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The Perceived Utility of Smartphone and Wearable Sensor Data in Digital Self-tracking Technologies for Mental Health

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Abstract

Mental health symptoms are commonly discovered in primary care. Yet, these settings are not set up to provide psychological treatment. Digital interventions can play a crucial role in stepped care management of patients' symptoms where patients are offered a low intensity intervention, and treatment evolves to incorporate providers if needed. Though digital interventions often use smartphone and wearable sensor data, little is known about patients' desires to use these data to manage mental health symptoms. In 10 interviews with patients with symptoms of depression and anxiety, we explored their: symptom self-management, current and desired use of sensor data, and comfort sharing such data with providers. Findings support the use digital interventions to manage mental health, yet they also highlight a misalignment in patient needs and current efforts to use sensors. We outline considerations for future research, including extending design thinking to wraparound services that may be necessary to truly reduce healthcare burden.

Keywords

digital mental health; mobile phone app; sensing; tracking; self-management; depression; anxiety; primary care

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1 INTRODUCTION

Mental health conditions like depression and anxiety are common, yet an estimated 30% of people with these conditions receive no treatment, and many in treatment receive inadequate care [47, 98]. Though these conditions are often first identified within primary care settings (including primary care and family medicine clinics) when patients come in for routine check-ups, the healthcare system is not set up to provide the psychological treatment indicated. Healthcare providers are limited in their ability to provide adequate treatment due to constraints of time, training, and resources. As a result, patients are often referred to outside mental health providers at which point they encounter barriers due to the shortage of psychologists, counselors, and social workers who can deliver psychological treatment, as well as transportation problems, cost, and other factors impacting the desire for formal treatment (e.g., stigma) [69, 70, 75].

One way to buffer the loss in this transition from diagnosis to securing treatment may be to offer or deploy low-cost, evidence-based digital mental health interventions (DMHIs) at this opportune point of care [25, 37]. DMHIs are highly flexible and offer myriad opportunities to bridge gaps in care for patients on wait-lists or those who prefer to self-manage. They can also be used to augment services by providing clinicians and other healthcare providers with access to specific and granular data about patient symptoms between visits. Indeed, multiple meta-analyses have shown that DMHIs focused on improving mental health can be efficacious [33, 36]. DMHIs have particular promise as low-intensity interventions within stepped care treatment models, which aim to deliver minimally time and resource intensive treatments before higher intensity treatments in healthcare settings that are overburdened, like primary care.

Increasingly, DMHIs incorporate smartphone and wearable sensors which provide continuous data streams that can be leveraged by providers or patients to understand and improve symptoms without placing significant burden on users. Yet, to date little is known about how individuals with common mental health conditions currently use smartphone and wearable technologies to manage their symptoms, and whether the data these devices produce align with their mental health goals. Such an understanding is necessary if we are to develop DMHIs that are usable and acceptable to primary care patients with symptoms of depression and anxiety. The overarching goal of this project was identify the mental health self-management needs of patients whose symptoms of depression and anxiety are discovered in primary care, with the intention of developing a DMHI that contributes little additional burden to this healthcare setting and supports patients' self-management of symptoms. We explored self-tracking technologies, in particular, due to their ubiquity, their prior use for behavior change [43, 61, 88], and the potential for the data generated from these devices to be of value in patient self-management. We specifically aimed to explore (1) patients' mental health self-management, (2) their interest in, and preferences for, a self-tracking technology to assist in mental health self-management, and (3) their comfort with sharing data from such a technology with primary care providers.

This paper makes four contributions in service of exploring the potential use of DMHIs that leverage sensors to support primary care patients managing mental health symptoms as part

of an early stage of a stepped care program. First, we provide a descriptive understanding of primary care patients' diverse experiences of mental health symptoms and self-management. In general, mental health symptoms made it difficult for participants to engage in activities that brought them enjoyment and a sense of accomplishment. Maintaining mental health involved striking a comfortable balance between engaging in valued activities and doing so with a sense of ease. Though technologies were not central to participants' experiences of mental health self-management, they were a common resource to access beneficial activities and social support, underscoring their potential as an accessible and acceptable means of intervention. Second, we identify their needs and preferences regarding self-tracking for mental health, including what types of tracked information would be helpful, and when it would be most helpful. Participants were particularly interested in tracking behavioral markers of mental health, including engagement in beneficial activities, if it could help them to better manage symptoms during periods of high symptomology. Third, we identify ways smartphone and wearable sensor and self-report data can be leveraged to support mental health maintenance and active symptom management, which participants experienced as two distinct periods in need of different technological support. Finally, given participant receptivity to sharing DMHI data with their providers, we consider structures and services that would need to be in place in order for a DMHI to successfully integrate within primary care and reduce burden in this setting.

2 RELATED WORK

2.1 Depression and Anxiety in a Primary Care Context

Depression and anxiety are two of the most prevalent mental health conditions [47, 64]. Left untreated they can have long-term consequences for physical and psychological health and contribute significantly to rates of global disability [19, 31, 78]. Highly efficacious and evidence-based treatments for both depression and anxiety exist such as cognitive behavior therapy (CBT) which focuses on identifying and changing thoughts, attitudes, beliefs and behaviors that negatively impact mental health [21, 41]. However, most people with these conditions do not receive any mental health treatment [97], and even fewer receive evidence-based mental health treatment [34]. Structural (cost, time, geography), systemic (structures built within racism, ableism), and attitudinal barriers (stigma, mental health literacy) impact access and uptake of mental health care [69, 70, 75]. Further, many individuals with symptoms of depression or anxiety do not identify them as meriting care, reducing the likelihood of them seeking, and benefiting from, support [35, 38, 84]. Early identification and referrals to accessible and acceptable treatments for these common mental health conditions are needed.

