendation is "almost unheard of for physical health conditions".

> *"Like on Psychology Today [...], it can be really, I think, overwhelming for clients when you choose all of the areas that you're [not] proficient in."*

> *"It's such a pressure cooker out there because people can't get in."*

> *"Most people I work with don't have the ability to find the right provider, sometimes I even struggle to find the right person when making a referral."*

Thus, our proposed mental health service referral platform has the potential to mitigate such barriers by streamlining and simplifying the process of mental health help-seeking. In particular, our referral platform made several critical changes: (i) our Classification Module leverages user-generated text data to predict the most possible mental health concern as well as its context of the distressed individual, thus sensing their mental health needs. This reduces the distressed individual's need to self-diagnose; (ii) our Chatbot Module collects information such as preferences for providers, insurance provider, and zip code which are necessary to conduct personalized service recommendation. This step has several potential benefits. First, by interacting with an AI agent instead of a real person, the distressed individual is easier to open up and share their information due to the reduced stigma in such an environment. Second, the questions asked in this step ensure the distressed individual that our AI agent understands their concern and learns their basic information. This alleviates the distressed individual's fear of lack of awareness of how to seek help; (iii) our Service Recommender Module generates an URL which contains personalized, available provider recommendations presented directly to the distress individual. This step greatly simplifies the process of finding a matched provider on Psychology Today. Taken together, our proposed mental health service referral platform is capable of navigating the distressed individual in the right direction and shortening the duration of the help-seeking pathway, increasing the likelihood that the distressed individual would access professional mental healthcare.

Therefore, within the 12 interviews, 50% of the mental health professionals agree that this proposed referral platform would help distressed individuals find matched mental health services and make the help-seeking process easier. For those who are neutral towards or disagree with the effectiveness of our service referral platform, they mainly have concerns in two aspects. First, guided by the mental health help-seeking pathway theory, we seek to shorten the pathway by collecting necessary information and directly recommend professional mental health services (in this case, mostly available therapists) to the distress individual. However, suggested in stepped care model, patients may not be ready to take traditional therapy right away (Bower & Gilbody, 2005).

> *"If this is the first time [that this distressed individual] reaching out and talking about this. And then, if you just met with the provider, what might happen on my end is. I might then follow up with someone who's just not ready for therapy."*

The practitioner then suggested, instead of always shortening the help-seeking pathway, the AI agent might need to be more intelligent by incorporating the stepped care model and start with providing some education around mental health, assess and build distress individuals' readiness for change, and finally suggest professional care.

> *"If we want to build readiness for change. The first thing might be like, okay, here's a blog that talks about developing any disorders [...] So then the person can cognitively read and hear themselves and recognize the not alone, and that maybe they are experiencing something. [... You need to] bring in education, normalization, and psych education, [...] It's great reaching out and normalizing that you're not alone, but maybe jumping into psycho [education] first soon as it gets, and then going to provider."*

The other most cited reason for disagreeing that our referral platform would help their potential clients access professional mental healthcare is that their target client base would be unlikely to start using this AI tool for mental health needs. This leads to our second theme which will be discussed below.

3.5.3.2 Target users of the service referral platform

Although our proposed AI-powered service referral platform has the potential to connect distressed individuals with professional mental health services, our interviews reveal that not all populations would benefit from such a technology. First, if the patients are already seeking professional mental healthcare (and thus already found care and can likely get further referrals from the current provider), they are less likely to use our referral platform.

> *"[My current client population] probably not likely [to use this technology], because they're already using resources to find a therapist as it is. So I don't know that they would use something like this just given my current client population. It could generate some new clients... My client population is now already empowered to use other search engines and to get to me rather than another layer."*

In addition, there is a consensus that the most likely users of our proposed referral platform are young adults with less family or friends available, already using digital tools extensively, and who are not aware of available mental health services.

> *"If [the user] is a sophisticated mental health services consumer, I don't think they are somebody who would follow through with it. But [if they are not sophisticated mental health service consumer], they would follow through with it."*

> *"Demographically, you're talking about mostly younger individuals. You're also talking about people who are social media types."*

> *"A little younger, a little bit more tech Savvy, doesn't really have anybody to turn to."*

> *"YouTube gaming culture individuals that really promote mental health access and like ... there are these spaces that already kind of exist."*

Therefore, the best platforms to deploy the proposed mental health service referral platform would be those existing mental health mobile apps or other online platforms where users are already seeking help but there lack escalation mechanisms to connect those users with professional help. One example of such platforms suggested in the interviews is online platform for women with maternity care needs. The interviewed professional told us:

> *"There are already tons of support groups online [for women with maternity care needs]. I think, and what I hear from a lot of those groups is that people have a hard time finding a provider, and that, you know infertility clinics, don't do a great job of giving resources. So people often turn to the Internet for that. So I could see that as being really helpful."*

However, the same provider also told us her other client base, namely the first responders, would be unlikely to use such tools because they are rarely found online. For those populations, providers have to create personal connections with them in an in-person setting, gain trust with them, and finally provide mental healthcare to them.

3.5.3.3 Service referral platform and underserved communities' access to mental health services

One of the goals of our proposed mental health service referral platform is to connect underserved communities with professional mental health services. Regarding this design goal, surprisingly, we first find that providers, in general, do not have incentives or the tools and capabilities to enhance underserved communities' access to professional mental healthcare even if all of them acknowledged that it was a significant issue in the mental healthcare delivery.

> *"Yeah, if you're like a practicing clinician, and your case load is full, and they're like showing up. And you're getting reimbursed for their visits, like you have no incentive to increase [underserved communities'] access because it's easier for you to just keep your existing clients."*

This observation confirms the value of our referral platform in reducing disparities in mental healthcare delivery against the underserved communities. Specifically, in our design of the prototype, there are several factors that can potentially help with such a goal: (i) the entire system is AI-powered and thus creating a stigma-reduced and psychologically safe environment for distressed individuals from the underserved communities; (ii) by collecting information around preferences for providers such as gender, sexual orientation served, race-ethnicity served, and languages, we make sure that the system can recommend a better matched and culturally competent provider to the distressed individual especially those from the underserved communities. Together with a recent study finding that underserved communities would use and benefit from digital tools like mental health mobile apps similarly to the better-served population (Tang et al., 2024), we are confident that our proposed mental health service referral platform can help connect distressed individuals from the underserved communities with professional mental health services.

> *"It might perhaps open doors that otherwise folks would not knock on."*
>
> *"The selecting of identities of provider is really interesting to think from like a psychodynamic perspective like I make sure not to disclose specific identities virtually [in the therapy space]. And it's interesting when these types of services ask me to identify specific identities, because not all of a sudden that's like in the therapy space."*
>
> *"Some individuals would really appreciate having somebody who understands their culture, or more similar to them, [but] difficult to do it, because of the supply and the demand issue."*
>
> *"When black men [don't] go to therapy, it's because they don't have people like them very often in it."*
>
> *"I really like that. You include that cultural component in multiple domains. So not only not only like ethnic racial identity, but also sexual orientation."*
>
> *"I think that something like this, that could be a resource for people [from the underserved communities], would allow them to seek services independently rather than relying on resources, such as their family or friends or other people."*
>
> *"The social component is important, reduce the stigma, not being ok is ok, feeling of community, knowing others are going is validating and normalizing might make people not accessing care more comfortable."*

However, for underserved communities, assuming they would have more needs for culturally competent providers and may have language preferences, there is a greater probability that the Service Recommender Module (which leverages the Psychology Today provider information) would return 0 recommendations due to too many restrictions about the providers. This is likely to negatively affect the users' willingness to explore further into available professional mental health services.

3.5.3.4 Patient-provider matching through the service referral platform

Finally, another theme identified through the interviews about our mental health service referral platform is patient-provider matching. We assume that with a better understanding of the demand (i.e., the core topic, context, provider preferences, insurance, zip code etc. of the patients), our referral platform can enhance the patient-provider matching. However, we receive mixed feedback from the mental health professionals, with about 1/3 of them agreed that this referral platform would increase their confidence in accepting patients, 1/3 of them were neutral, and 1/3 of them thought it wouldn't have an impact. In general, practitioners acknowledged that matching the mental health patients with a provider is hard and this is the main reason why all of the participating practitioners in our interviews conduct extensive screening of the patients before admitting them even if the patients are referred from a known source. One primary reason for such an extensive screening is to make sure that the patient falls into the core competency of the provider in terms of the disease type and also age (e.g., most practitioners are not competent in treating adolescents or younger kids). This is why some providers reject up to 40% of the referrals from Psychology Today.

> *"We're not able to do any other more refined matching in a way that I think would be helpful [without screening]."*

> *"Yeah, I definitely think that I would feel more confident, knowing that that was vetted in some way."*

One particular challenge that a practitioner mentioned during the interview is that while we have a reasonably good understanding of the patient through the proposed Classification Module and Chatbot Module, we still rely on the Psychology Today dictionary for information about providers. In reality, providers can claim that they are capable of treating certain diseases, have experience serving certain sexual or racial groups while they really are not. Thus, unless there is a way to assess the *"real skills"* instead of the *"claimed skills"* of the providers, we may still end up with sub-optimal matching between the patients and providers. This argument further confirms the importance of having a better understanding of both the supply and demand in order to make a better match.

> *"Usually, if you see people in psychology today [...], many clinicians are really casting a wide net, and [...] they will have [...] like 30 terms [to attract business]."*

Taken together, the four themes identified from the first-order coding of the interview transcripts confirm the overall value of our proposed mental health service referral platform in connecting individuals experiencing distress, especially those from underserved communities, with professional mental health services but also draw several boundary conditions where the referral platform may work better.

First, the mental health help-seeking pathway theory predicts that it is necessary to guide the individuals in distress in the right direction and also shorten the duration of the help-seeking pathway in order to connect them with professional mental health services. Our proposed mental health service referral platform achieves such goals through a clear path towards professional mental healthcare resources by: (i) analyzing existing user-generated text data using NLP classification models; (ii) collecting additional relevant socio-demographic information of the distressed individuals using a chatbot; and (iii) generating and presenting customized Psychology Today search results to the distressed individuals.

Second, our proposed mental health service referral platform does not suit any mental health patients and should have its target user base. In particular, such referral platform will help find customized mental health services for younger population with less family or friends available, already using digital tools extensively, and those who are not aware of available mental health services. Therefore, an ideal place to deploy this referral platform would be the existing mental health mobile apps or online communities which lack a clear function for users to find professional help when needed. Mental health patient-provider matching websites such as Psychology Today can also deploy such tool to simplify how the users can find matched providers.

Third, underserved communities are less likely to access professional mental health services mainly due to reasons such as higher stigma towards seeking mental health help, cultural norms which guide their help-seeking pathways into the wrong direction or longer duration (thus longer delay before getting professional help), and the lack of awareness of affordable and available mental healthcare resources. Our proposed mental health service referral platform can be particularly useful to help distressed individuals from the underserved communities since it provides a stigma-reduced AI-powered agent to guide them towards getting professional mental health services that match their personalized need and are affordable (i.e., accepting their insurance) and immediately available.

Finally, it is less certain whether our proposed mental health service referral platform would enhance the patient-provider matching so that the provider can rely less on screening to admit patients referred from our service. This is because mental health providers need to be certain that a specific patient's condition is within their competence. Although our service ensures a better understanding of the patient, we do not observe the *"real skill"* of the practitioners.

3.6 Refinement of the Theory

Through the design, development, and evaluation of our proposed intervention, we find that the existing 3A-framework (*affordability, access, awareness*) proposed by Sinha and Kohnke (2009) is not sufficient to guide the healthcare supply chain design which aims at bridging the gap between the unmet healthcare demand and supply in the situation where patients may exhibit unwillingness to seek professional care. In our context of mental healthcare delivery, a significant portion of unmet demand results from patients' hesitancy or resistance to professional mental health services due to various reasons such as self-stigma, social-stigma, cultural/gender/ethnic norms, among others. In such scenarios, patients stay untreated even if all 3As are met, i.e., they are aware of their mental health needs, can afford treatment, and have access to such treatment. This limitation of the 3A-framework also explains the phenomenon where mental health patients who seek help online often stay untreated despite that existing technology such as Psychology Today provides comprehensive information about care providers and search capabilities to facilitate matching between supply and demand of mental health services.

Through the design of our proposed AI-enabled mental health service referral platform, we find it essential to address patients' unwillingness to seek professional care. To achieve such goals, we complement the 3A-framework with a mental health-specific theory: mental health help-seeking pathway. With the guidance from the help-seeking pathway theory, we implement several design propositions to ensure that our technological solution can shorten patients' help-seeking process while maintaining the right direction of the pathways. For example, we design a chatbot which will automatically launch when users from mental health online platforms write posts about their mental health concerns.

By doing this, we effectively change the default option from inaction to action, which has proven to be highly effective in driving better healthcare help-seeking behavior (Halpern et al., 2007). In addition, in order to shorten the help-seeking pathway, the core function of the proposed referral platform is to "push" the matched care options to the online platform users instead of waiting for the patients to "pull" such information from internet by themselves. Lastly, by interacting with the users to gather their preferences for providers in terms of gender, sexual orientation, race-ethnicity, and language spoken, we increase the likelihood of finding a better match between the users with unmet mental health needs and care providers, ultimately increasing the users' willingness to follow the recommendations and initiate professional care.

To conclude, the additional design elements we propose in this study are primarily addressing patients' *acceptance* for health services. We argue that the new 4A-framwork—by adding the 4^{th} "A" (acceptance) to the existing framework—can better guide the design of healthcare supply chain which can bridge the unmet healthcare demand with the supply of effective treatments. Although this theory refinement is derived from our intervention designed in the context of mental healthcare, we believe that the 4A-framework can be generalized to other healthcare contexts. Many physical conditions, such as sexually transmitted infections (STIs), reproductive health issues, and various chronic conditions like diabetes, can trigger *acceptance* issues due to stigma, fear, inconvenience / longevity of treatment. In these broad healthcare contexts, the 4A-framework (affordability, access, awareness, acceptance) should be adopted to guide the supply chain design so that we can reach the historically "hard-to-reach" populations of such disease conditions, ultimately leading to a more effective and equitable healthcare delivery.

3.7 Conclusion and Discussion

In this essay, we propose an AI-enabled platform for one of the unique challenges facing mental healthcare delivery which has been existing for decades: "*The great majority of those who are most psychologically distressed receive no mental health treatment even when care is free*" (Rogler & Cortes, 1993). By reviewing several streams of literature on mental health delivery gap and disparities, online platforms for mental health, AI applications in mental healthcare, the 3A-framework, and mental health help-seeking pathway, we establish the theoretical foundation that guides the design of our proposed platform. Specifically, we aim to develop an AI-enabled online mental health service referral platform which senses the personalized mental health needs of distressed individuals (i.e., a combination of their core concern, context of problems, socio-demographic identities, and preferences for mental health providers) and also responds to those needs by recommending matched and immediately available providers to the distressed individuals. By doing so, we could guide them in the right direction and also shorten the duration of the help-seeking pathways which are both correlated with higher chances of accessing professional mental health services for distressed individuals.

With close collaboration with a selective sample of mental health professionals, we conduct our first round of interviews with mental health practitioners, entrepreneurs, and scholars to identify the issues in the current mental health help-seeking pathways and subsequently design a three-module online mental health service referral platform. Specifically, the platform consists of three interconnected modules: (i) the Classification Module which leverages state-of-the-art NLP models to classify distressed individual-generated text data to understand the core topic and context of their mental health concerns;

(ii) the Chatbot Module which takes the classification outputs of the Classification Module and further collects the system users' preferences for providers, insurance, zip code, and other information necessary to make personalized recommendations; (iii) the Service Recommender Module which uses all the information inferred and collected and generates a URL which provides personalized provider recommendations to the platform users.