Recognizing the value of early identification, the U.S. Preventive Services Task Force recommends systematic screening for depression in adults and adolescents in primary care settings, and that adequate systems are in place to ensure those with positive screens receive appropriate treatment [90, 91]. Though rates of diagnoses increase as more patients are screened, there is not a similar trend for mental healthcare service utilization [16, 86], with some studies showing 2/3rds of those screened for depression do not receive treatment [79]. Moreover, primary care physicians can, and do, prescribe medications for mental health

conditions, but studies have shown that up to 2/3rds of patients prefer psychotherapy, to pharmacological treatment [18, 26, 82].

There are not nearly enough mental healthcare providers to respond to those who already seek mental health treatment, however, which means that even when individuals are identified within our healthcare systems, they are unlikely to receive quality mental healthcare [45]. For example, in a large national survey of over 9,000 individuals, just 21.5% with a psychiatric disorder received treatment from a qualified mental health professional, with other studies similarly reporting around 30% of people with a mental health diagnoses receiving treatment [47, 98]. The percentage of people receiving care is even lower among marginalized communities and those in high hardship areas, in part because they are less likely to initiate mental health treatment, and more likely to drop out from treatment [76]. Low-intensity services that can be recommended or delivered to people when their mental health symptoms are first identified could increase the likelihood that they will gain access to evidence-based resources, and possibly prevent the worsening of symptoms.

2.1.1 Mental Health Treatment Under Constrained Resources.—In response to the aforementioned shortages, several models of condition management have been used in primary care to more adequately and efficiently address the needs of individuals with depression and anxiety, including stepped care treatment models [23, 95]. In traditional stepped care, patients begin with a low intensity treatment and their symptoms are monitored on a routine basis. Patients that do not respond, or do not show meaningful improvement in symptoms with the lowest intensity intervention, “step up” to higher intensity interventions until improvement is seen. In general, research has shown that stepped care models can be effective in the treatment of depression [95], and meta-analyses have shown that stepped care models have similar effect sizes to other care models for depression like collaborative care [5]. A typical first step in a stepped care program would be to monitor for symptoms through regular assessment. This is already commonly done by administering the depression and anxiety screeners in routine care. When symptoms are detected and intervention is indicated a second step may be to recommend patients a self-management or self-help intervention. Often these early interventions include pamphlets or online sources of information to reduce burden on healthcare providers. If symptoms do not improve with DMHI self-management, more intensive interventions such as facilitated or guided self-management, where a care manager offers low intensity support to increase adherence and motivation or face-to-face intervention with a provider, an so on until there is symptom improvement. Among the benefits of stepped care models are the ability to provide evidence-based resources in a way that does not overly burden the healthcare system, and the ability to scale services to more patients in need. Digital interventions can play a crucial role in the early steps of stepped care.

2.2 Digital Mental Health Interventions

Digital mental health interventions are tools that leverage commonly available technologies such as apps and websites to deliver mental health treatment in alignment with the Task Force’s call for “adequate” care [77]. DMHIs are a promising method to address the need for services as they enable expeditious delivery of evidence-based treatments to

individuals in a scalable and cost-effective manner. In addition to studies showing that individuals with psychiatric conditions have interest in using DMHIs to improve their mental health [54, 92], several meta-analyses have shown that DMHIs are efficacious [32, 33]. Further these tools are flexible as they can be designed to help individuals self-manage their symptoms by providing psychoeducation on their illness, coping strategies, and tools for tracking symptoms/progress or to augment existing treatment, by providing support to patients between treatment sessions [54]. For example, Intellicare is a mobile app intervention that focuses on self-management of depression and anxiety symptoms through interactive cognitive and behavioral skills training [72, 73], whereas ACT skills in a mobile app designed to support patients with Generalized Anxiety Disorder between sessions of Acceptance and Commitment Therapy [51]. This flexibility of DMHIs to both facilitate self-management and augment traditional mental health treatment, make them uniquely suited as a modality for integration within early stages of stepped care programs to provide quality care and reduce burden in primary care.

2.3 Self-Tracking for Self-Management

Increasingly, systems that support self-tracking are used as a means to support health and mental health self-management [49, 59]. Self-tracking systems have long been a focus of empirical study in the HCI community, with research identifying overall self-tracking practices, and tracking for chronic illness management [27, 30, 55]. Some self-tracking systems are specifically designed to closely align with CBT's emphasis on increasing individuals' awareness of thoughts, attitudes, and behaviors that impact mental health and well-being [28–30, 46]. For example, Mobilyze! is a CBT mobile intervention that collects data on the users' self-reported mood as well as their activities and provides feedback based on correlations in data and depression scores [12]. Self-tracking is conducted primarily in two ways: (1) manually via patient self-report and (2) passively using built in smartphone sensors or commercial wearables.

2.3.1 Manual Symptom Tracking.—Given the subjective nature of mental health experiences, self-tracking systems have often relied on symptom self-report [13]. Indeed, in CBT for depression and anxiety, clinicians commonly ask patients to track their symptoms and thoughts, behaviors, and emotions related to symptoms between appointments. DMHIs can easily facilitate this type of tracking through repeated prompts of standardized clinical measures or informal mood tracking through emojis [62] or colors associated with mood [17]. As an example, IntelliCare allows users to track mood after completing specific mood-boosting activities [73]. Though manual tracking enables systematic evaluation of mental health over time, systems that rely on manual logging are burdensome and are therefore often unsustainable for users with chronic conditions, like depression or anxiety. Prior research has shown that overly relying on manual inputs can result in gaps in data [88] or no tracking at all [63]. Alternatively, tracking behaviors such as the amount of physical activity one has had in a day or the minutes spent inside one's home, both of which can be correlated with depression and anxiety, can be virtually effortless with the use of sensors [7].

2.3.2 Passive Behavioral Sensing.—DMHIs that incorporate passive sensing typically collect continuous data on several behavioral and physiological markers of mental

state including sleep, physical exercise, and arousal, through accelerometers, location, and audio sensors [6, 94]. Due to the large complement of sensors built into everyday technologies, like smartphones and smartwatches, interest has grown around the use of sensor data to passively monitor and intervene on symptoms of depression and anxiety [7, 14, 83, 99]. Work in this area has indeed provided evidence for several sensor-based features that relate to these conditions. For example, studies have shown relationships between depression and anxiety and mobility data, physical activity, speech patterns, sleep duration, mobility, and general phone usage [20, 58, 66, 80, 85, 87]. While sensor data have increased opportunities for researchers to understand these conditions and detect new digital signals reflecting behaviors that are related to mental health symptoms, there are several known limitations that impact the potential for these tools to improve symptoms in the wild.

First, self-tracking tools have the potential to increase a person's awareness of symptoms, but research has shown that this awareness can be overwhelming or discouraging for users [28, 29, 46, 88], and can ultimately lead to lapses in technology use making gains unlikely. Secondly, behavioral markers are understood to be proxies for users' experiences of depression and anxiety; however, little work has focused on which signals users need from sensors and, equally critical, when. Finally, sensor data do not often provide clear information on what a person can do to improve symptoms without further interpretation or clinician feedback, yet these tools are often designed for self-management with limited support from providers or other trained personnel. Understanding how to best support the general primary care patient population with these technologies is subject to empirical attention.

2.4 Summary

To understand the value of DMHIs that incorporate sensor data for primary care patients with symptoms of depression or anxiety, we need to understand how these individuals envision these data could be used to support their mental health and if, or how, these data relate to their personal mental health goals and existing self-management practices. Understanding that primary care is a common touchpoint for mental health screening and diagnosis, it is also imperative to understand users' comfort with sharing tracked data with their providers as well as the perceived benefits and expectations users may have, if and when more intensive intervention is indicated. This understanding could help us develop a low-intensity digital intervention designed to address the needs of the large number of patients with depression and anxiety symptoms in a way that is acceptable to users and feasible in primary care.

3 METHODS

3.1 Recruitment and procedure

Participants were recruited from primary care and family medicine clinics housed within an urban healthcare system serving communities with high hardship indexes [52]. Recruitment involved the distribution of flyers in clinics and community organizations, as well as email and MyChart messages to patients within the care system. Interested individuals completed an online questionnaire to determine eligibility. Those meeting the following inclusion

criteria were eligible to participate: English speaking, over 12 years old, US citizen/resident, and self-reported depression or anxiety symptoms. The age range of interest shifted over the course of our early elicitation work as we became more familiar with our clinical stakeholders' needs. Noting that an app could be useful for a younger cohort of users we extended our recruitment from an adult population to adolescents. While we were open to younger adolescents, the youngest participant we recruited was 17 years old. Also, to ensure access to a smartphone device (which is the technology of interest in this study), all eligible participants needed to indicate that someone in their family owned a smartphone. The study team settled on this criterion instead of individual smartphone ownership to ensure that younger adolescents could participate. We intentionally sampled broadly to reflect the diverse population (in terms of age, race, ethnicity, and mental health symptom severity) served through the healthcare system.

All eligible participants were contacted via phone or email by a member of the research team to alert them to their eligibility and initiate the consent process. Participants that were interested in providing consent were sent a link to an online consent document and were asked to provide their digital signature. Participants that provided consent then scheduled an interview time with the study research assistant and completed a baseline survey which included questions on demographics, and symptoms of depression (via Patient Health Questionnaire, PHQ-9) and anxiety (via the Generalized Anxiety Disorder Questionnaire, GAD-7). Ten individuals participated in semi-structured interviews with a PhD-level research assistant trained in the study procedure. One-on-one virtual interviews were conducted over zoom to ensure participant comfort speaking about their experiences of mental health symptoms (a potentially stigmatized topic) and to ensure participant safety, since the study took place during the Covid-19 pandemic. The interview guide was developed and iteratively refined by multiple members of the research team including a clinical psychologist, a qualitative researcher, and two PhD-level trainees. The guide included questions and probes focused on understanding participants' mental health needs and preferences (e.g., How does your mental health, like feeling stressed, nervous, or down, affect your life? How do you choose the strategy you'll use to manage your mental health in any particular instance?), their current self-management strategies (e.g., Can you tell me about a recent day when you were feeling stressed, anxious, or down and what you did to try to make yourself feel better?), and their current use of technologies, including self-tracking devices, in self-management (e.g., Which technologies are particularly helpful for your mental health?). Interviews lasted between 45 and 65 minutes for a total of 586 minutes (9.77 hours) of audio.

3.2 Data analysis

Interviews were audio-recorded and transcribed. Data were analyzed through a conventional qualitative content analysis approach, as defined by [42]. This process included data familiarization, identification of individual codes, grouping codes into categories based on conceptual similarity, reviewing and refining categories to reduce overlap and redundancy, defining and naming final groupings common across the whole dataset, and selecting examples from the data to accurately illustrate each.