To evaluate the effectiveness of our proposed online mental health service referral platform and also gain insights into the mental health help-seeking theories, we conduct our second round of interviews with 12 randomly selected mental health practitioners. The qualitative case data collected and summarized for this round of interviews result in four second-order themes around the effectiveness of our platform: (i) overall, the platform can increase the probability that a distressed individual accesses professional mental health services; however, (ii) the target users of the platform tend to be young adults with less family or friends available, already using digital tools extensively, and those who are not aware of available mental health services; and (iii) the platform has the potential to reduce disparities in access to professional mental healthcare among the underserved communities by providing distressed individuals from such communities with culturally competent provider recommendations.

We believe that this research contributes to several streams of literature. For the mental health help-seeking literature, our study shows that AI-enabled platform can be leveraged to create an effective escalation mechanism in online communities where some users may have needs for professional mental health services instead of relying solely on self-support or peer-support. The platform can help those users sense their escalation needs and introduce them immediately to available, affordable, and matched provider options.

The current model of mental health service referrals depends on primary care or service provider search websites like Psychology Today or Fast Tracker MN. However, this model relies too much on the proactivity of mental health patients themselves to either report their mental health-related concerns to the primary care doctors or seek help by searching for available mental healthcare providers. On the other hand, our platform automatically senses and responds to the personalized mental health needs of distressed individuals in online communities. For the literature on AI applications in mental healthcare, previous studies focused either on early identification of mental illnesses or suicide ideation, or automation and digitization of tasks in mental health treatments. This study fills in an important gap in this stream of literature by proposing an AI-enabled platform to connect distressed individuals with available professional mental health services, aiming at increasing the utilization rate of such professional services for people from all socio-demographic backgrounds, especially those from historically underserved communities. Finally, the iterative process of designing our AI-enabled mental health service referral platform also reveals the shortcomings of the existing theory (i.e., the 3A-framework) guiding healthcare supply chain design. We provide refinement to the 3A-framework (*affordability, access, awareness*) by adding the 4th A (*acceptance*). We believe that the new 4A-framework is more comprehensive in guiding healthcare supply chain design especially for disease conditions or treatments for such conditions that are associated with stigma and unwillingness to seek help by the patients.

Like most studies, this research is not without limitations. The fact that we received mixed evaluations in terms of the effectiveness of the proposed online mental health service referral platform opens up future research opportunities. First, since AI applications in connecting people with mental health needs with professional services have not been well studied, we take a case study methodology and provide initial evaluations of the proposed platform through qualitative case data analysis. To further incorporate the findings from the exploratory evaluations, future research should iterate the proposed AI-enabled platform and conduct field experiments to formally test the effectiveness of such platform in: (i) driving more people with mental health needs to access professional mental health services; (ii) identifying who and in what conditions such referral platform work the best; (iii) reducing disparities in access to professional mental health services among underserved communities. Second, with the launch of next generation LLMs such as ChatGPT, chatbot becomes more intelligent like never before and can facilitate human-like interactions, which makes it promising for applications in mental healthcare delivery. In particular, it is much easier to incorporate the stepped care model as suggested by one of the second-round interviews into ChatGPT type of LLMs compared to our pre-defined interaction model. However, ChatGPT also has the potential downside risk of producing harmful content that hurts users' menta health. Future research should compare the performances and risks of our proposed pre-defined interaction model versus ChatGPT type of chatbots in connecting people with professional mental health services. Third, as suggested by another second-round interviews, a better matching between mental health patients and providers can only be achieved if we have a better assessment of both the demand- and supply-side. Future research can consider applying NLP techniques to assess the "real skills" of mental health providers using structured and unstructured data collected from provider rating websites, and developing a matching algorithm to achieve better patient-provider matching that aims at reducing the need for screening when admitting patients by the providers. Moreover, the mental health help-seeking pathway theory suggests that starting to access professional mental health services is not the end of the pathway, rather it becomes part of the pathway (Rogler & Cortes, 1993). Thus, AI-enabled platforms have the potential not only for initiating access to professional mental health services for distressed individuals, but also for sustaining the treatment. Future research can expand on our proposed online mental health service referral platform and aim at developing an AI-enabled platform for the entire mental health help-seeking cycle. Finally, while our proposed platform is designed for users of online mental health services, our exploratory evaluation was conducted exclusively with mental healthcare providers. Consequently, this study does not capture patient perspectives on the platform's effectiveness and ease of use. To address this gap, future research should involve designing and conducting field experiments that include patient participants. These studies should focus on identifying which design principles of the referral platform lead to higher patient engagement and improved referral outcomes. By incorporating patient feedback, we can better understand user needs and refine the platform to enhance its overall efficacy and user experience.

Chapter 4: Telemental Health Service Uptake and Population Mental Health Outcome

4.1 Introduction

In recent years, the integration of digital technologies in healthcare supply chain has transformed the delivery of healthcare services, creating new pathways for treatment and patient management. Among these technologies, telemedicine has emerged as a pivotal solution, particularly in the realm of mental health care (Speedie et al., 2008; Suleiman, 2001). Telemedicine, defined as the use of telecommunications or videoconferencing technology to provide health services remotely (NIH, 2021), has become increasingly relevant due to the growing need to expand access to mental health services in a landscape where such resources are often scarce and unevenly distributed. The importance of telemedicine in mental health, termed *telemental health* (NIH, 2021), has become even more pronounced, driven by an increasing awareness of mental health issues and the need for accessible, timely, and cost-effective care (Barnett, Ray, et al., 2018; Hilty et al., 2013).

Telemental health services promise to bridge significant gaps in mental health care delivery, especially in underserved or rural areas where traditional mental health services are limited (Spivak et al., 2020). This alternative channel of delivering mental health services can also reduce the stigma associated with visiting a mental health clinic and offers the convenience of receiving care in a comfortable setting (Aboujaoude et al., 2015). Additionally, telemental health can facilitate timely interventions, which are critical for conditions such as depression, anxiety, and other mental health disorders (Shore et al., 2018). The convenience and flexibility of telehealth appointments also enhance patient adherence to treatment plans, potentially leading to better health outcomes (Schaffer et al., 2020; Talarico, 2021). Regarding clinical efficacy, telemental health has been proven effective in diagnosing and treating mental illnesses across individuals with different socio-demographic characteristics (Hilty et al., 2013).

Despite the significant upside potential, several challenges impede the widespread uptake of telemental health. Broadband access remains a significant barrier, particularly in rural areas where internet infrastructure is often inadequate. Furthermore, regulatory and reimbursement issues pose significant challenges. While some states have enacted telehealth parity laws mandating equal reimbursement for telehealth and in-person services, these policies are not uniformly adopted across the country (Dills, 2021). These disparities in policy create inconsistent access to and affordability of telemental health services (Zhang & Weng, 2024).

The existing literature on telemental health is rich with studies demonstrating its efficacy and benefits (Bulkes et al., 2022; Hilty et al., 2013; Schaffer et al., 2020; Shigekawa et al., 2018). Recently, literature has also started to understand the factors impacting the adoption of telemental health such as facility-level factors (e.g., veteran affiliation, information technology capacity, public ownership, quality improvement practices etc.) and state-level factors (e.g., parity laws, audio-only telehealth service reimbursement, interstate licensure compacts etc.) (Jacob et al., 2021; McBain et al., 2023; Zhao et al., 2019). However, due to data limitations, these studies only generated insights around the binary decision of telemental health adoption for healthcare facilities or patients. The nuances of how facility-level and state-level operational factors impact the uptake (i.e., the volume) of telemental health remain unstudied. Current literature also relied on crosssectional analyses and thus cannot identify the causal effects driving telemental health uptake (Barnett & Huskamp, 2020). Moreover, the long-term impact of telemental health uptake on mental health condition at the population level has not been thoroughly investigated. Addressing these gaps is crucial for developing strategies to promote telemental health and optimize its benefits.

To this end, this essay seeks to address two primary research questions:

(i) *What are the operational drivers of telemental health uptake?*

(ii) *How does telemental health uptake impact population mental health condition?*

These questions are crucial for understanding the barriers to and facilitators of telemental health, as well as for evaluating its effectiveness in improving mental health condition among diverse populations. To address these questions, our study explores two operational factors that can potentially influence the adoption of telemental health services—*technological infrastructure* and state-level *telehealth parity law*. Specifically, technological infrastructure refers to provider's access to broadband services, and telehealth parity encompasses both coverage parity (a telehealth service is covered by insurance if the corresponding in-person care is covered) and payment parity (equal reimbursement rate to physicians and equal patient co-pay between telehealth and in-person services). We focus on these factors due to extensive literature discussing their roles in expanding telemental health usage and equity (Dills, 2021; Picher et al., 2021). However, as far as we know, few studies have investigated how these factors interact to impact the actual telemental health uptake (i.e., the volume) and mental health condition at the population level.

To address these questions, we compiled a unique panel dataset from multiple sources, focusing on 3-digit Zip Code Tabulation Areas (ZCTAs) in the United States from 2016 to 2019. The data on telemental health service usage were obtained from FairHealth, a non-profit organization that maintains the largest database of private health insurance claims in the U.S. We supplemented this with mental health outcome data from the Centers for Disease Control and Prevention (CDC) and socio-demographic data from the U.S. Census and the American Community Survey (ACS). We collect state telehealth parity policies from state law data maintained by Justia (a firm providing longitudinal legal data) and restrict the study sample to states with both coverage parity and payment parity, and to states without any telehealth parity during our study period. The final sample of the data includes 226 ZCTAs in 19 states.

Our study leverages an exogenous policy shock—the 2018 increase in funding for the Rural Health Care Program (RHCP) by the Federal Communications Commission (FCC)—as a natural experiment to identify the causal effects of improving telehealth infrastructure. This policy change increased the annual RHCP funding cap from $400 million to $571 million, significantly impacting telehealth infrastructure in both rural and urban areas. However, since this policy change was simultaneously enacted nationwide in 2018, we do not observe treatment and control groups typically in difference-in-differences (DiD) settings, making it difficult to isolate the causal effects of this increase in RHCP funding from other confounding factors which potentially impact telemental health uptake. To address this challenge posed by a "global" intervention, we follow recent literature (Alpert et al., 2018; Parker et al., 2016; Yurukoglu et al., 2017) by exploiting variations in pre-intervention consumer broadband penetration across ZCTAs to construct low and high treatment groups. The guiding logic here is that pre-intervention consumer broadband access is a proxy for potential telehealth demand as high-speed internet access is a necessary condition for consuming telehealth services (Kobeissi & Hickey, 2023). ZCTAs with low pre-intervention exposure to consumer broadband are less likely to benefit from the RHCP funding increase than those with high exposure. We follow a DiD framework with artificially assigned low and high treatment groups based on pre-intervention consumer broadband penetration to estimate the causal effects of enhancing telehealth technological infrastructure on telemental health uptake. Upon establishing this causal effect, we adopt an instrumental variable design to assess the causal impact of telemental health uptake on population mental health condition by leveraging the RHCP funding increase as the instrument which has proven to drive telemental health uptake but does not directly impact population mental health condition[15]. We evaluate the impact of state telehealth parity policy by conducting sub-sample analyses and comparing results between parity and non-parity sub-samples.

We present two main findings. First, surprisingly, we do not find a causal effect of improving telehealth technological infrastructure on telemental health uptake when analyzing the full study sample. However, re-running the analysis within parity and non-parity sub-samples reveals that the lack of causal effect for the full sample is driven by ZCTAs within non-parity states. Specifically, technological infrastructure building positively impacts telemental health uptake only in ZCTAs within full parity states. This positive effect is equivalent to an additional increase of 848 telemental health visits for the

[15] RHCP provides funding to eligible healthcare providers to access broadband. Any impact of RHCP on population mental health outcome ought to be fully mediated by the provision of telemental health.

high treatment group compared to the low treatment group. We conclude that merely providing healthcare providers with broadband access without ensuring equal reimbursement rate to physicians and equal patient co-pay will not drive telemental health uptake at the population level.

Second, we find that telemental health uptake has a positive impact on population mental health condition. Similarly, this positive impact for the full sample is driven by the ZCTAs within the full parity states. For this sub-sample, 1 standard deviation increase in telemental health uptake (1074 visits) leads to 0.149% reduction in mental illness prevalence (714 people in an area with median population). This finding emphasizes the synergy between telehealth technological infrastructure building and parity. When these two operational factors are both in effect, they drive telemental health uptake, ultimately leading to better population mental health condition.

Taken together, by investigating the operational drivers and impacts of telemental health, this research makes the following contributions. First, it builds upon recent studies in healthcare operations management assessing the impacts of telehealth—as an alternative channel for delivering health services—on patient access to healthcare, health outcomes (Bavafa et al., 2018; Delana et al., 2023), and physician operations (Bavafa et al., 2018). Our study is unique as it primarily examines the antecedents determining the telehealth uptake (i.e., the volume of telemental health visits), which are often overlooked in current healthcare operations literature. We find that the two operational drivers—*telehealth technological infrastructure* and *telehealth parity*—must work together to drive telemental health uptake and ultimately improve population mental health condition. Second, this study contributes to the telemental health literature documenting the effectiveness of this digital technology-enabled mental healthcare delivery channel (Hilty et al., 2013). While telemental health is proven capable of providing comparable treatment efficacy across many mental health conditions, there is no guarantee that providers and patients will adopt this service or that the realized care quality through telehealth is comparable to in-person care. Without telehealth coverage and payment parity, improving access to technological infrastructure does not lead to telemental health uptake or better population mental health condition. This finding is significant for policymakers and lawmakers seeking to boost telehealth usage for better patient access to health services. Different stakeholders, including the Federal Communications Commission, insurance companies, and state legislators, should collaborate to provide access to telehealth technology and ensure its affordability through comprehensive parity laws.

4.2 Literature Review and Background

4.2.1 *Mental Health: Service Delivery Gaps and Disparities*

From 1999 to 2017, the Center for Disease Control and Prevention reported that suicides increased 33% (Barnett & Huskamp, 2020). As the demand for mental health grows, the behavioral health workforce supply has faced supply and distribution challenges (National Center for Health Workforce Analysis, 2023). In 2018, it was estimated that nearly 115 million Americans lived in areas that were considered to be mental health professional shortage areas. More alarmingly, nearly 25% of adults with mental illness reported that they had an unmet need for mental health treatment (Kaiser Family Foundation, 2024).

While this shortage of providers remains problematic, telehealth, specifically, telemental health, has been touted as a way to close the gap in coverage for mental health conditions. The rapid rise in telehealth usage underscores its promise in enhancing accessibility to mental health services, specifically in provider shortage areas (Barnett, Ray, et al., 2018). However, there are barriers that remain in terms of telehealth accessibility, most notably broadband internet access. In addition, there are questions as to whether telehealth can provide comparable care to in-person visits. Given the complexity of the problem, we explore the multifaceted nature of telehealth delivery.

4.2.2 *Telehealth and Mental Health*

Telehealth has emerged as a promising solution to address the delivery gap in mental health service provision. Notable advancements in telehealth, especially with direct-to-consumer options, have helped telehealth emerge as a promising solution to address the current mental health service delivery shortage (Barnett, Ray, et al., 2018). The convenience and accessibility of telemental health can potentially reduce the barriers related to the provision of mental health care. Of note, telehealth is particularly well suited for mental health diagnosis given the initial interviews with patients do not require a physical examination (Barnett & Huskamp, 2020). Additionally, recent research suggests that telehealth can provide comparable outcomes to in-person consultations under certain circumstances (Armstrong et al., 2015, 2018; Boothe et al., 2022). Given the improved accessibility to care, telemental health provides a promising solution to address the current challenges related to mental health delivery.