Two authors read through the transcripts in full to familiarize themselves with the data. Then, these authors applied codes to two transcripts independently to identify an initial set of open codes (e.g., playlists to manage mood, group chats for support, Netflix to distract). They met to discuss these codes for face validity and conceptual clarity. Then the two authors conducted axial coding to group open codes into categories based on conceptual similarity (e.g., media use). At this stage and onward, discrepant codes were discussed and resolved via a consensus process [39]. This hierarchical code structure was revised to reduce overlap, and the remaining transcripts were divided evenly among the two authors to code independently. Finally, the authors organized categories under broader clusters of shared meaning (e.g., mental health self-management practices). Once these clusters were solidified, examples were drawn from the data for the write-up. All analyses were conducted in Dedoose, a qualitative data analysis software.

3.3 Study ethics and reflexivity statement

We recognize our responsibility, as researchers, to ensure participant comfort in discussing factors related to their mental health. We sought to create a safe environment for participants to share their personal experiences. This included reiterating at multiple points that they could discontinue the interview or skip over questions that they felt uncomfortable answering or reflecting on. Participants were also able to keep their camera off on zoom to increase comfort during the interview itself.

The research team included several clinical psychologists who provided clinical guidance throughout the study design and data collection periods. In addition, individuals with lived experience of some of the mental health concerns addressed here were part of the research team. Our team aimed to support participants in sharing their lived experiences of mental health and their perceptions, and did so through a human-centered design approach. All study procedures were approved by our human subjects board.

3.4 Participant demographics

Table 1 includes participant demographics. Participants in our sample were mostly female (n=8, 80%), and were racially diverse: Asian (n=3), American Indian (n=2), African American or Black (n=2), White (n=2), and more than one race (n=1). Four participants identified as Hispanic. On average, participants reported mild to moderate symptoms of depression (PHQ-9=6.56) and anxiety (GAD-7=7.25).

4 FINDINGS

Our findings are organized under five main headings: (1) Experiences with mental health symptoms, (2) Mental health self-management practices, (3) Histories with self-tracking technologies, (4) Desired self-tracking for mental health and (5) Comfort with, and expectations for, sharing data with providers. Overall, participants described that their mental health symptoms made it difficult for them to engage in activities that typically brought them a sense of enjoyment and accomplishment. To maintain good mental health, participants made proactive and intentional efforts to balance valued activities with task-oriented activities in their daily life. When this balance was disrupted, either due to

symptoms (e.g., lethargy, motivation) or external and environmental factors outside of participants' control (e.g., lack of access, Covid pandemic), they experienced difficulties re-establishing equilibrium and a need to shift their focus to more manageable goals. Notably, in these periods of high symptomology, participants reported different needs relative to periods of low symptomology, which has important implications for the design of supportive self-tracking technologies for this population. Many participants were also comfortable sharing data from a self-tracking technology with their providers in service of more personalized treatment, and saw the sharing of data as a way to initiate conversations and enable timely interventions, underscoring the potential to integrate support from providers if, and when, indicated. We expand upon these findings below, beginning with patients' experiences of mental health symptoms, and progressing to the use of, and interest in, technology for symptom management.

4.1 Experiences with mental health symptoms

Participants' experiences of depression and anxiety included changes in mood, blunted enjoyment, and lack of motivation which resulted in difficulties completing routine activities. The presence of these symptoms was a reminder to participants that their mental health required their attention, and was often a source of further stress. The three most common experiences participants described were: (1) decreased enjoyment and motivation in daily life, (2) a sense of internal uneasiness, and (3) increased difficulty relating to and interacting with others.

Changes in mood, enjoyment, and motivation were highly salient in participant experiences, and a significant source of distress in daily life. For example, Participant 10 described that exercise was something he did to lift his mood when he was feeling relatively well; however, he struggled to initiate physical activity when his symptom load was high. Reflecting on these periods of high symptomology, Participant 10 described:

"My mind feels like – I'm thinking about something else when I'm doing a certain task or I'm just not as motivated. So, when I was feeling down, for example, I just wasn't motivated to exercise like I usually would be, regardless of it's just two days a week, I still wouldn't want to do those two days. So, I feel like ... the drive is not the same." (P10)

Other participants similarly commented on the impact motivation has on their pursuit of activities that they usually enjoy when they are experiencing mental health symptoms. For example, Participant 6 described that needing to put energy towards mitigating his symptoms of anxiety, stunted his motivation to pursue pleasurable activities that were necessary for depression management. Specifically, Participant 6 said that he was: *"less motivated to engage in enjoyable activities in the sense that I might feel like I have to devote extra time towards those important responsibilities and matters in the hopes that doing so will decrease the source or mitigate the source of that stress and anxiety."* (P6)

Relatedly, some participants described specific activities that they used to like, but that they lost interest in over periods of time managing symptoms. Participant 5 described that she *"...used to love to write poems, but I stopped that maybe a year ago,"* when her symptoms of depression increased. In these periods of poor mental health, participants

needed to re-prioritize their efforts towards activities that were manageable and that could quell symptoms.