In addition to improved accessibility, telehealth also provides an avenue to improve access to the type of care available. For example, telehealth may allow individuals in rural areas to more easily access specialists dealing with behavioral health treatment (Office of the Assistant Secretary for Planning and Evaluation, 2017). In addition, telehealth also allows individuals in smaller communities to overcome the stigma and lack of privacy related to seeking treatment in smaller communities (Office of the Assistant Secretary for Planning and Evaluation, 2017). However, challenges remain in the delivery of telehealth to bridge the increasing need for access to mental healthcare.

While the technology related to direct-to-consumer telehealth has improved, the underlying structural factors continue to hinder access and uptake of telehealth. Most recently, the Substance Abuse and Mental Health Services Administration (SAMHSA) noted that internet access was becoming a "super determinant" of health (Turcios, 2023). The digital divide as it pertains to broadband may restrict the ways individuals receive healthcare services, especially as it pertains to telehealth services. In addition, broadband quality for both patients and providers often impacts the willingness of individuals to participate in the uptake of telehealth services (Dorsey & Topol, 2016; O'Shea et al., 2022). Therefore, it is important to understand the policy environment enabling the delivery of telehealth.

4.2.3 *Telehealth Technological Infrastructure*

The effectiveness of telemental health is heavily dependent on the underlying technological infrastructure, specifically broadband internet access. However, uneven broadband penetration, often referred to as the digital divide, poses a significant barrier to the adoption of telehealth services. Broadband access is critical to the delivery of high-quality telehealth services, which impacts both providers' and patients' abilities to engage in effective virtual consultations (O'Shea et al., 2022; Turcios, 2023). Understanding the importance of broadband in the adoption of telehealth, the United States federal government has pursued policies that would improve the availability of broadband internet in an effort to close the digital divide.

Established in 1997, the Rural Health Care Program (RHCP) provides funding to eligible healthcare providers for telecommunications and broadband services necessary for the provision of healthcare. Over the years, this program has evolved with two distinct components: the Healthcare Connect Fund and the Telecommunications Program. The Telecommunications Program, which was established in 1997, was used to subsidize the difference between urban and rural rates for telecommunications services (Federal Communications Commission, 2024). The Healthcare Connect Fund Program was established 2012 with the aim of providing high-capacity broadband to eligible healthcare providers in an effort to improve connectivity, which could be used for the transmission of patient data or telehealth services (Federal Communications Commission, 2024).

Notably, as the perception of what constitutes telehealth evolves, e.g., over the phone versus synchronous video chat, the demands for telehealth delivery increase. However, the perception of modern telehealth delivery revolves around a synchronous or asynchronous format utilizing both video and audio data transmission. In addition, while the Rural Health Care Program suggests coverage is limited to rural areas, the reality is that the eligibility requirements allow providers in non-rural areas to get RHCP funding under certain conditions. In some cases, post-secondary educational institutions, teaching hospitals, medical schools, community health centers, and local health agencies can also receive funding to deliver telehealth services.

4.2.4 *Telehealth Parity*

While broadband infrastructure plays an important role in the delivery of telehealth, the legal environment governing coverage of telehealth services and payment for telehealth services plays an important role in the uptake and delivery of telehealth. Parity laws surrounding coverage parity and payment are important to ensure that physicians are incentivized to deliver telehealth services and that patients can receive services either in person or via telehealth channels. There are two types of parity as it pertains to telehealth: coverage parity and payment parity. Coverage parity requires insurance to cover services whether they are delivered via telehealth or in-person (Dills, 2021). Payment parity ensures that providers are reimbursed equally for telehealth services and in-person services when delivering the same treatment (Dills, 2021). Without parity, the incentives for providers to offer telehealth services are limited, which can hinder the benefits related to telehealth infrastructure investments, such as broadband (Younts, 2019). Therefore, it is important to understand how parity laws interact with infrastructure investments to drive telemental health adoption and ultimately population mental health condition.

4.3 Theoretical Framework

4.3.1 *Technological Infrastructure and Telemental Health Usage*

Telehealth, specifically telemental health, has often been touted as a solution to address the gaps in mental health service delivery; however, telehealth adoption is ultimately dependent on the availability of adequate technological infrastructure, in particular broadband internet. Broadband access is a critical component in the delivery of telehealth services as it directly impacts the ability of patients and providers to conduct effective virtual consultations (Kobeissi & Hickey, 2023; Turcios, 2023). However, the digital divide, which is characterized by disparities in broadband penetration, continues to hinder the widespread adoption of telehealth.

The digital divide has remained a hindrance for many individuals who may have previously been interested in pursuing treatment via telehealth (Adetosoye et al., 2023). This problem is particularly apparent in in rural and underserved areas where broadband infrastructure is either inadequate or nonexistent (Adetosoye et al., 2023). Given that broadband is considered a social determinant of health, the impact of reliable high speed internet access will likely determine the ability and efficacy of telehealth treatment (Adetosoye et al., 2023; Turcios, 2023). As studies have shown, areas with better broadband infrastructure experience higher rates of telehealth adoption and utilization (American Telemedicine Association 2020). Therefore, it is important to understand the relationship between broadband availability and telehealth usage. By examining the broadband uptake of both patients and providers, we can improve our understanding of the structural characteristics related to telemental health uptake. This leads to our first hypothesis:

> **Hypothesis 1 (H1)**: *Improving technological infrastructure of telehealth leads to higher telemental health uptake.*

4.3.2 *The Role of Parity and Telemental Health Adoption*

While technological infrastructure is important for telehealth adoption, the policy environment surrounding telehealth uptake can play a significant role. Policies surrounding parity related to telehealth improve access to telehealth services while reducing financial barriers for providers and patients. In this case, there are two distinct types of parity laws:

coverage parity and payment parity. Under coverage parity, insurers are required to cover telehealth services if the corresponding in-person service is covered (Dills, 2021). Payment parity ensures that insurers reimburse physicians at an equal rate for telehealth and in-person services (Dills, 2021).

Without parity, the incentives for physicians to provide telehealth services over in-person services may be limited. Notably, in 2017, the law firm Foley & Lardner conducted a study related to the barriers hindering telehealth adoption (Younts, 2019). Nearly 60% of the healthcare providers interviewed noted that lack of third-party reimbursement was a challenge to implementing telehealth within their respective organizations (Younts, 2019). By ensuring equitably reimbursement and equal coverage of conditions via telehealth, parity laws augment the impact of technological infrastructure by encouraging telemental health adoption. Therefore, we hypothesize that a combination of parity and broadband availability ultimately drives the uptake of telemental health services.

> **Hypothesis 2 (H2)**: *Telehealth parity strengthens the positive relationship between technological infrastructure and telemental health uptake.*

4.3.3 *Telemental Health Usage and Population Mental Health Condition*

With telehealth providing improved access to mental health treatment, it is expected that population mental health condition will improve given the new availability of treatment. Telemental health can minimize the travel time, avoid stigma, and reduce wait times for mental health services, ultimately improving timely access to care (Armstrong et al., 2015; Hilty et al., 2013) However, the extent to which increased usage results in better mental health condition requires additional investigation.

To better understand how usage impacts outcomes with telemental health, we explore the relationship between the number of reported visits and perceived poor mental health days. This allows us to observe how the increased access to telehealth services impacts mental health condition at a population level. We expect that increased uptake of telemental health services will result in improved population mental health condition.

> **Hypothesis 3 (H3)**: *Higher telemental health uptake leads to better population mental health condition.*

4.3.4 ***Telehealth Parity and Mental Health Outcomes***

Parity is not only important to the adoption of telehealth services, but it also has the potential to enhance the impact of the services delivered on mental health condition. By ensuring that conditions are equally covered and physicians are reimbursed at a comparable rate to in-person visits, parity laws can ensure more consistent use of telemental health services. With increased uptake of telemental health services, population mental health condition is expected to improve. Most recently, the American Medical Association advocated for parity to ensure that physicians would continue to provide telehealth services after the pandemic (American Medical Association, 2023). Without parity, telehealth services may not be accessible to patients and not financially viable for providers. With parity laws in place, it is expected that patients would adhere better to treatment plans and receive more consistent care from their providers. Therefore, we seek to understand how parity impacts population mental health condition specifically through the provision of telehealth.

> **Hypothesis 4 (H4)**: *Telehealth parity strengthens the positive relationship between telemental health uptake and population mental health condition.*

4.4 Research Design

4.4.1 *Data*

In this essay, we seek to investigate whether improving telehealth technological infrastructure drives telemental health service uptake and whether such uptake improves population mental health condition. We are also interested in exploring whether telehealth parity policy has any moderating effects on those relationships. To test our hypotheses, we assemble a unique panel dataset from various sources to identify such causal effects. Our study is situated in the U.S., and the unit of analysis is 3-digit Zip Code Tabulation Area (ZCTA) by year. The adoption of 3-digit ZCTA in our analysis is consistent with recent public health studies on social determinants of care (e.g., Boyd et al,. (2023) and Jacob et al. (2021)) to ensure that our data are compliant with the Health Insurance Portability and Accountability Act (HIPAA). Specifically, to protect patient privacy as ruled by HIPAA, the most granular data on telehealth usage available to us is at the 3-digit ZCTA level—a level that HIPAA describes as low distinguishability while 5-digit Zip Code level suffers from high distinguishability (HIPAA, 2012, Table 1 on p.14).

First, we use proprietary data from FairHealth to collect information on the usage of telemental health services. FairHealth is an independent non-profit organization which maintains U.S.'s largest database of private health insurance claims. The original data recorded the total number of visits (in-person or telehealth) within a 3-digit ZCTA for each disease condition (including both physical and mental health conditions) in a given year. We leverage the provider specialty variable provided by FairHealth to identify data related to mental health conditions. Specifically, we retain the rows with the following specialties: *Psychiatric Nurse, Addiction Medicine, Psychology, Psychiatry, Pediatric – Psychiatry,* *and Psychiatry – Geriatric*. The top 10 disease conditions in terms of the volume of visits identified through this step are: *Major Depressive Disorder*, *Other Anxiety Disorders, Reaction to Severe Stress and Adjustment Disorders, Bipolar Disorder, Depressive Episode*, *Attention-Deficit Hyperactivity Disorders, Persistent Mood Affective Disorders, Alcohol Related Disorders*, and *Obsessive-Compulsive Disorder*, providing face validity for our filtering strategy. We then aggregate this subset of data related to mental health conditions by summing up the number of telehealth visits, the number of in-person visits, the number of telehealth providers, and the number of in-person care providers across all the disease conditions for a 3-digit ZCTA in a given year. The data spans from 2016 to 2019. We choose to focus on the data periods before COVID-19 to avoid any confounding factors due to the lockdown policies and relaxation of telehealth provision restrictions which could impact telemental health uptake and quality.

In addition, we further restrict our data to two groups of states regarding their telehealth parity laws: *full parity* (both coverage parity and payment parity), and *non-parity*. Coverage parity ensures that if telehealth is provided for a disease condition and the in-person care for this condition is covered by insurance, the telehealth service is also covered by insurance. Payment parity further requires that the reimbursement to the physicians and patient co-pay for a disease condition are the same for in-person care and telehealth (Dills, 2021). The full-parity states are those instituting both coverage parity and payment parity whereas the non-parity states have passed neither one of the two parity laws. Thus, the affordability of telehealth is higher in the full-parity states than the non-parity states. We exclude those states which only institute the coverage parity but not the payment parity to create a clear contrast between the two groups of states regarding the affordability of telehealth, enabling us to compare the telemental health uptake as well as the effect of such uptake on mental healthcare quality between the states with higher affordability and those with lower affordability—a key operational lever for healthcare service delivery (Sinha & Kohnke, 2009). This results in the inclusion of 226 ZCTAs of 8 full-parity states (Arizona, Arkansas, California, Colorado, Delaware, Georgia, Hawaii, and Virginia) and 11 non-parity states (Alabama, Florida, Iowa, Idaho, Massachusetts, North Carolina, Ohio, Pennsylvania, South Carolina, Wisconsin, and Wyoming) in our sample. Therefore, our study sample consists of 226 ZCTAs $\times$ 4 years = 904 observations. We collect the state-level parity law information from Justia (https://www.justia.com/). Justia is a firm maintaining and providing access to longitudinal legal data. Appendix J documents the state-level parity legislation details.

Next, we leverage the 500 Cities Project data (Centers for Disease Control and Prevention, 2023) from U.S. Centers for Disease Control and Prevention (CDC) to collect information on the mental healthcare outcome of each ZCTA in a given year. This dataset contains a mental health-related indicator at the census tract level in a given year which measures the prevalence of mental illnesses. We leverage ArcGIS (a geographic information system) to map the mental health indicator onto each 3-digit ZCTA for a specific year by assigning each census tract to its closest ZCTA by distance.

Finally, we supplement our panel data with socio-demographic variables for each ZCTA-year collected from sources such as U.S. Census and American Community Survey (ACS). Next, we introduce the exogenous shock we leverage to identify the causal relationships of interest.

4.4.2 *Exogenous Shock and Empirical Strategy*

To help build the technological infrastructure for the provision of telehealth, Rural Health Care Program (RHCP) was established in 1997 by the U.S. Federal Communications Commission (FCC) to "provide funding to eligible health care providers for telecommunications and broadband services" (Federal Communications Commission, 2024). Although with the word "rural" in the program name, RHCP targets not only rural health clinics, but also other eligible non-profit or public healthcare providers such as teaching hospitals and community mental health centers which may be located in urban areas. The annual RHCP funding was capped at $400 million when FCC established the program and stayed unchanged until 2018. Due to insufficient funding in the years 2016 and 2017, FCC was forced to prorate the funding provided to eligible healthcare providers at the rate of 92.5% for 2016 and 84.4% for 2017. In light of this situation, on June 25, 2018, FCC released the RHCP Funding Cap Order which effectively increased the RHCP funding cap to $571 million, ensuring that eligible healthcare providers could continue to keep or improve their telehealth technological infrastructure by receiving the full requested RHCP funding (Federal Communications Commission, 2018). We leverage this exogenous shock to identify the causal effects of technological infrastructure on telemental health uptake and the causal effects of the telemental health uptake on mental health condition.

Note that the RHCP Funding Cap Order applied to the entire nation starting from 2018. Therefore, the 19 states included in our sample all belong to the treatment group of this exogenous shock, disabling us to conduct a normal difference-in-differences (DiD) estimation to recover the causal effect of the RHCP Funding Cap Order. In recent literature, researchers have implemented several methodologies to recover the causal effect of such exogenous shock where control group is missing. The main idea is to construct an "exposure" measure where the exogenous shock may have different levels of impacts on different treatment sub-groups (Parker et al., 2016) or the causal effect of the exogenous shock is a linear function of a continuous exposure measure (Alpert et al., 2018; Yurukoglu et al., 2017). We follow this trend and use the consumer broadband penetration of a ZCTA in 2017 (right before the exogenous shock) as the exposure measure. We argue that if the consumer broadband penetration (a demand-side measure) is close to 0 for a ZCTA, the shock of an increase in RHCP funding—which reflects a supply-side effort to build telehealth infrastructure—should have lower effect compared to those ZCTA which has higher consumer broadband penetration. The intuition is that a provider-side operations improvement (RHCP funding increase) can only have effects on transactions (telemental health uptake) when there is demand (consumer broadband, a necessary condition for telehealth visits if the patient does not have wireless coverage).

Guided by this empirical strategy, we introduce our study variables and their operationalization.

4.4.3 *Variable Definitions and Measurements*

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

4.4.3.1 Outcome Variables

Total Telemental Health Uptake is defined as the total number of telemental health visits within the *i*-th ZCTA in year *t*. This variable captures the volume of telemental health visits across all mental health conditions in a given area-year.

Mental Illness Prevalence reflects the overall prevalence of mental illnesses among population within the *i*-th ZCTA in year *t*. It is CDC's estimate for the percentage of adult population who report "mental health not good for ≥ 14 days". The raw data is at the census tract level, and we use ArcGIS to determine the assignment of a census tract to a 3-digit ZCTA based on distance.

4.4.3.2 Independent Variables and Treatment Exposure

Post is "post" variable for our DiD design. Since the RHCP Funding Cap Order is effective in 2018, *Post* is coded as 0 in 2016 and 2017, and it is coded as 1 in 2018 and 2019 for all ZCTAs.

Exposure to Consumer Broadband is the treatment exposure measure which we construct to identify the heterogeneous treatment effects. It captures the percentage of fiber coverage within the *i*-th ZCTA in 2017 which is right before the exogenous shock. Fiber optic cable represents a future proof technology that is only limited by the speed of light and the decoding of signals. In addition, fiber provides symmetrical upload and download speeds unlike the asymmetrical speeds observed in other broadband technologies. In the past, it has been noted that poor quality connections can often times be the dealbreaker for telehealth services. Even recently, the American Medical Informatics Association (AMIA) noted that broadband should be classified as a social determinant of health given its importance to healthcare outcomes (O'Dowd, 2018). Following the literature with similar DiD design (Parker et al., 2016), we operationalize the exposure variable as a dummy variable differentiating the low and high treatment exposure groups. We code the variable as 0 if the *i*-th ZCTA has consumer fiber penetration smaller than 1% in 2017 and 1 otherwise. We choose 1% as the threshold to construct the low and high treatment group because it ensures that there is a large enough low treatment exposure group while maintaining an extremely low fiber penetration. In this case, 37 out of the 226 ZCTAs (16.2%) in our sample belong to the low treatment group. Within these 37 ZCTAs, a majority of them have relatively low number of telemental health visits in 2017 as expected due to the lack of telehealth technological infrastructure on the demand side. To provide face validity for our artificial assignment of low and high treatment groups using 1% fiber penetration as the cutoff, we statistically compare the telemental health visit volume between the low and high treatment groups. We find that the average number of telemental health visits is 122.3 for the low treatment group and 241.9 for the high treatment group. A two-sample t test confirms that the low treatment group has a statistically significantly lower number of telemental health visits in 2017 compared to the high treatment group ($p < 0.001$). Similarly, the high (low) treatment group has an average of 185.2% (147.1%) increase in RHCP funding in 2017 from 2016, and an average of 54.04% (40.83%) increase in 2018 from 2017[16], demonstrating that the high treatment group benefits more from the RHCP Funding Cap Order than the low treatment group. Later, we run several robustness tests where we use different cutoffs (e.g., median fiber penetration). We find that our research findings stay qualitatively the same.

4.4.3.3 Control Variables

Demographic Control Variables: In order to control for the socioeconomic characteristics for each 3-digit ZCTA, we utilize the American Community Survey (ACS) 5-year

[16] The actual sudden increase of RHCP funding is first seen in the final report of RHCP funding for year 2017 because the RHCP Funding Cap Order passed in 2018 was applied retrospectively to year 2017. However, the hospitals, clinics, and community healthcare providers received the additional funding in 2018.

estimates. Our ACS data focuses specifically on the demographic characteristics of the privately insured population. These controls include age groups (*Age: Under 18, Age: 18 to 24, Age: 25 to 34, Age: 35 to 44, Age: 45 to 54, Age: 55 to 64*), racial composition (*Black, Native, Asian, Other*), unemployment, individuals with private insurance that have a high school education or equivalent, married population, separated or divorced population, and average household income.

In addition to general population characteristics, we also elect to control for the type of private insurance individuals have. In our study, the variable Employer Insurance accounts for individuals with private insurance that is provided by a person's respective employer. For those buying insurance through a health insurance exchange, we denote these individuals as having Direct Purchase Insurance.

Additional Control Variables: To establish a baseline for healthcare utilization and care availability, we control for a series of usage and provider measures. To account for general population characteristics for healthcare uptake, we utilize the Checkup measures outlined by the Center for Disease Control's Behavioral Risk Factor Surveillance Survey. Checkup Crude Prevalence refers to the number of adults (Individual 18 or Older) who reported visiting the doctor for a checkup within the past year. We include this variable to control for an individual's awareness of their mental health conditions and available treatment options—a factor which impacts healthcare utilization (Kohnke et al., 2017; Sinha & Kohnke, 2009).

To address supply and demand patterns in our sample of ZCTAs, we utilize the FairHealth data set to account for the provider availability and patient utilization. The variable Total Number of Visits accounts for the overall volume of psychiatric visits within a given ZCTA3. To account for the supply of physicians and the services provided, we control for providers providing synchronous care and providers providing in-person care.

The summary statistics for all study variables are shown in Table 4-1.

Table 4-1: Summary Statistics

	Mean	SD	Min	Max
Dependent and Independent Variables				
Total Telemental Health Uptake	314.29	769.77	0.00	9318.00
Exposure to Consumer Broadband	0.84	0.37	0.00	1.00
Mental Illness Prevalence	12.60	2.23	7.40	22.00
Demographic Controls				
Total Visits	43341.11	68540.13	948.00	574414.00
Asian %	0.05	0.07	0.00	0.35
Black %	0.11	0.12	0.00	0.53
Native %	0.01	0.03	0.00	0.36
Other %	0.04	0.05	0.00	0.34
% Married	0.38	0.05	0.21	0.48
% Separated/Divorced	0.10	0.02	0.06	0.16
% Widowed	0.05	0.01	0.02	0.09
Age: Under 18 %	0.22	0.03	0.13	0.30
Age: 18 to 24 %	0.10	0.03	0.06	0.26
Age: 25 to 34 %	0.13	0.03	0.08	0.27
Age: 35 to 44 %	0.13	0.01	0.09	0.16
Age: 45 to 54 %	0.13	0.01	0.10	0.17
Age: 55 to 64 %	0.13	0.02	0.09	0.18
Education: Greater Than High School %	0.51	0.04	0.40	0.68
% Part Time	0.12	0.02	0.07	0.24
% of Full Time	0.32	0.04	0.22	0.47
Synchronous Providers	20.08	75.08	0.00	969.00
In Person Providers	1384.14	1786.71	44.00	18332.00
Direct Purchase Insurance	72234.08	59549.36	7426.00	346121.00
Employer Based Insurance	284345.46	232083.99	15368.00	1601331.0
Prevalence: Routine Checkup Past Year	70.84	5.15	55.26	82.81
Observations	904			

4.5 Empirical Analysis

In this section, we introduce our econometric model specification and present the estimation results.

4.5.1 ***Model Specifications***

Following the discussion of empirical strategy in Section 4.4.2 , we specify our econometric model for testing H1 following a DiD design with heterogeneous treatment effects which allows us to recover the causal effect of improving telehealth technological infrastructure on telemental health uptake. The identifying assumption for DiD is that before the introduction of RHCP Funding Cap Order, different ZCTAs may have differences in the level of telemental health uptake, but such differences are consistent along the years (i.e., they follow a parallel trend) and such trend would have continued in the absence of RHCP Funding Cap Order in 2018. The model is specified as follows:

$$\begin{aligned}\text{Total Telemental Health Uptake}_{it} &= f(\alpha_0 + \alpha_1 \text{Post}_t + \alpha_2 \textit{Exposure to Consumer Broadband}_i \\ &+ \alpha_3 \text{Post}_t \times \textit{Exposure to Consumer Broadband}_i + \boldsymbol{X_{it}\alpha_4} + u_i + v_t + \varepsilon_{it}) \quad (1)\end{aligned}$$

where $\boldsymbol{X_{it}}$ is a vector of control variables, u_i is the ZCTA fixed effects, v_t is the year fixed effects, and ε_{it} is the idiosyncratic error term. α_3 is the parameter of interest.

Since *Total Telemental Health Uptake* is operationalized as a count variable and we observe the existence of excessive zero values (142 out of 904 observations), we use a zero-inflated negative binomial (ZINB) model to fit our data. The excluded restriction (inflate predictor) we use to predict the zero values is the availability of telehealth providers (coded as 1 if there is at least 1 telehealth provider, 0 otherwise). The relevance of this predictor comes from the intuition that if an area does not have any telehealth provider, there will not be telemental health visits. On the other hand, only knowing the existence of telemental health providers does not have any predictive power of the total number of telemental health visits.

For H2, we seek to compare the causal effects identified through Equation 1 among full-parity states and non-parity states. Therefore, we re-estimate Equation 1 in a sub-sample setting: one for the 3-digit ZCTAs within full parity states and another for the 3-digit ZCTAs within non-parity states.

Suppose we have identified the causal relationship between improving telehealth technological infrastructure (the RHCP Funding Cap Order) and telemental health uptake in H1 and H2, we can leverage this relationship to recover the causal effect of telemental health uptake on population mental health condition by adopting an instrumental variable (IV) approach. Specifically, we adopt the general control function method of two-stage residual inclusion (2SRI) to execute the IV estimation (Park et al., 2023; H. Song et al., 2021; Terza et al., 2008; Wooldridge, 2014). To start with, we estimate Equation 1 as we did for H1 and derive the residuals of the estimation[17]. We then add this residual variable into the following linear model to test H3:

$$\begin{aligned}\text{Mental Illness Prevalence}_{it} &= \beta_0 + \beta_1 \text{Total Telemental Health Uptake}_{it} + \beta_2 residual + \boldsymbol{Y_{it}}\boldsymbol{\beta_3} \\ &\quad + u'_i + v'_t + \tau_{it} \qquad (2)\end{aligned}$$

where $\boldsymbol{Y_{it}}$ is a vector of control variables, u'_i is the ZCTA fixed effects, v'_t is the year fixed effects, and τ_{it} represents the idiosyncratic error term. β_1 is the parameter of interest. Finally, for H4, we repeat the analysis for H3 in a sub-sample setting within full parity states and non-parity states separately.

[17] Due to the zero-inflated negative binomial specification of Equation 1, we follow a three-step approach to calculate the residuals: (i) generate the predictions; (ii) reverse them back to the original value by taking an exponential for each prediction; (iii) calculate the residuals by subtracting the predicted telemental health visit count from the actual visit count.

4.5.2 *Estimation Results*

We estimate the ZINB model using maximum likelihood estimation and present the results in Table 4-2. The “No Controls” model demonstrates the estimation of Equation 1 with only the independent variables. The “With Controls” model adds the control variables, ZCTA fixed effects, and year fixed effects. We observe that adding the control variables and fixed effects does not qualitative change the main effects of the model. We use the full model to test H1. With respect to the effect of improving telehealth technological infrastructure on telemental health uptake, the estimated coefficient of the interaction term *Post* × *Exposure to Consumer Broadband* is positive but not statistically significant ($\alpha_3 = 0.211, p = 0.293$), indicating the absence of a causal effect. Together with the positive and significant coefficient of *Post* ($\alpha_1 = 1.229, p = 0.002$), we find that there is an increase in telemental health uptake following the RHCP Funding Cap Order. However, we do not observe a difference in such effects between the low and high treatment groups. Hence, we cannot claim that such an increase in telemental health uptake is causally driven by improving telehealth technological infrastructure. H1 is not supported.

Next, we examine whether we observe the same lack of causal effect of improving telehealth technological infrastructure in two sub-samples: ZCTAs within the full parity states and non-parity states. We re-estimate Equation 1 using maximum likelihood estimation and the results are presented in Table 4-3. We observe that the estimated coefficient of the interaction term *Post* × *Exposure to Consumer Broadband* is not statistically significant for the non-parity sub-sample ($\alpha_3 = -0.001, p = 0.998$). However, for the full parity sub-sample, the coefficient is positive and statistically significant ($\alpha_3 = 0.790, p = 0.000$). This comparison indicates that improving telehealth technological

Table 4-2: Equation 1 Estimation Results for the Full Sample

	No Controls β(SE)	With Controls β(SE)
Main Effects		
Post	0.550 (0.260)*	1.299 (0.425)**
Exposure to Consumer Broadband	0.458 (0.383)	-6.496 (6.183)
Post × Exposure to Consumer Broadband	0.303 (0.287)	0.211 (0.200)
Coverage Controls		
Fiber Penetration %		-0.310 (0.709)
Total Visits		0.000 (0.000)
Demographic Controls		
Asian %		29.559 (18.763)
Black %		-26.008 (15.027)†
Native %		-72.729 (48.751)
Other %		5.085 (5.097)
% Married		4.561 (12.539)
% Separated/Divorced		-14.969 (27.053)
% Widowed		-78.099 (36.144)*
Age: Under 18 %		-11.612 (24.867)
Age: 18 to 24 %		-14.161 (34.022)
Age: 25 to 34 %		25.323 (24.635)
Age: 35 to 44 %		23.469 (26.510)
Age: 45 to 54 %		-18.522 (23.004)
Age: 55 to 64 %		-50.969 (29.112)†
Education: Greater Than High School %		-4.053 (6.313)
% Part Time		21.427 (19.823)
% of Full Time		-3.216 (15.928)
Prevalence: Routine Checkup Past Year		0.012 (0.026)
Synchronous Providers		-0.002 (0.001)*
In Person Providers		0.001 (0.000)***
Direct Purchase Insurance		0.000 (0.000)**
Employer Based Insurance		-0.000 (0.000)†
Constant	4.959 (0.333)***	13.753 (20.259)
[First Stage]		
Telehealth Providers Available	-22.971 (0.175)***	-29.941 (0.149)***
Constant	-1.446 (0.146)***	-1.419 (0.123)***
ln Alpha [Dispersion Parameter]	0.804 (0.077)***	-1.321 (0.084)***
Year FE	No	Yes
ZCTA FE	No	Yes
Number of Observations	904	904

Note: Robust standard errors clustered at the ZCTA level in parentheses; † $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

infrastructure has a positive causal effect on telemental health uptake, but such effect only exists in 3-digit ZCTAs within the states that implement both coverage parity and payment parity for telehealth. The two operational drivers studied in this study (telehealth infrastructure and parity) have to be implemented at the same time to drive telemental

Table 4-3: Equation 1 Estimation Results for Sub-samples

	Non-parity β(SE)	Full Parity β(SE)
Main Effects		
Post	1.502 (0.748)*	0.733 (0.482)
Exposure to Consumer Broadband	-5.712 (3.182)†	0.638 (5.816)
Post × Exposure to Consumer Broadband	-0.001 (0.305)	0.790 (0.188)***
Coverage Controls		
Fiber Penetration %	-2.862 (2.142)	0.119 (0.814)
Total Visits	-0.000 (0.000)	0.000 (0.000)
Demographic Controls		
Asian %	10.895 (46.668)	21.326 (23.001)
Black %	-39.490 (22.742)†	-11.726 (20.258)
Native %	-172.330 (102.926)†	-2.902 (55.254)
Other %	-8.285 (17.762)	9.644 (5.643)†
% Married	8.470 (23.990)	-5.961 (17.293)
% Separated/Divorced	30.351 (42.454)	-56.218 (34.532)
% Widowed	-109.164 (62.641)†	-30.051 (41.906)
Age: Under 18 %	-11.087 (47.277)	-47.113 (25.151)†
Age: 18 to 24 %	-49.886 (50.272)	-19.084 (51.287)
Age: 25 to 34 %	74.620 (52.674)	-10.040 (28.750)
Age: 35 to 44 %	37.615 (48.479)	12.565 (35.282)
Age: 45 to 54 %	-24.518 (39.068)	-13.664 (28.495)
Age: 55 to 64 %	-51.141 (63.972)	-69.727 (36.852)†
Education: Greater Than High School %	-26.229 (14.438)†	10.028 (10.239)
% Part Time	39.053 (41.452)	13.712 (24.886)
% of Full Time	7.477 (29.328)	-12.325 (17.385)
Prevalence: Routine Checkup Past Year	0.036 (0.041)	-0.016 (0.037)
Synchronous Providers	-0.001 (0.002)	-0.002 (0.001)*
In Person Providers	0.001 (0.001)†	0.001 (0.000)***
Direct Purchase Insurance	0.000 (0.000)†	0.000 (0.000)
Employer Based Insurance	-0.000 (0.000)	-0.000 (0.000)
Constant	10.933 (32.331)	35.033 (22.287)
[First Stage]		
Telehealth Providers Available	-1.892e+13 (.)	-23.662 (0.349)***
Constant	-1.260 (0.156)***	-2.448 (0.333)***
ln Alpha [Dispersion Parameter]	-1.196 (0.112)***	-1.679 (0.129)***
Year FE	Yes	Yes
ZCTA FE	Yes	Yes
Number of Observations	564	340

Note: Robust standard errors clustered at the ZCTA level in parentheses; † p<0.10, * p<0.05, ** p<0.01, *** p<0.001

health uptake. This positive effect is equivalent to an additional increase of 848 telemental health visits for the high treatment group compared to the low treatment group. H2 is hence supported.