In addition to noticeable shifts in motivation which impacted how, and what, activities participants engaged in daily, they also described an internal discomfort that came from noticing symptoms in daily life. For example, Participant 10 felt “*a sense of uneasiness, just internally*” when he recognized that he didn’t “*get the same joy out of things,*” like eating his favorite foods. Similarly, Participant 8 described feeling “*listless*” when reflecting on how it was “*hard to get up in the morning.*” And, Participant 4 reported feeling “*out of place*” when experiencing difficulties completing routine work:

“I feel like I’m slowed down. I can’t get anything done and I just feel really distracted especially when it comes to work. Just like it’s like I’ll be doing something that I know I can do incredibly well or really easily. I’ve done it hundreds of times before and I’ll mess it up or what have you or I’ll type my name on something. Small, little things like that, it’s just like...It’s so frustrating because it’s like I know I can do this.” (P4)

Though many of the symptoms participants described were experienced internally, they also contributed to a growing strain on interpersonal relationships. For example, Participant 8 described changes in how she related to others like this: “*I’m not appreciative of just general things happening around me or people. I’m maybe more snappish,*” and Participant 10 said: “*I think it really comes through with how I interact with people. So, if I am feeling a certain way, it definitely [affects] how I communicate.*” Implicit in these comments was the sense that internal changes in mood, and the sense of uneasiness it caused, made for difficult interactions that could cause further tension and impact the support they were able to receive from close others.

Overall, shifts in motivation and how participants related to, and experienced, important activities and people in their lives were central to their experiences of mental health symptoms. Though participants could easily identify these symptoms when they were present, and were aware of the impact they had on their day-to-day existence, addressing them required consistent effort and energy, which was particularly limited in periods when their symptoms were highly salient.

4.2 Mental health self-management practices

When recounting experiences of mental health self-management, participants described periods of poor mental health (characterized by active symptom management) relative to periods of good mental health (mental health maintenance). In periods of good mental health, participants more regularly engaged in activities that lifted their mood like exercise, connecting with others socially, and eating and sleeping well. The ease with which participants engaged in these activities was a sign of health, and critical to mental health maintenance. Periods of poor mental health, in contrast, were characterized by symptoms that made it difficult for participants to engage in these activities, and often required participants to take action in other ways to rebuild momentum. Specifically, participants described engaging in focused activities that brought them a sense of

accomplishment, productivity, or enjoyment as being most helpful when they experienced high symptomology.

Participant 10 describes their process of goal setting when they experience symptoms like this:

“On a recent day where I have been feeling down, I would say that the thing that I did to feel better – I would try to engage myself in some activity where I felt some sense of accomplishment to get me out of the doldrum that I was in.” (P10)

Similarly, Participant 4 described how setting incremental goals and providing self-affirmations or rewards to reinforce her efforts was helpful:

“I won’t set up a big, hard goal for myself. I’ll just be like, ‘Okay, we’ll just reorganize the desk’ and then once I’m done with the desk I’ll be like, ‘Okay, you did so good. Great. Let’s go reorganize the bookshelves’ and then I’ll just do small goals like that and then a nice, little easy reward system to give myself perks or little pep talks like, ‘Hey, there you go. That’s what you did’ and then it helps motivate me to do the next item.” (P4)

Participants were generally in agreement that pursuing intentional practices that were goal-oriented and attainable helped them restore good mental health in a period characterized by many symptoms. For example, Participant 6 described the importance of intentionality in pursuing meaningful activities like this: *“It can be any activity, it just has to be something that ideally you’ve chosen actively to do.”* What participants defined as meaningful activities varied, however. Some participants undertook task-oriented projects at home or work where it was easy to track progress. For example, Participant 4 described: *“One of the things I like to do is either throw myself into work and/or a new project at home – it makes me feel good when I do something successfully or do it well.”* While others set intentions to pursue new hobbies or do something they enjoyed. For Participant 7, that activity was learning to bake: *“I’m learning how to make a cake. That is something that I wanted to achieve. I definitely want to be able to know how to make a cake. So, that is what I’m working on now.”* Participant 1 described painting: *“My painting. I would like to get that done.”* Notably, these activities supported both the desire to intentionally do something for oneself and feel productive. Participant 1 described it like this: *“I feel accomplished like I did something for myself that day. So, I would be feeling happy that I did that for myself.”*

Though all participants described personal activities and goals as part of their self-management of mental health symptoms, several also acknowledged the importance of checking in with others. Participant 4 described how her boyfriend provided accountability and validation when things weren’t going so well symptom-wise: *“my boyfriend really helps me manage my mental health. He’ll be the one who will sometimes see how I am that day. If I’m really stressed or I’m really sad that day, he’ll be like, ‘Hey, let’s go on a walk or let’s do this or let’s do that’”* (P4). Participant 2 similarly described that he checked in with a therapist when he was in treatment and he purposefully scheduled *“meetings with her just to keep myself accountable for my mental health.”* Now that Participant 2 is no longer seeing therapist he described “self check-ins” as a way to take stock in his mental health. While social accountability was important for mental health management, and so was social

support. For example, Participant 10 described that talking to his wife helped him to: *“think through why I was feeling the way I was. So, I think that too was probably the bigger help than just thinking through the tasks”* (P10). Participant 8 similarly noted that she often felt better after *“sharing with sister and husband.”* Though participants reported strategies to manage their mental health alone, for some support from others was essential to motivate to follow through on activities and to help them reflect on their symptoms.

In general, participants’ experience of mental health included periods of low and high symptomology. When asked to reflect on activities that helped them overcome symptoms when they experienced more symptoms, or poor mental health, they described activities that provided them with a sense of accomplishment or enjoyment. Notably, these activities were highly variable across participants and differed from those that we typically attribute to mental and physical health like physical activity, eating behaviors, and sleep. Instead, they were “simplified,” shorter-term goals that provided participants with more immediate and tangible satisfaction. Family and significant others were also important to mental health maintenance – providing both accountability and support.