Following the empirical strategy outlined in Section 4.5.1 , we estimate Equations 1 and 2 together following the 2SRI process to recover the causal impact of telemental health uptake on population mental health condition. Since we only observe a causal relationship between our instrumental variables (the independent variables in Equation 1) and telemental health uptake for ZCTAs within full parity states, the 2SRI results are less reliable when analyzing the full sample or non-parity sub-sample due to weak instrument issue. Nonetheless, we present the 2SRI estimation results for the full sample, non-parity sub-sample, and full parity sub-sample in Table 4-4. Note that in order to avoid excessively small coefficients, we normalize the independent variable *Total Telemental Health Uptake* so that it has mean = 0 and s.d. = 1. From Table 4-4, we first observe that the residual term is significant in all three models, indicating the endogeneity of the independent variable *Total Telemental Health Uptake*, necessitating the use of instrumental variable approach. We also find that telemental health uptake has a negative impact on mental illness prevalence when conducting the analysis for the full sample ($\beta_1 = -0.071, p = 0.014$), and this negative impact is largely driven by the benefits of telemental health uptake in ZCTAs within the full parity states ($\beta_1 = -0.149, p = 0.007$) as the coefficient of *Total Telemental Health Uptake* is insignificant for ZCTAs within non-parity states ($\beta_1 = -0.043, p = 0.174$). For ZCTAs within the full parity states, this causal effect translates into 0.149% reduction in mental illness prevalence (714 people for an area with median population in the full parity state sub-sample) if there is 1 standard deviation increase in telemental health uptake (1074 visits for the full parity state sub-sample). This finding, once again, emphasizes the synergy effect between telehealth technological infrastructure building and telehealth parity if the ultimate goal is to improve population mental health

Table 4-4: Equation 2 Estimation Results

	Full Sample β(SE)	Non-parity β(SE)	Full Parity β(SE)
Main Effects			
Normalized Total Telemental Health Uptake	-0.071 (0.029)*	-0.043 (0.031)	-0.149 (0.054)**
Residuals from 1st Stage	0.000 (0.000)***	0.000 (0.000)*	0.000 (0.000)***
Coverage Controls			
Fiber Penetration %	0.308 (0.233)	0.913 (0.333)**	-0.348 (0.396)
Total Visits	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)†
Demographic Controls			
Asian %	-9.308 (11.494)	28.373 (23.230)	-29.436 (12.715)*
Black %	-11.440 (9.959)	-4.241 (13.505)	-15.189 (14.447)
Native %	-18.475 (37.516)	4.335 (43.715)	-34.914 (50.244)
Other %	-6.498 (2.476)**	-5.612 (9.878)	-4.404 (2.272)†
% Married	-13.385 (8.760)	-11.289 (11.298)	-12.721 (12.320)
% Separated/Divorced	-12.262 (14.085)	-3.612 (18.820)	-30.463 (16.816)†
% Widowed	31.976 (23.949)	53.515 (32.178)†	-9.212 (35.151)
Age: Under 18 %	-9.724 (15.516)	6.116 (22.697)	-25.869 (20.782)
Age: 18 to 24 %	0.743 (18.159)	-21.119 (23.148)	55.905 (26.819)*
Age: 25 to 34 %	-44.735 (16.750)**	-37.707 (22.503)†	-47.159 (21.656)*
Age: 35 to 44 %	-3.903 (17.213)	-15.932 (20.998)	12.889 (26.029)
Age: 45 to 54 %	-45.471 (15.449)**	-50.649 (23.309)*	-75.151 (19.839)***
Age: 55 to 64 %	-31.037 (17.625)†	-41.301 (25.927)	-0.107 (23.698)
Education: Greater Than High School %	8.618 (5.268)	8.926 (6.907)	11.995 (7.880)
% Part Time	-9.114 (11.169)	-6.637 (14.961)	-29.358 (15.075)†
% of Full Time	-7.011 (7.971)	10.707 (10.607)	-27.541 (9.931)**
Prevalence: Routine Checkup Past Year	-0.087 (0.013)***	-0.102 (0.017)***	-0.050 (0.024)*
Direct Purchase Insurance	-0.000 (0.000)***	-0.000 (0.000)***	-0.000 (0.000)*
Employer Based Insurance	0.000 (0.000)*	0.000 (0.000)	0.000 (0.000)*
Constant	41.844 (12.751)**	33.983 (17.121)*	46.467 (16.754)**
Year FE	Yes	Yes	Yes
ZCTA FE	Yes	Yes	Yes
Number of Observations	904	564	340

Note: Robust standard errors clustered at the ZCTA level in parentheses; † p<0.10, * p<0.05, ** p<0.01, *** p<0.001

condition through telemental health. Therefore, H3 is partially supported (with potential weak instrument concern) and H4 is supported.

4.5.3 *Robustness Checks*

In this section, we conduct several robustness checks to test whether our main results are consistent across several model specifications and variable operationalization.

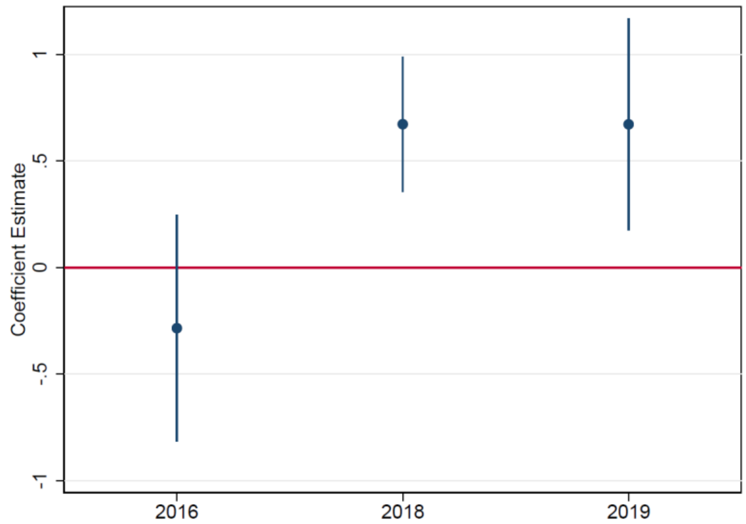
4.5.3.1 Relative Time Specification and Parallel Trend Assumption

In this study, the parallel trends assumption required for a Difference-in-Differences (DiD) research design posits that, in the absence of the RHCP Funding Cap Order, the trends in telemental health uptake across ZCTAs would have remained consistent. Following Angrist and Pischke (2009), we adopt a relative time specification to test this assumption. The model for this robustness check is specified as follows:

$$\begin{aligned}\text{Total Telemental Health Uptake}_{it} &= f(\alpha_0 + \alpha_1 \delta_t + \alpha_2 Exposure\ to\ Consumer\ Broadband_i \\ &+ \boldsymbol{\alpha_3} \delta_t \times Exposure\ to\ Consumer\ Broadband_i + \boldsymbol{X_{it}} \boldsymbol{\alpha_4} + u_i + v_t + \varepsilon_{it}) \quad (3)\end{aligned}$$

Equation 3 is a more flexible version of Equation 1, where δ_t denotes the time difference between the year of the observation and 2018, operationalized as a full set of year fixed effects (i.e., dummy variables). Following Angrist and Pischke (2009), we set the year 2017 (one year before the exogenous shock) as the base year and normalize its coefficient to zero. The coefficients of δ_t will then indicate whether the difference in telemental health uptake between the low and high treatment groups in other years is different from the same statistics in 2017. The estimation results for the full-parity state sub-sample are shown in Table 4-5, and Figure 4-1 plots these coefficients. We observe that the coefficient is not significant pre-shock (year 2016) but becomes significant right after the shock (year 2018) and remains significant in 2019. These results support the absence of diverging pre-trends, further suggesting a causal relationship between improving telehealth technological infrastructure and telemental health uptake.

Figure 4-1: Coefficient Estimates for the Yearly Interaction Terms



4.5.3.2 Alternative model specification for Equation 1

We initially estimate a ZINB model for Equation 1. Another common way of handling count variables is to take the log transformation. We thus estimate a linear model for Equation 1 with the log transformed dependent variable *Total Telemental Health Uptake*. The estimation results are presented in Table 4-6. Note that the model ignored the main effect of *Exposure to Consumer Broadband* as this time-invariant variable is absorbed in the ZCTA fixed effects. It is evident from Table 4-6 that our initial results about the relationship between improving telehealth technological infrastructure and telemental health uptake stays qualitative the same: there is a positive causal effect only in the full parity state sub-sample.

4.5.3.3 Alternative operationalization of treatment exposure

In the main analysis, we use 1% as the cutoff to construct the treatment exposure measure to differentiate ZCTAs with or without fiber penetration. It is also conceivable that the ZCTAs with high consumer broadband penetration may see a larger effect than those with low consumer broadband penetration. Therefore, we construct our exposure measure using

Table 4-5: Estimation Results for Relative Time Specification for Equation 1

	ZINB β(SE)
Main Effects	
Exposure to Consumer Broadband	0.617 (5.895)
Year 2016	-0.311 (0.307)
Year 2018	-0.006 (0.178)
Year 2019	0.332 (0.357)
Interactions	
Year 2016 × Exposure to Consumer Broadband	-0.284 (0.272)
Year 2018 × Exposure to Consumer Broadband	0.673 (0.162)***
Year 2019 × Exposure to Consumer Broadband	0.672 (0.253)**
Coverage Controls	
Fiber Penetration %	0.152 (0.813)
Total Visits	0.000 (0.000)
Demographic Controls	
Asian %	19.400 (23.326)
Black %	-11.761 (20.607)
Native %	-6.136 (56.576)
Other %	9.737 (5.634)†
% Married	-6.912 (17.298)
% Separated/Divorced	-58.152 (34.643)†
% Widowed	-30.075 (41.933)
Age: Under 18 %	-46.097 (25.453)†
Age: 18 to 24 %	-16.730 (52.069)
Age: 25 to 34 %	-9.217 (29.525)
Age: 35 to 44 %	13.186 (35.948)
Age: 45 to 54 %	-15.660 (28.838)
Age: 55 to 64 %	-72.058 (37.688)†
Education: Greater Than High School %	11.327 (10.959)
% Part Time	15.163 (25.196)
% of Full Time	-13.365 (17.622)
Prevalence: Routine Checkup Past Year	-0.015 (0.037)
Synchronous Providers	-0.002 (0.001)*
In Person Providers	0.001 (0.000)***
Direct Purchase Insurance	0.000 (0.000)
Employer Based Insurance	-0.000 (0.000)
Constant	35.628 (22.599)
[First Stage]	
Telehealth Providers Available	-21.725 (0.350)***
Constant	-2.450 (0.333)***
ln Alpha [Dispersion Parameter]	-1.683 (0.129)***
Year FE	Yes
ZCTA FE	Yes
Number of Observations	340

Note: Robust standard errors clustered at the ZCTA level in parentheses; † $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 4-6: Estimation Results for Alternative Equation 1 Specification

	DV: Log-transformed Telemental Health Uptake		
	Full Sample β(SE)	Non-parity β(SE)	Full Parity β(SE)
Main Effects			
Post	1.972 (0.572)***	2.683 (0.811)**	0.176 (0.726)
Exposure to Consumer Broadband	-	-	-
Post × Exposure to Consumer Broadband	0.091 (0.221)	0.029 (0.274)	0.741 (0.237)**
Coverage Controls	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
ZCTA FE	Yes	Yes	Yes
Number of Observations	904	564	340

Note: Robust standard errors clustered at the ZCTA level in parentheses; † p<0.10, * p<0.05, ** p<0.01, *** p<0.001

the median fiber penetration as the alternative cutoff and re-construct the treatment exposure measure. In this case, the low and high treatment groups have equal size (452 observations each). We re-run the entire set of analyses (Equations 1 and 2) by adopting this new cutoff for treatment exposure on full sample, non-parity sub-sample, and full parity sub-sample. As the results in Table 4-7 indicate, our conclusions regarding all four hypotheses stay the same.

4.6 Conclusion and Discussion

Mental health issues are increasingly recognized as a significant public health concern, with substantial societal and economic costs (NAMI, 2021a). Traditional mental health services often fail to meet the growing demand, particularly in rural areas where resources are scarce and stigma can deter individuals from seeking help (Speedie et al., 2008; Suleiman, 2001). Telemedicine, specifically telemental health, has emerged as a promising solution to these challenges, enabling remote delivery of mental health services through telecommunications technology (NIH, 2021). However, the uptake and impact of telemental health services are not uniformly understood, and several barriers, such as

Table 4-7: Estimation Results for Alternative Operationalization of Treatment Exposure

	Treatment Exposure Cutoff: Median Fiber Penetration		
	Full Sample β(SE)	Non-parity β(SE)	Full Parity β(SE)
[Equation 1]			
Post	1.401 (0.412)***	1.381 (0.706)+	1.079 (0.480)*
Exposure to Consumer Broadband	-7.187 (6.164)	0.426 (6.018)	-4.289 (5.160)
Post × Exposure to Consumer Broadband	0.081 (0.130)	0.146 (0.218)	0.303 (0.172)+
Coverage Controls	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Constant	Yes	Yes	Yes
[Equation 2]			
Normalized Total Telemental Health Uptake	-0.072 (0.029)*	-0.045 (0.031)	-0.152 (0.065)*
Residuals from 1st Stage	0.000 (0.000)***	0.000 (0.000)*	0.000 (0.000)***
Coverage Controls	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
ZCTA FE	Yes	Yes	Yes
Number of Observations	904	564	340

Note: Robust standard errors clustered at the ZCTA level in parentheses; † $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

inadequate broadband infrastructure and inconsistent telehealth reimbursement policies, impede its widespread adoption (Barnett, Ray, et al., 2018; Spivak et al., 2020). Understanding these barriers and finding facilitators is crucial for developing strategies to optimize telemental health services. To this end, this essay investigates the operational drivers and impacts of telemental health uptake on population mental health condition. These research goals are motivated by the need to identify actionable factors that can enhance the adoption of telemental health services and to evaluate their effectiveness in improving mental health condition. By investigating these questions, we aim to provide insights that can inform policy and operational decisions to better support mental health care delivery.