4.3 Experiences with self-tracking technologies

Participants were asked about their use of self-tracking technologies with smartphone or wearable sensors as part of their efforts to self-manage mental health symptoms. Though many participants described using devices like Apple Watch and Fitbit to track metrics related to physical health and well-being, very few endorsed the use of self-tracking technologies for mental health specifically.

In regard to physical health, participants most often described how they used and reflected on data from sensors embedded within technologies they used every day. They noted that these technologies helped them to identify and reflect on patterns, set goals, and send reminders to help them accomplish goals. For example, Participant 6 described how data from his wearable made him more aware of his poor sleep hygiene, and motivated him to set incremental goals to get to bed earlier:

“I think I use it to motivate myself to sleep better. I mean, without having documentation of it, I wouldn’t be able to say, “Oh, for the early weeks of January, I didn’t sleep that much,” or, “In the past week, I’ve been going to sleep past 4:00 a.m. Let’s try to pull that back to 3:00 a.m. or 2:00 a.m. or let’s go to bed at 12:00 every day now, and let’s see if I can keep that up.” (P6)

One of the features that facilitated self-tracking for Participant 6 was the way data was stored and easily accessible through his online calendar: *“I can pull up my calendar and it’ll be there automatically just makes it seem nice and easy to track. So, it doesn’t require much effort at all.”* Being able to visualize this information in a system that he already engaged with daily without requiring extra steps was important.

Participants also described and appreciated self-tracking technologies that reminded them to engage in activities that were beneficial, and/or provided insight into behaviors that felt actionable. For example, Participant 4 described:

“I recently got an Apple watch and it’s been really neat because it has ... I got an older model but it still has all these really neat apps for tracking how much you move in a day and it’s cool because it reminds you every hour like, “Hey, you’ve been sitting down for too long. Stand up and stretch” So, I really like that. I’ve had it for six months now.” (P4)

These reminders helped several participants to maintain good habits targeting physical health, which may as a result help with mental health.

By contrast, very few participants described using self-tracking technologies for mental health. Of those who had used technologies to self-track mental health data in the past, journaling, mood tracking, or meditation apps were most common. However, all but one participant reported discontinuing use because the apps did not feel useful and they failed to capture nuance in participants’ experiences, or they did not provide workable insights. For example, Participant 6 described his experience using a journaling app like this:

“[It] wasn’t that useful for me, and then I just kind of fell off and didn’t use as much. It wasn’t as granular as I think I wanted it to be, and because it wasn’t granular, I couldn’t picture a situation in which looking back on it would be useful for me, because I would always pick “today was okay” versus “today was good”, and there’s nothing to correlate with that, so it wasn’t personally useful.” (P6)

This lack of perceived usefulness was a shared concern across several participants with prior self-tracking experience. Participant 5 described a mood tracking app like this:

“I felt like I was putting the same emotion every day. Sometimes [I found it helpful], but not really because I felt like I was just being the same emotional person that I am all the time and it’s just reminding me that I’m being the same emotional person every day.” (P5)

In this participant’s experience, the app emphasized a lack of change in symptoms rather than offering actionable strategies or insights to better support her mental health, which, ultimately, made her feel worse and led her to disengage with the app.

Boredom and lack of interest were other attitudinal barriers to mental health self-tracking. When discussing the mood tracking app mentioned above, Participant 5 said: *“I’ll just end up getting bored of it so I’ll stop doing it.”* Similarly, Participant 10 noted that his Apple Watch had some features that could be of value to mental health: *“it has this breathing thing on it – I used to have it scheduled when I first got my watch,”* but that he hadn’t used it on over a year because he tends to get *“caught up in whatever I’m doing and I don’t prioritize.”*

As mentioned, one exception to the negative experiences most participants described regarding prior mental health tracking, was Participant 2 who self-described as an *“app girl.”* She was currently using meditation apps to help her with sleep and anxiety, and her use increased through the pandemic: *“There are even five to ten minute ones during the day that you can just use for yourself to calm down, and feel a little re-centered, and refocused.”* She most appreciated the variety of meditations offered and the ability to easily access and use them throughout her day. Rather than manually tracking symptoms, the systems Participant

2 described involved tracking engagement in activities (e.g., meditations) and collecting passive behavioral data for sleep.

In sum, participants' prior experiences with self-tracking varied. Most participants reported some form of self-tracking with smartphone or smartwatch sensor data for physical health, but the majority of participants were not currently engaged in self-tracking for mental health. Participants that had prior experiences with self-tracking technologies for mental health, largely discontinued use because the tools they used were not perceived to be useful, suggesting the importance of re-evaluating participants' wants and needs for self-tracking for future design.

4.4 Desired self-tracking for mental health

Most participants expressed interest in, or curiosity about, a self-tracking tool that could help them better manage their mental health symptoms. They were particularly interested in a smartphone-app that could: (1) quantify the good things that they do for themselves daily, and (2) help them discern patterns that they could change to improve their mental health when they experienced many symptoms.

Though participants could easily identify symptoms associated with poor mental health, it was difficult to initiate activities to improve mental health, and to recognize the small things they do to improve mental health day-to-day. Participants imagined an app feature that would help them to take stock of the small things they do to improve mental health, and reflect on this data in aggregate. For example, Participant 2 imagined a way for her phone to help her to reflect on her weekly accomplishments:

“I think sometimes it would be nice to – if I had an option of – like, if my phone just popped up, and was like, “What did you do to take care of yourself today?” And, I could be like, “Oh, I did this.” And, then, if I get to see I’ve done x, y and z for the past week, like, wow That’s cool.” (P2)

For this participant, being able to see what they did to care for themselves on a weekly basis provided evidence and needed validation for their efforts. Participant 2 goes on to describe:

“I think it’s just another way of laying out the progress, and taking care of myself that I do. I feel like a lot of times, I don’t give myself enough credit for what I do for myself. So, getting to see it reflected on a table, or something would be effective for me.” (P2)

Other participants similarly described a desire for brief interactions with a DMHI through a prompt or nudge that would require little daily effort. Participant 4 mentioned *“if there is something as simple as my pill app with clicking and stuff like that, I think that would be really good for being a “How am I feeling today?” tracker.”* Importantly, check-ins like this were perceived to be helpful if they increased awareness of moments when they pursued activities that made them feel good and could facilitate reflection to discern patterns that were unhelpful.

Identifying potentially unhelpful patterns was important to many participants, but only if the app also provided insights on how to make changes to prevent further declines in mental

health. Participant 3 thought that an app may be able to “*help me understand what was going on in my brain, but then also, the best way to go about fixing it if there were things that needed to be fixed.*” Participant 3 similarly imagined that a self-tracking app would help them to take a “*look at the grand scheme of things*” and highlight things that accumulate over time. Another participant had a similar reflection, describing that an app could help her to identify common triggers (or situations that were bad for their mental health) so she could better understand them and intervene. Participant 9 commented that she’d like to see: “*how many times that actually my triggers kicked in and I was able to balance it out. I know that’s a trigger. Now, what did I do? I know that’s a trigger. So, why am I frustrated? And why do I let that frustrate me? That’s what I would learn if I had history*” (P9).

Interestingly, most participants wanted to notice or reflect on the accumulation of many things over time. While it felt comfortable to reflect on proactive activities for mental health daily, they were more interested in reflecting on actions, behaviors, and experiences that may contribute to more symptoms historically. In this way an app could be useful to prevent declines in mental health through increasing one’s awareness and knowledge of patterns.

While many participants were interested in the potential usefulness of an app for mental health, several were more ambivalent either due to past experiences with ineffective apps, or uncertainty around what to track. For example, Participant 10 described that couldn’t imagine what to track:

“I just don’t know what the right metric is for me to pay attention to. Or I don’t know what should I be doing better to improve it? So, I don’t know, mental health is so hard to nail down, so you either feel a certain way or you don’t, broadly speaking. So, I just don’t know if you can unpack those steps and there’s some kind of outcome associated with it that you can track or activities, then maybe, yeah.”
(P10)

Despite this, Participant 10 was interested in tracking activities over time in service of pattern recognition or uncovering “steps” they could take to improve their well-being.

Although most participants were not using smartphone or wearable sensor technologies to self-track mental health symptoms, they expressed interest in tracking behavioral markers of mental health if they could quantify the good things they do for themselves and make patterns salient for change and/or intervention. Notably, participants were more interested in tracking things that were within their control (activities, tasks), and less interested in tracking things that were perceived to be outside of their control (heart rate, quality of sleep).

4.5 Comfort with, and expectations for, sharing data with providers

As mentioned one common problem with self-tracking technologies is the interpretability of information to direct action. One way around this is to deliver feedback to providers who can assist users in interpreting data and provide recommendations. To this end, we wanted to get a sense of how comfortable participants would be with sharing information from the self-tracking tool with their provider, as well as what they expected from sharing that information. Interestingly, despite being recruited from primary care settings, most participants reported that their primary care providers did not speak with them in depth

about their mental health. A few participants mentioned that their providers asked screening questions without much follow-up, and several mentioned being unsure whether their provider would be the right person to discuss mental health with. For example, Participant 7 described that when providers *“don’t ask questions, it’s very uncomfortable for you to just ask – how you’re supposed to manage your mental health, what activities can you sort of engage in so that you’re able to better your mental health?”*

When participants were asked if they would be comfortable sharing information gathered from a self-tracking DMHI with their healthcare provider, most described that they would be, and they had specific ideas about how that information may be used. For some participants, they imagined that sharing mood or passive sensor data with their provider would help the provider to alert them to declining mental health, and provide guidance on problem solving. For example, Participant 9 imagined that providers would be *“better able to evaluate your well-being... just like any other test. It’s like, ‘These numbers don’t look good.’”* Moreover Participant 9 described:

“[A provider could] help you know that you’re either near the end of your rope or you about to get to the end of your rope, I would think. Or they want to help you not get to the end of your rope, so they could have a picture that they could see where you’re headed to and help you see if you don’t know you’re getting there.”
(P9)

Participant 6 imagined sharing data may result in better treatment. They described *“By sharing it with my PCP or healthcare providers, they have additional insight and theoretically would be able to provide me more personalized treatment or response, and there’s nothing indicating harm to myself or others”* (P6). In these cases, the provider’s role was to monitor the data, interpret it, notice patterns, and provide recommendations to improve patients’ mental health.

By contrast, other participants imagined that sharing data could help them to initiate conversations with their primary care provider. Participant 8, for example, described that it had been difficult for them to have conversations about mental health with their provider, and that they often felt like conversations about mental health were not welcomed: *“it’s hard to be – completely frank with your healthcare provider”* and *“I get the feeling that the healthcare providers don’t have time for – to be with my emotions, they just talk about my emotions.”* In cases like this, data was seen as a catalyst to both initiate and legitimize conversations about mental health symptoms. Similarly, Participant 3 hoped that sharing data from a smartphone app might also help them to get better support from their provider because they had trouble describing their symptoms: *“I would be very willing to share that because sometimes it’s hard to explain it, just because you don’t know how to explain it or because you don’t want to explain it, even though you want the help”* (P3).