To explore these questions, we compiled a unique panel dataset from multiple sources, focusing on 3-digit Zip Code Tabulation Areas (ZCTAs) in the United States from

2016 to 2019. Our research design leverages an exogenous policy shock—the 2018 increase in funding for the Rural Health Care Program (RHCP)—to identify the causal effects of improving telehealth infrastructure. This policy change increased the annual RHCP funding cap from $400 million to $571 million, significantly impacting telehealth infrastructure in both rural and urban areas.

Our findings indicate that the enhancement of telehealth technological infrastructure alone is insufficient to drive telemental health uptake. Instead, this effect is significant only in states with telehealth parity laws, which mandate equal reimbursement for telehealth and in-person services. These laws are crucial in ensuring that investments in telehealth infrastructure translate into increased utilization of telemental health services. Furthermore, telemental health uptake positively influences population mental health condition, with significant effects only observed in states with telehealth parity laws. These findings underscore the complex interplay between technological infrastructure and policy support in promoting telemental health uptake and assessing its impact on population-level mental health condition.

4.6.1 *Contributions*

This study makes several contributions to the healthcare operations literature. First, it extends the current understanding of the antecedents of telehealth uptake, particularly the operational factors impacting the volume of telemental health visits. By examining the roles of technological infrastructure and telehealth parity laws, we highlight the necessity of these factors working in tandem to drive telemental health uptake. This complements existing literature that primarily focuses on the effectiveness and patient outcomes of telehealth (Bavafa et al., 2018; Delana et al., 2023; Hilty et al., 2013). Our findings suggest that without adequate technological infrastructure and supportive policies like telehealth parity laws, the potential benefits of telehealth services cannot be fully realized.

Second, our research emphasizes the importance of telehealth parity in ensuring the efficacy of telehealth infrastructure investments. We observed that the causal effect of enhanced telehealth infrastructure on telemental health uptake was significant only in states with telehealth parity laws. This finding aligns with studies highlighting the role of policy frameworks in facilitating telehealth adoption and ensuring equitable access (Dills, 2021; Picher et al., 2021). Our study contributes to a nuanced understanding of how policy and infrastructure must align to drive meaningful adoption and utilization of telehealth services.

Furthermore, this research contributes to the broader telemental health literature by documenting the conditions under which telemental health can effectively improve mental health condition at the population level, taking into consideration the social determinants of health. The positive impact of telemental health uptake on mental health condition, particularly in states with telehealth parity laws, underscores the synergy between policy and infrastructure in achieving public health goals. This aligns with findings from other studies that emphasize the importance of integrated approaches to telehealth implementation (Shore et al., 2018; Spivak et al., 2020).

4.6.2 *Practical Implications*

The practical implications of our findings are significant for healthcare providers, government agencies, and state legislators. For healthcare providers, our study underscores the necessity of robust broadband infrastructure to facilitate effective telehealth services and confirms the value propositions of RHCP and its Funding Cap Order in 2018 in promoting telemental health uptake. Providers should continue to advocate for and invest in high-quality telecommunication technologies to support the delivery of mental health services, especially in underserved areas. This is consistent with the literature that highlights the role of infrastructure in telehealth service delivery (American Medical Informatics Association, 2017; Kobeissi & Hickey, 2023).

Moreover, government agencies, particularly those involved in telehealth policy and funding, should recognize the critical role of telehealth parity laws in maximizing the benefits of telehealth infrastructure investments. Our findings suggest that without telehealth parity laws, investments in telehealth infrastructure may not translate into increased utilization of telemental health services. Agencies like the Federal Communications Commission (FCC) should continue to support and expand programs like the RHCP to enhance telehealth infrastructure while also advocating for uniform telehealth parity laws across states.

Finally, state legislators should consider enacting or strengthening telehealth parity laws to ensure equitable access to telehealth services and improve mental health condition across diverse populations. Telehealth parity laws ensure that telehealth services are reimbursed at rates comparable to in-person services, reducing financial barriers for both providers and patients. This is particularly important for mental healthcare, where the delivery of services via telehealth is not inherently less costly than in-person care due to the nature of diagnosis and treatment. Consequently, the frequently cited argument by insurance companies—asserting that telehealth is a cost-saving alternative to in-person care—does not hold true for mental health services. Addressing this misperception is crucial, as it undermines efforts to achieve reimbursement parity and equitable access to essential mental health services.

4.6.3 *Limitations and Future Research*

Despite its contributions, this study has several limitations that warrant future research. Our data is limited to private insurance claims, providing little insight into telemental health uptake among Medicare and Medicaid populations. This limitation suggests that our findings may not be generalizable to all segments of the population. Future research should incorporate data from public insurance programs to provide a more comprehensive understanding of telemental health uptake across different insurance types. Studies examining the impact of telehealth on Medicare and Medicaid populations could offer valuable insights into the accessibility and equity of telehealth services for vulnerable groups.

Additionally, our analysis is based on pre-COVID-19 data. Although we believe the primary findings regarding the synergistic effects of telehealth infrastructure and parity is generalizable to post-COVID-19 era, we acknowledge that the pandemic has significantly altered healthcare delivery, accelerating the adoption of telehealth services across the globe. It is essential to assess whether our findings hold in the post-COVID-19 context, where telehealth usage has increased dramatically. Future research should investigate the long-term impacts of the COVID-19 pandemic on telehealth adoption and mental health condition, considering the potential changes in patient and provider behaviors, regulatory environments, and technological advancements.

Furthermore, our study focuses on the immediate effects of telehealth infrastructure enhancements and telehealth parity laws. Longitudinal studies that examine the sustained impacts of these factors on mental health condition over extended periods would provide deeper insights into the long-term benefits and challenges of telehealth services. Such research could explore the evolving dynamics of telehealth adoption, patient satisfaction, and health outcomes, offering valuable guidance for policymakers and healthcare providers.

In conclusion, our study underscores the critical interplay between technological infrastructure and supportive parity policies in driving telemental health uptake and improving population mental health condition. By addressing these operational drivers, stakeholders can optimize the benefits of telemental health services, ensuring broader access to quality mental health care and better health outcomes for diverse populations.

Chapter 5: Conclusion and Contribution

This dissertation sets out to address the significant challenges in mental health service delivery, particularly the inequities faced by underserved populations. Motivated by the growing mental health crisis, the disparities in access to care, and the promising potential of digital health technologies, this research explored how digital technologies could enhance mental health service delivery at various stages of the help-seeking pathway: initiating care, escalating to professional care, and delivering professional care. Through three essays, this dissertation provided insights into how mental health mobile apps (MHMAs), AI-enabled online platforms, and telemental health services can improve accessibility, effectiveness, and equity in mental health services.

5.1 Major Findings

The first essay explores whether MHMAs can help patients, especially those from underserved populations, be connected to mental health self-support and peer-support. Detailed usage data from 1,688 users of a MHMA reveals that app usage and benefits are statistically equivalent between underserved and better-served populations. These findings suggest that MHMAs can promote equality in mental health support by encouraging help-seeking behavior and providing effective self-management and peer-support tools (Lipschitz et al., 2020; Yan & Tan, 2014). The study highlights the potential of MHMAs to make mental health support more equally available.

The second essay focuses on improving the referral process for patients who have already initiated help-seeking. It evaluates an AI-enabled platform designed to enhance referral efficiency and accuracy by matching users with suitable mental health services based on their needs. The results demonstrate significant the potential value of more tailored approaches to connecting patients to mental health services, although the solution is most effective for specific target populations. By encouraging patients from underserved populations to connect with professional care, the platform addresses the lack of incentive for providers to focus on equity due to long waiting lists.

The third essay investigates the delivery of professional mental health care through telemental health services, examining how enhanced broadband access and telehealth parity laws influence service uptake and mental health condition. Using a difference-in-differences and instrumental variable identification strategies, the study finds that these improvements have a synergistic effect: both enhanced broadband access and telehealth parity laws must work together to drive higher uptake of telemental health services and improve mental health condition. This synergy is crucial for maximizing the benefits of telemental health and improving overall population mental health.

5.2 Contribution to Healthcare Operations Management Literature

This dissertation makes several theoretical contributions to healthcare operations management literature, particularly in the context of mental health services. First, it highlights the importance of addressing the entire help-seeking pathway, not just the interaction between patients and professional care providers. By focusing on digital technologies that facilitate the initiation of care and escalation to professional services, the research expands the scope of healthcare operations management to include early stages of help-seeking behavior, which are critical for improving overall care accessibility and effectiveness (Alegría et al., 2002; Aneshensel, 2009).

Additionally, this dissertation challenges the traditional 3A-framework of affordability, access, and awareness in healthcare service delivery. We argue that patient acceptance is a crucial factor in effective mental health service delivery. Ensuring that patients are willing to engage with the services offered, particularly through digital platforms, adds a new dimension to healthcare operations management by considering psychological and social factors influencing service utilization (Aneshensel, 2009; Masuda et al., 2012; Rickwood et al., 2007). The resulting refined 4A-framework, which includes *affordability*, *access*, *awareness*, and *acceptance*, better guides healthcare supply chain design, especially for disease conditions where patients may be hesitant to seek care due to stigma, fear, or inconvenience. The 4A-framework can be generalized to other healthcare contexts, helping to reach historically "hard-to-reach" populations and ultimately leading to more effective and equitable healthcare delivery (Kalkanci et al., 2019; Sinha & Kohnke, 2009).

5.3 Practical Implications

The practical implications of this dissertation are significant for policymakers, healthcare providers, and technology developers. For policymakers, the research highlights the necessity of supporting telehealth infrastructure and enacting telehealth parity laws to enhance the uptake of telemental health services. Enhanced provider broadband access combined with telehealth parity laws can synergistically improve mental health condition. Policymakers should also consider incentives and policies that encourage the development and adoption of AI-enabled referral platforms and MHMAs, particularly for underserved populations.

Healthcare providers can leverage AI-enabled platforms to improve the efficiency and accuracy of connecting patients with appropriate services, addressing a critical gap in the current healthcare system. Providers should also recognize the importance of digital health solutions that promote patient acceptance and engagement, integrating these technologies into routine practice to maximize their benefits.

For technology developers, the findings underscore the importance of designing digital health solutions that are accessible, affordable, and acceptable to target populations. Developers should focus on creating user-friendly and culturally competent digital tools that encourage engagement and provide effective support across different stages of the help-seeking pathway (Rogler & Cortes, 1993).

5.4 Conclusion

In conclusion, this dissertation demonstrates the significant potential of digital technologies—specifically MHMAs, AI-enabled online mental health service referral platforms, and telemental health services—to enhance mental health support. By addressing the unique challenges of mental health care delivery and focusing on underserved populations, this research contributes to a broader understanding of healthcare operations management and offers valuable insights for policymakers, healthcare providers, and technology developers. The findings underscore the importance of leveraging digital solutions to promote equity and efficiency in mental health care, ultimately leading to better population health outcomes.

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Appendices

Appendices for Chapter 2

Appendix A: A Review of MHMAs for Non-clinical Use

To assess the representativeness of Hope (i.e., the focal MHMA we study), we review all the MHMAs for non-clinical use that are listed in Dorwart's "Best Mental Health Apps" as of September 2023 (Dorwart, 2023) with respect to the functions they offer and their scale in terms of # of downloads (i.e., Small scale: # of downloads is less than 10,000; Large scale: # of downloads is greater than 10,000). We expand this list by adding three more MHMAs for non-clinical use that, as with Hope, are not in Dorwart's list. Table A1 summarizes the function offerings across our focal app (highlighted in grey) and the 11 popular MHMAs reviewed. As seen in the table, all the listed 11 MHMAs offer self-support and/or peer-support functions. Among the 11 MHMAs, 10 offer a self-support function for different uses (e.g., mental health self-reflection, journals, knowledge sharing etc.) and 4 offer an online community function (e.g., chat groups, virtual groups, and anonymous online community). Similar to Hope, 3 MHMAs, all in Dorwart's list, offer both self-support and peer-support functions. In sum, we conclude that Hope is representative of MHMAs for non-clinical use in the market as of September 2023.

Table A1: A Listing of MHMAs with their Functions and Scale

App Name	Self-support Functions	Peer-support Functions	Scale (based on # of downloads)	Dorwart's List
Focal MHMA: Hope	Mental health self-reflection	Anonymous online community	Small	No
Huddleverse	N/A	Anonymous online community, messaging	Small	No

Iona: Mental Health Support	Mental health self-reflection, cognitive-behavioral therapy (CBT) exercises through chatbots	N/A	Small	No
Alkeme: Black Mental Health	Mental health knowledge sharing	N/A	Small	No
MoodKit	Mental health self-reflection, evidence-based activities rooted in CBT principles	N/A	Small	Yes
Worry Watch	Mental health self-reflection, guided anxiety journal, guided coping techniques, and guided positive reinforcement	N/A	Small	Yes
Breath, Think, Do with Sesame	Child problem-solving skill building and self-soothing strategy training	N/A	Small	Yes
I am Sober	Sobriety and recovery milestone tracking, sobriety calculator	Virtual groups	Large	Yes
Headspace	Mental health self-reflection, guided meditation, guided physical exercises	N/A	Large	Yes
Sanvello	Mental health self-reflection, guided meditation, CBT	Themed chat groups	Large	Yes
Calm	Mental health self-reflection, gratitude/sleep check-ins, daily calm reflection, guided meditations, grown-up bedtime stories, physical exercises	N/A	Large	Yes
Happify	Mental health self-reflection, strength assessment, games, meditation, and exercises	Anonymous online community	Large	Yes

Appendix B: Hope's Mental Condition Survey Items

Question	**Scale**
S1. (Sense of Self & Belonging) How connected, supported, comfortable, and included do you feel?	**0-100**[a]
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?	
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 C: 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 Mental Condition 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 C1. 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 unidimensionality and convergent validity.

Table C1: 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 C2. 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 C2: 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

Appendix D: Pilot Study to Assess the Face Validity of Self-reflection Score

To further establish face validity for *SRS (Self-reflection Score)*, we conducted a pilot study between February 2017 and April 2017 to investigate how the mental condition measured by the Hope's Mental Condition Survey is comparable to that measured by the clinically approved *PHQ-9* and *GAD-7* questionnaires. For this study, we recruited 61 college students at a public research university in the mid-western United States. The participants were asked to first complete both *PHQ-9* and *GAD-7* questionnaires, and then register for the Hope app to complete Hope's Mental Condition Survey. We use the data from the pilot study to operationalize mental condition using *SRS*, *PHQ-9*, and *GAD-7*. Table D1 reports the descriptive statistics and correlation matrix for the three variables. We found that both *PHQ-9* and *GAD-7* scores have negative and significant correlations with *SRS.*

Table D1: Descriptive Statistics and the Correlation Matrix for Hope's *Self-reflection Score* and *PHQ-9 / GAD-7*

Variable	Mean	SD	Correlation Matrix 1	2	3
1. *SRS (Self-reflection Score)*	58.37	27.25	1.00		
2. *PHQ-9*	16.54	6.08	-0.65***	1.00	
3. *GAD-7*	13.84	5.18	-0.46***	0.75***	1.00
Number of observations	61				

Note: *** p<0.001, ** p<0.01, * p<0.05, † p<0.1

We also estimated two OLS regressions in which PHQ-9 and *GAD-7* scores are regressed on *SRS*. As demonstrated in Table D2, the results indicate that Hope's *Self-reflection Score* is significantly and negatively associated with both *PHQ-9* ($\beta = -0.14, p < 0.001$) and *GAD-7* ($\beta = -0.09, p < 0.001$) scores. This is expected because an increase in *PHQ-9* or *GAD-7* scores represents a more severe condition related to depression and anxiety disorder, respectively, whereas an increase in *SRS* represents a better mental condition. Overall, the pilot study results provide face validity for Hope's *Self-Reflection Score* as a measure of mental condition.

Table D2: OLS Model Estimation Results for Evaluating the Association of Hope's *Self-reflection Score* with the *PHQ-9* and *GAD-7 S*cores

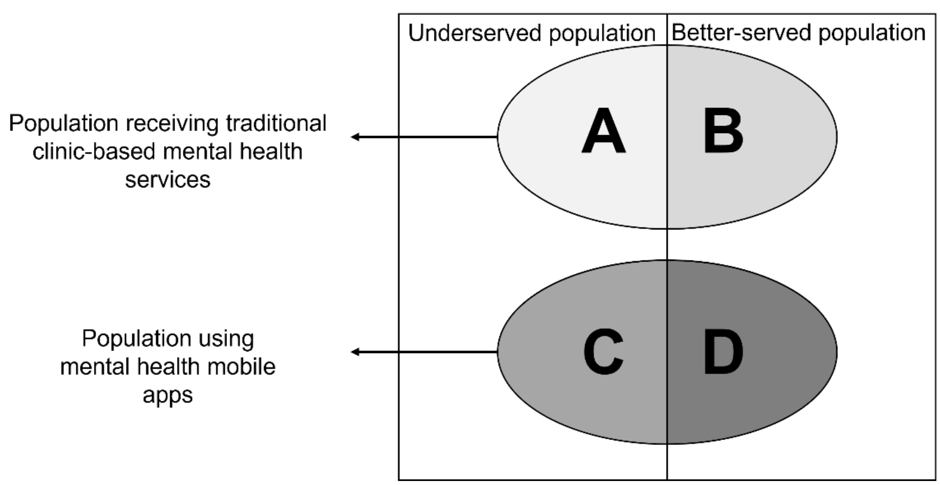
VARIABLES	*PHQ-9 Score*	*GAD-7 Score*
SRS (Self-reflection Score)	-0.14***	-0.09***
	(0.02)	(0.02)
Constant	24.95***	18.89***
	(1.54)	(1.47)
Observations	61	61
R-squared	0.42	0.21

Robust standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Appendix E: MHMA Users vs. the Mental Health Patient Population

In this appendix, we illustrate in detail the two likely relationships between the MHMA users and the traditional mental health patient population, and discuss how these relationships can map with our empirical findings in the main analysis. Consider the following figure:

Figure E1: Illustration of MHMA Users vs. Traditional Mental Health Patients



The figure demonstrates the underserved population (i.e., the left rectangle) and the better-served population (i.e., the right rectangle), who are classified based on exogenously determined socio-demographic characteristics (i.e., gender, sexual orientation, and race-ethnicity). Within these populations, the two circles represent the population seeking professional support delivered through the traditional clinic-based mental health services (i.e., the circle on top) and the population seeking help through MHMAs (the circle at the bottom). The well-documented inequity in the traditional clinic-based mental health services between the underserved and better-served populations in the extant literature implies that $A \neq B$ with respect to usage and benefit. The results of our study imply that $C = D$ with respect to usage and benefit in MHMAs. Within this illustration, we can think of two scenarios for leveraging MHMAs in the traditional clinic-based mental healthcare delivery.

In the first scenario, the underserved and/or better-served populations in the MHMA vs. professional settings (i.e., C vs. A and/or D vs. B) can inherently be different, i.e., the population using MHMAs is different from the population seeking professional support. This implies that MHMA users can be those that do not seek traditional clinic-based professional help, yet seek peer-support and self-support help on their own in the app. In other words, the mobile app may expand the mental health services (through self-support and peer-support) to a new population segment who otherwise would not seek traditional clinic-based professional support, creating a market expansion effect. It is plausible that, if the underserved and better-served populations in this new segment (i.e., C and D) had used professional services, they would not have experienced any inequity, implying an already equity between them before using the app. It is also plausible that the underserved new segment (i.e., C) would have experienced inequity in the professional setting if they had used the professional services, and thus using the mobile app advances equity for them. Regardless of these two possible explanations, this scenario may imply that MHMAs may expand the mental health services (through peer-support and self-support) to a new segment that either: (i) already has equity between the underserved and better-served populations or (ii) achieves equity between the underserved and better-served populations with the help of the mobile app.

In the second scenario, in contrast to the first one, it is possible that the underserved and better-served populations in the MHMA vs. professional settings (i.e., C vs. A and D vs. B) can inherently be the same population, i.e., the population using MHMAs is the same as the population seeking professional support. This implies that MHMA users can be those that also seek traditional clinic-based professional support. In other words, the self-support and peer-support functions of MHMAs can complement the delivery of mental health services for those seeking traditional clinic-based professional support, creating a multi-channel mental health help-seeking effect. In this case, considering the well-documented inequity in the mental healthcare literature (i.e., $A \neq B$), our results (i.e., $C = D$) may imply that MHMAs advance the equity between the underserved and better-served populations through: (i) providing an alternative channel for seeking help for those who experience inequity in the professional settings and (ii) potentially facilitating some behavioral changes among those populations.

Appendices for Chapter 3

Appendix F: Chatbot Interaction Model

[text]: intent inferred from user responses
{number}: node index

1. Hi, Avy here, finding mental health services that suit your needs can be challenging. That's why the Avalo team has developed an AI-based algorithm that provides you with personalized service recommendations while protecting your personal information. **Would you like to give this new functionality a try?**
    a. [Yes] – *proceed to {2}*
    b. [No] – *proceed to {20}*

2. Great! Avy is now analyzing your Avalo journey so far. Rest assured that no information will be shared outside the app. (short delay) Thanks for your patience! Avy has learned from your self-reflections and posts that you might have the following feelings. **Can you select the one(s) that are bothering you recently?**
    a. Option(s) returned from the core topic classification NLP model – *proceed to {3}*

    The options are the following items ordered based on the core topic classifier outputs:
    - Depression, low mood, or hopelessness (depression)
    - Stress, agitation, or racing thoughts (anxiety)
    - Addiction or uncontrolled substance use (substance use)
    - Restricting food intake or excessive overeating (eating disorder)
    - Elevated mood, excessive sleeplessness, long periods of depression or low mood (bipolar disorder)

3. Avy also has identified the following potential reasons that may have contributed to the symptoms above. **Can you select the one(s) that have been most challenging for you?**
    a. Option(s) returned from the context classification NLP model – *proceed to {4}*

    The options are the following items ordered based on the context classifier outputs:
    - Purpose, sense of meaning, or motivation
    - Relationship with relatives, partner, and/or colleagues
    - Sexual orientation
    - Gender identity
    - Racial or ethnic identity
    - Work and/or school
    - Physical health such as sleep, obesity, chronic conditions etc.
    - Other (please type)

4. Thanks for confirming! You are only a couple of questions away from Avy's personalized mental health service recommendations. Over the last 2 weeks, have you been experiencing difficulties in accomplishing what you'd like to accomplish without significant distress? **Select the areas(s) that you find most difficult:** - *proceed to {6} if any of option a through option i is selected*

    a. Sleep and get up on time
    b. Maintain a regular daily routine
    c. Maintain social contact with friends or other people
    d. Maintain interest or pleasure in usual activities or hobbies
    e. Regular appetite and not over or under eating
    f. Feeling good about yourself
    g. Concentrate on things

h. Move or speak at a normal speed
i. Stay away from suicidal or self-harm thoughts
j. None of the above – proceed to {5}

5. Glad to hear that! Sometimes it can be helpful to have some additional support, **would you be interested in learning more?**
    a. [Yes] – *proceed to {8}*
    b. [No] – *proceed to {19}*

6. **Do you want to work together to try and change that?**
    a. [Yes] – *proceed to {7}*
    b. [No] – *proceed to {19}*

7. Great! Avy is developed to help you do that. **Is now a good time to consider a recommendation for additional support services?**
    a. [Yes] – *proceed to {8}*
    b. [No] – *proceed to {19}*

8. **Would you prefer that we recommend a service provider from a particular demographic group or cultural backgrounds?**
    a. [Yes] – *proceed to {9}*
    b. [No] – *proceed to {14}*
    c. [Prefer online services] – *proceed to {17}*

9. **Which of the following are important to you?** – *According to the options selected in this question, proceed to corresponding nodes from {10} to {13}, and then proceed to {14}*
    a. Gender
    b. Race/Ethnicity
    c. Sexual orientation
    d. Language

10. **Please select your preferred provider gender:**
    a. Female
    b. Male
    c. Transgender
    d. Other

11. **Please select your preferred provider race/ethnicity:**
    a. American Indian or Alaskan Native
    b. Asian
    c. Black or African American
    d. Hispanic or Latino
    e. Mixed race
    f. While or Caucasian
    g. Other

12. **Please select your preferred provider sexual orientation:**
    a. Heterosexual
    b. Homosexual
    c. Bisexual
    d. Other

13. **Please select your preferred provider language:**
    a. English
    b. Spanish

c. Chinese
d. Somali
e. Hmong
f. Vietnamese
g. Other

14. **Please select your health insurance provider:**
    a. Drop-down menu for health insurance providers – *proceed to {15}*

15. **Please enter your zip code:**
    a. 5-digit zip code – *proceed to {16}*

16. Thanks for confirming! Avy is trying hard to find service provider(s) that match your needs and are near you... (short delay) **Here is one recommendation:** (recommendations returned from API call from the service search engine FastTrackerMN)
    a. Looks good, I will call them for an appointment – (provide the phone number and proceed to {19})
    b. Looks good, I will visit their website for an appointment – (provide the URL and proceed to {18})
    c. Show me another recommendation – proceed to {16} with a new recommendation
    d. I am not ready to seek help - proceed to {19}

17. Thanks for confirming! Avy is trying hard to find online service provider(s) that match your needs... (short delay) **Here is one recommendation:** (recommendations based on symptoms)
    a. Looks good, I will visit their website and access service they provide – *provide the URL and proceed to {18}*
    b. Show me another recommendation – *proceed to {17} with a new recommendation*

18. Thanks for giving Avy a chance to help you. Feel free to click the Avy icon to chat at any time. To help us better serve you, please complete the Survey. – *survey URL*

19. No problem. Avy is always here 24/7 should you change your mind. Feel free to click the Avy icon to chat at any time. To better serve you in the future, **would you share with us some of the concerns preventing you from wanting to seek help right now?** – *based on options selected, provide education modules containing relevant information*
    a. I don’t think I need it
    b. I don't think I’m ready
    c. I don’t think anything is going to work
    d. I am worried about negative consequences
    e. I don’t think I will feel connected to a mental health provider or type of service
    f. Seeking mental health help is not accepted by my culture
    g. I cannot afford help
    h. Other (please type)

Appendix G: Data Coding Manual

Coding is completed in an Excel spreadsheet following this manual.

Column A: Contains posts that have been uploaded by users of the mental healthcare delivery platform.

Column B: Core Topic
Read post in Column A. Determine the topic(s) being discussed in the post based on the following list of pre-determined codes. The post may explicitly mention the topic(s) or may use language that relates to the topic(s):

- Depression
  - Post mentions a depressed mood (e.g., feeling sad, empty, or hopeless).
  - Post mentions loss of interest or pleasure in doing activities.
  - Post mentions feelings of worthlessness, uselessness, or inappropriate guilt for something beyond control.
  - Post mentions feelings of loss or disappointment.
  - Post mentions feeling trapped or stuck.
  - Post mentions thoughts of death or suicide.
- Anxiety
  - Post mentions difficulties controlling anxiety, worry, or prolonged stress.
  - Post mentions feelings of restlessness (e.g., being on edge, feeling tense).
  - Post mentions symptoms related to panic attacks (e.g., racing heart, sweating, difficulty breathing).
- Substance use
  - Post mentions using or thinking about using substances.
  - Post mentions inappropriate use of legal and/or prescribed medication.
  - Post mentions using in large amounts or spending a lot of time using substances.
  - Post mentions feelings of wanting to stop or cut down usage and/or difficulties stopping.
  - Post mentions cravings or urges to use substance(s) or feelings of withdrawal.
- Eating disorder
  - Post mentions negative emotions (e.g., distress, embarrassment, guilt, depression) related to food or eating.
  - Post mentions inappropriate food intake (e.g., eating too little or too much, hiding food or eating at night).
  - Post mentions feelings of excessive control or lack of control related to food.
  - Post mentions issues or fears related to gaining weight or being fat.
  - Post mentions inappropriate behaviors to prevent weight gain (e.g., vomiting/purging, using medications or laxatives, fasting/dieting, excessive exercise).
- Bipolar disorder
  - Post mentions experiencing a manic or hypomanic episode.
  - Post mentions periods of elevated or irritable mood that may include feelings of inflated self-esteem, decreased need for sleep, increased talking and/or racing thoughts, behavior that feels uncontrolled.
  - Post mentions “mood swings” that appear to fluctuate between elevated/irritable to depressed moods.
- “Other”
  - Use this code if the topic of the post does not fit any of the existing codes.

<u>Column C:</u> Context
Read post in Column A. Determine the context(s) that the topic is being discussed within based on the following pre-determined list (e.g., substance use [B] related to work or school [C]).

- Positive meaning of life
  - Post is based on positive emotions or mood (e.g., happiness, motivation, excitement).
  - Post may mention positive feelings about the app.
- Relationships
  - Post is based on relationships with individuals that are real or desired (e.g., friends, family, child, partner or significant other).
- Sexual orientation
  - Post is based on issues, unease, discomfort, or confusion related to romantic or sexual attraction toward others.
  - Post may mention sexual orientation using specific labels (e.g., LGBQA+).
- Gender identity
  - Post is based on gender, gender dysphoria (i.e., unease or dissatisfaction with sex assigned at birth), gender identity, gender presentation, transitioning, etc.
- Racial/ethnic identity
  - Post is based on race, skin color, ethnicity, culture, immigration status, etc.
- Work and/or school
  - Post is based on work, employment, income, etc.
  - Post is based on school, assignments, exams, etc.
- Physical health
  - Post is based on physical health or illness.
  - Post may mention symptoms related to physical health, such as sleep, energy, fatigue, etc.
- "Other"
  - Use this code if the context of the post does not fit any of the existing codes.

Appendix H: Hypothetical Scenario for Prototype Demo

Person B identifies as an 18-year-old, female, African American, high school student who has been struggling with self-image issues, fitting in at school, and preparing for college. She doesn't feel supported in her home life or school to express her mental health thoughts or feelings and she has not told anyone about her concerns despite feeling something has been 'wrong' since age 14 when she started to think often about food and food intake. She's been losing significant weight recently and is getting concerned because of experiencing some physical pain. She doesn't feel a safe enough connection to anyone in person and has been searching online for tools. She is not confident that she can seek professional help because she is unaware of the medical industry and to her knowledge, nobody close to her has consumed mental health services. While searching online, she discovered the Avalochat app, and she wrote her first post as follows:

"I've been having trouble eating lately. It's mainly due to my school and social life, but also I just haven't been wanting to eat. I'll eat just once a day and can't even finish my food. I feel sick every time I eat and now I'm eating less. It's getting harder and harder for me to eat. Now on top of it, I'm getting very ill every time I eat now. I almost threw up and my stomach wouldn't stop hurting. I'm not on any meds so I'm not sure why I'm like this."

Appendix I: Pre-interview Survey and Interview Guide for Prototype Evaluation

Introduction:

As a mental health professional, your insights are crucial for our research on improving the client-provider matching process, particularly in identifying ideal client populations for mental health services. By using a chatbot intervention, we aim to facilitate better therapeutic relationships. Your responses will be kept confidential, and with your permission, we would like to record your comments for data collection purposes.

Pre-interview Survey

Background Information:

- Email:
- License type:
- Years of practice:
- Types of therapeutic services provided:

Client Engagement:

Average duration of client engagement (choose one):

- 1-3 months
- 4-12 months
- 1-3 years
- 4+ years

Preferred duration of client engagement (choose one):

- 1-3 months
- 4-12 months
- 1-3 years
- 4+ years

Average number of sessions per client (choose one):

- 1-10 sessions
- 10-50 sessions
- 50-100 sessions
- 100+ sessions

Preferred number of sessions per client (choose one):

- 1-10 sessions
- 10-50 sessions
- 50-100 sessions
- 100+ sessions

Ideal Client Population:

Do you have a preferred client population? (Y/N)

Describe the characteristics of this population (age, race/ethnicity, sex/gender, sexual orientation, faith, geography):

Percentage of your current caseload that is made up of your ideal client population (choose one):

- 0-20%
- 20-40%
- 40-60%
- 60-80%
- 80-100%

Desired percentage of your current caseload that you would want to be your ideal client population (choose one):

- 0-20%
- 20-40%
- 40-60%
- 60-80%
- 80-100%

Rate your agreement with the following statement: "I have a high amount of control in determining which clients I accept onto my caseload." (choose one):

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Client screening:

Do you have a screening process for new clients?

(Y/N)

If yes, please describe the process:

Are there any characteristics of clients (conditions or other character traits like age, sex, ethnicity, faith, political affiliation, etc.) you would regularly choose not to provide services to?

(Y/N)

If yes, please list these characteristics: ______

Rate your agreement with the following statement: "My screening process is effective at filtering out the client population that I'm not interested in working with in my practice." (choose one):

- Strongly agree

- Agree
- Neutral
- Disagree
- Strongly disagree

Marketing:

Are you currently accepting new clients?

(Y/N)

Do you market your services?

(Y/N)

If yes, through which mediums (check all that apply):

- Print ads
- Radio/TV
- Online search
- Social media
- Digital content (blogs, videos, podcasts appearances)
- Directories
- In-person marketing/events
- At other providers/professionals practices
- Word of mouth

Rate your agreement with the following statement: "I am effective at attracting my ideal client population to my caseload." (choose one):

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Rate your agreement with the following statement: "I am interested in exploring options to increase the proportion of my ideal client population in my caseload." (choose one):

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Which mediums are most effective in attracting your ideal client population (check all that apply):

- Print ads
- Radio/TV
- Online search
- Social media
- Digital content (blogs, videos, podcasts appearances)
- Directories
- In-person marketing/events
- Referrals from other providers/professionals
- Word of mouth

Additional thoughts inspired by these questions:

Client Questions:

In your professional experience, which factors or events commonly prompt clients to schedule their first therapy session? Please select all that apply.

- Encouragement or support from family members or friends
- Involvement with the criminal justice system or other mandated participation (e.g., court-ordered therapy)
- Recommendations or referrals from school or youth programs
- Workplace support programs, such as Employee Assistance Programs (EAPs)
- Referrals from non-mental health medical professionals (e.g., primary care physicians, specialists)
- Changes in the client's or provider's financial situation, enabling access to care (e.g., insurance coverage, sliding scale fees)
- Exposure to online content related to mental health or therapy (e.g., blogs, social media, videos)
- Experiencing a significant life event or stressor (e.g., loss of a loved one, relationship issues, job loss)
- Realization of a concern, seeking personal growth or self-improvement (e.g., building self-esteem, enhancing communication skills)
- Referrals from community-based organizations or support groups
- Participation in religious or spiritual communities that encourage seeking therapy
- Public awareness campaigns or mental health advocacy efforts
- Media exposure (e.g., TV shows, movies, or books featuring mental health topics or therapy)
- Telehealth services and online therapy platforms, which can increase accessibility and convenience

What activities do you feel are the most helpful in traversing barriers of your client to accessing your services?

- Financial assistance or sliding scales
- Multilingual capabilities
- Convenient geographic location
- Telemedicine services
- Availability (i.e. 24 hour support, on call service, text/phone access, etc.)
- Practice brand, design, and environment (logo, design, messaging, physical environment, etc.)
- Flexible scheduling options (e.g., evening or weekend appointments)
- Clear and user-friendly online presence (e.g., informative website, appointment booking system)
- Coordination with other healthcare providers (e.g., integrated care, collaborative care, sharing information with consent)
- Offering a range of therapeutic approaches (e.g., cognitive-behavioral therapy, psychodynamic therapy, couples or family therapy)
- Providing a variety of therapy formats (e.g., individual, group, or workshops)
- Offering specialized services for specific populations (e.g., LGBTQ+ individuals, veterans, survivors of trauma, different cultural backgrounds)
- Engaging in community outreach and education (e.g., workshops, seminars, presentations)
- Participation in professional networks or associations (e.g., provider directories, referral networks)
- Offering evidence-based treatments and maintaining professional development

Interview Guide

- Initial thoughts after watching the video:
    - ____
- Likelihood of clients engaging with a service like this (choose one):
    - Highly likely
    - Moderately likely
    - Neutral
    - Moderately unlikely
    - Not at all likely
- Which elements of the chatbot interaction do you think will drive increased likelihood of engagement?
    - Personalized responses
    - Conversational design
    - Simple user interface design
    - Integration with an external system
    - Tone and personality of the responses
    - Other_____
- What is lacking in the current chatbot user experience?
    - _____
- Recommendations to improve the overall effectiveness of this experience:
    - ______
- Do you think this chatbot experience would build confidence with selecting treatment options.
    - Y/N
    - Why?
        - ____
- Do you think this chatbot experience would help clients overcome common mental barriers that inhibit accessing care.
    - Y/N
    - Why?
        - _____
- Do you think this chatbot experience would help clients with historical treatment disparities overcome common mental barriers that inhibit accessing care.
    - Y/N
    - Why?
        - ______
- Would you have more confidence that a referral would be more likely to be my ideal client population if it came through a recommendations experience like this.
    - Y/N
    - Why?
        - ______

Appendices for Chapter 4

Appendix J: State-level Telehealth Parity Legislation

(Table adopted from Xu (2022), data source: Justia)

State	Payment Parity Law before 2020	Coverage Parity Law before 2020
Alabama	No legal statute	No legal statute
Arizona	2013 Arizona Revised Statutes Title 20 - Insurance § 20-841.09 A. All contracts issued, delivered or renewed on or after January 1, 2015 must provide coverage for health care services that are provided through telemedicine if the health care service would be covered were it provided through in-person consultation between the subscriber and a health care provider and provided to a subscriber receiving the service in a rural region of this state. The contract may limit the coverage to those health care providers who are members of the corporation's provider network. 2015 Arizona Revised Statutes Title 20 - Insurance § 20-1057.13 Telemedicine; coverage of health care services; definitions A. An evidence of coverage issued, delivered or renewed by a health care services organization on or after January 1, 2015 must provide coverage for health care services that are provided through telemedicine if the health care service would be covered were it provided through in-person consultation between the enrollee and a health care provider and provided to an enrollee receiving the service in a rural region of this state. The evidence of coverage may limit the coverage to those health care providers who are members of the health care services organization's provider network.	2013 Arizona Revised Statutes Title 20 - Insurance § 20-841.09 A. All contracts issued, delivered or renewed on or after January 1, 2015 must provide coverage for health care services that are provided through telemedicine if the health care service would be covered were it provided through in-person consultation between the subscriber and a health care provider and provided to a subscriber receiving the service in a rural region of this state. The contract may limit the coverage to those health care providers who are members of the corporation's provider network. 2015 Arizona Revised Statutes Title 20 - Insurance § 20-1057.13 Telemedicine; coverage of health care services; definitions A. An evidence of coverage issued, delivered or renewed by a health care services organization on or after January 1, 2015 must provide coverage for health care services that are provided through telemedicine if the health care service would be covered were it provided through in-person consultation between the enrollee and a health care provider and provided to an enrollee receiving the service in a rural region of this state. The evidence of coverage may limit the coverage to those health care providers who are members of the health care services organization's provider network.
Arkansas	2016 Arkansas Code Title 23 - Public Utilities and Regulated Industries Subtitle 3 - Insurance Chapter 79 - Insurance Policies Generally Subchapter 16 - -- Coverage for Services Provided Through Telemedicine § 23-79-1602. Coverage for telemedicine **(2)** Subject to subdivision (d)(1) of this section, a health benefit plan shall reimburse a physician licensed by the board for healthcare services provided through telemedicine on the same basis as the health benefit plan reimburses a physician for the same healthcare services provided in person.	2016 Arkansas Code Title 23 - Public Utilities and Regulated Industries Subtitle 3 - Insurance Chapter 79 - Insurance Policies Generally Subchapter 16 - -- Coverage for Services Provided Through Telemedicine § 23-79-1602. Coverage for telemedicine **(c) (1)** A health benefit plan shall cover the services of a physician who is licensed by the Arkansas State Medical Board for healthcare services through telemedicine on the same basis as the health benefit plan provides coverage for the same healthcare services provided by the physician in person.
California	Telehealth Advancement Act of 2011 (AB 415) Section 1374.13 (d) No health care service plan shall limit the type of setting where services are provided for the patient or by the health care provider before payment is made for the covered services appropriately provided through telehealth, subject to the terms and conditions of the contract entered into	CA Health & Safety Code § 1374.13 (b) It is the intent of the Legislature to recognize the practice of telehealth as a legitimate means by which an individual may receive health care services from a health care provider without in-person contact with the health care provider. (c) No health care service plan shall require that in-person contact occur between a health care provider

	between the enrollee or subscriber and the health care service plan, and between the health care service plan and its participating providers or provider groups.	and a patient before payment is made for the covered services appropriately provided through telehealth, subject to the terms and conditions of the contract entered into between the enrollee or subscriber and the health care service plan, and between the health care service plan and its participating providers or provider groups. (d) No health care service plan shall limit the type of setting where services are provided for the patient or by the health care provider before payment is made for the covered services appropriately provided through telehealth, subject to the terms and conditions of the contract entered into between the enrollee or subscriber and the health care service plan, and between the health care service plan and its participating providers or provider groups.
Colorado	2016 Colorado Revised Statutes Title 10 - Insurance Health Care Coverage Article 16 - Health Care Coverage Part 1 - General Provisions § 10-16-123. Telehealth - definitions (b) Subject to all terms and conditions of the health benefit plan, a carrier shall reimburse the treating participating provider or the consulting participating provider for the diagnosis, consultation, or treatment of the covered person delivered through telehealth on the same basis that the carrier is responsible for reimbursing that provider for the provision of the same service through in-person consultation or contact by that provider. A carrier shall not deny coverage of a health care service that is a covered benefit because the service is provided through telehealth rather than in-person consultation or contact between the participating provider or, subject to section 10-16-704, the nonparticipating provider and the covered person where the health care service is appropriately provided through telehealth. Section 10-16-704 applies to this paragraph (b).	2016 Colorado Revised Statutes Title 10 - Insurance Health Care Coverage Article 16 - Health Care Coverage Part 1 - General Provisions § 10-16-123. Telehealth – definitions (2) On or after January 1, 2002, no health benefit plan that is issued, amended, or renewed for a person residing in a county with one hundred fifty thousand or fewer residents may require face-to-face contact between a provider and a covered person for services appropriately provided through telemedicine, pursuant to section 12-36-106 (1) (g), C.R.S., subject to all terms and conditions of the health benefit plan, if such county has the technology necessary for the provision of telemedicine. Any health benefits provided through telemedicine shall meet the same standard of care as for in-person care. Nothing in this section shall require the use of telemedicine when in-person care by a participating provider is available to a covered person within the carrier's network and within the member's geographic area.
Delaware	2015 Delaware Code Title 18 - Insurance Code CHAPTER 33. HEALTH INSURANCE CONTRACTS § 3370 Telemedicine (e) An insurer, health service corporation, or health maintenance organization shall reimburse the treating provider or the consulting provider for the diagnosis, consultation, or treatment of the insured delivered through telemedicine services on the same basis and at least at the rate that the insurer, health service corporation, or health maintenance organization is responsible for coverage for the provision of the same service through in-person consultation or contact. Payment for telemedicine interactions shall include reasonable compensation to the originating or distant site for the transmission cost incurred during the delivery of health-care services.	2015 Delaware Code Title 18 - Insurance Code CHAPTER 33. HEALTH INSURANCE CONTRACTS § 3370 Telemedicine (d) An insurer, health service corporation, or health maintenance organization shall not exclude a service for coverage solely because the service is provided through telemedicine services and is not provided through in-person consultation or contact between a health-care provider and a patient for services appropriately provided through telemedicine services.
Florida	No legal statute	No legal statute
Georgia	O.C.G.A. 33-24-56.4 (2010) 33-24-56.4. Payment for telemedicine services (c) It is the intent of the General Assembly to mitigate geographic discrimination in the delivery of health care by recognizing the application of and payment for covered medical care provided by means of telemedicine, provided that such services are	O.C.G.A. 33-24-56.4 (2010) 33-24-56.4. Payment for telemedicine services (d) On and after July 1, 2005, every health benefit policy that is issued, amended, or renewed shall include payment for services that are covered under such health benefit policy and are appropriately provided through telemedicine in accordance with

	provided by a physician or by another health care practitioner or professional acting within the scope of practice of such health care practitioner or professional and in accordance with the provisions of Code Section 43-34-31.	Code Section 43-34-31 and generally accepted health care practices and standards prevailing in the applicable professional community at the time the services were provided. The coverage required in this Code section may be subject to all terms and conditions of the applicable health benefit plan.
Hawaii	2013 Hawaii Revised Statutes TITLE 24. INSURANCE 431. Insurance Code 431:10A-116.3 Coverage for telehealth. 2016 Hawaii Revised Statutes TITLE 24. INSURANCE 432D. Health Maintenance Organization Act 432D-23.5 Coverage for telehealth.	2013 Hawaii Revised Statutes TITLE 24. INSURANCE 431. Insurance Code 431:10A-116.3 Coverage for telehealth.
Iowa	No legal statute	No legal statute
Idaho	No legal statute	No legal statute
Massachusetts	No legal statute	No legal statute
North Carolina	No legal statute	No legal statute
Ohio	No legal statute	No legal statute
Pennsylvania	No legal statute	No legal statute
South Carolina	No legal statute	No legal statute
Virginia	2016 Code of Virginia Title 38.2 - Insurance Chapter 34 - Provisions Relating to Accident and Sickness Insurance § 38.2-3418.16. Coverage for telemedicine services D. An insurer, corporation, or health maintenance organization shall not be required to reimburse the treating provider or the consulting provider for technical fees or costs for the provision of telemedicine services; however, such insurer, corporation, or health maintenance organization shall reimburse the treating provider or the consulting provider for the diagnosis, consultation, or treatment of the insured delivered through telemedicine services on the same basis that the insurer, corporation, or health maintenance organization is responsible for coverage for the provision of the same service through face-to-face consultation or contact.	2016 Code of Virginia Title 38.2 - Insurance Chapter 34 - Provisions Relating to Accident and Sickness Insurance § 38.2-3418.16. Coverage for telemedicine services C. An insurer, corporation, or health maintenance organization shall not exclude a service for coverage solely because the service is provided through telemedicine services and is not provided through face-to-face consultation or contact between a health care provider and a patient for services appropriately provided through telemedicine services.
Wisconsin	No legal statute	No legal statute
Wyoming	No legal statute	No legal statute