Finally, participants were unanimous in their belief that if they shared information with their provider there would need to be transparency in both how it would be used, and how it would benefit them. On this, Participant 10 described: *“I’d be comfortable sharing information with a healthcare provider if there’s some kind of outcome for me.”* Moreover, participants were most comfortable sharing information if they knew who would have access

to it and how they would use that information. Participants described some concerns around specific data such as search behavior (which felt too personal) and greater comfort with other data, like exercise, mood, and activity data.

In sum, participants were interested in sharing data from a self-tracking DMHI with their provider if it would benefit them directly. They imagined that sharing data would help them to initiate conversations, provide their clinician with a more accurate understanding of their symptoms, and enable close monitoring for changes in treatment planning. This receptivity to sharing data provides some initial evidence for the possible integration of a self-tracking DMHI within primary care.

5 DISCUSSION

There is a need to bridge gaps in services between screening in primary care settings to acquiring mental health treatment. A DMHI deployed at this critical juncture, as part of self-management in early stages of stepped care, has the potential to provide evidence-based resources to individuals who may otherwise go without care. To date, DMHIs for self-management often involve manual self-tracking, however very little is known about how DMHIs designed with automated tracking can best support patients' existing self-management processes. In the current study, we sought to explore this potential through gaining an understanding of the self-management practices of patients recruited from primary care settings with symptoms of depression and anxiety, their needs and preferences for self-tracking technologies for mental health management, and their current and desired use of smartphone and wearable sensors to support their mental health journeys. Though our findings highlight the potential utility of self-tracking technologies to support people in contact with primary care providers, they also call attention to some misalignments in current efforts to leverage sensor data in DMHIs, and our participants' expressed needs. Additionally, consistent with past literature, we also found that participants were overwhelmingly supportive of sharing data with providers if it would directly benefit them [46, 100] underscoring the potential future integration of a self-management tool within clinical services, if and when a higher-intensity treatment is indicated.

In the discussion, we first describe **technology needs** supported by our findings and highlight some proposed, and new, solutions. Recognizing that our participants struggled with motivation and action as part of their symptoms of depression and anxiety, along with the consistent finding that DMHIs often have low engagement [92], we focused on self-management needs with an eye towards addressing these concerns if they should arise with a stepped care approach. We thus introduce an opportunity for the HCI community to extend focus to **wraparound services** alongside the self-management technology, as a means for healthcare providers to support use of the DMHI, and provide light-weight care aligned with the data. We argue that both technology and service designs may be necessary to sustainably bridge gaps in our healthcare system.

5.1 Self-management technology needs

As in other HCI studies, our findings underscored the need for a DMHI for primary care patients to support the personalization of goals, activities, and feedback, and to

accommodate shifts in user needs overtime. Consistent with both clinical understandings of the chronic and episodic nature of depression and anxiety [24] and prior research on depression from the HCI community [50], our participants characterized their experiences of mental health symptoms dichotomously. Specifically, they referred to periods of low and high symptomology, which corresponded to **mental health maintenance** and **active symptom management**. Participants had good insight on the types of activities that supported mental health when they were feeling well (e.g., exercise, eating and sleeping well), and many of these activities corresponded to behavioral markers captured by sensors in self-tracking tools for physical health. Yet, when reflecting on the things they do to help themselves when they actively manage symptoms, participants described needing to shift from their usual routines to accommodate changes in energy, focus, and motivation. In these periods, participants reported that smaller, focused tasks helped because they were more manageable and brought them a sense of enjoyment or accomplishment. In the following, we aim to translate the contrasting needs and activities perceived to be supportive when participants were maintaining mental health versus managing symptoms into considerations for technology design.

5.1.1 Mental health maintenance versus active symptom management.—

During **mental health maintenance** - when participants experienced few symptoms - little support was perceived to be necessary from a sensor-based self-tracking technology for mental health. Some participants already described using tracking tools, like Fitbits or smartwatches, to monitor and reflect on their physical health. For most, this was a way for them to keep track of physical activity or sleep patterns, and the ubiquity of these devices provided a subtle reminder to stay active and engage in healthy sleep hygiene. Though participants did not believe a tracking tool could offer more support during these periods, they consistently reported a desire to identify patterns in their mental health symptoms and to learn about potential triggers in order to take preventive action if declines in mental health were forecasted. These goals - to monitor their health and learn about triggers - commonly come up in work with people managing chronic conditions [60]. Some of this work has found that learning goals require more effort, and more intensive data collection, than monitoring goals [88]. Knowing that participant energy was limited in periods of high symptoms, it may be most feasible to leverage periods of good mental health to learn, while simultaneously collecting data for future forecasting in an unobtrusive way that would place little burden on the user. In line with prior research, our work underscores the opportunity to leverage periods with higher energy and motivation for the future [48, 50].

During **active symptom management participants** could envision a greater need for support from a self-tracking technology. When actively managing symptoms, participants focused on shortterm, well-defined activities that were perceived to be within their control. Despite knowing that small, manageable goals were helpful when symptom load was high, participants expressed difficulty following through on intentions and struggled to acknowledge their efforts and successes on a daily basis. Participants imagined that a self-tracking technology could help them to follow through on their intentions and take stock of their efforts to manage mental health through regular check-ins and validating messages. Interestingly, in this way, the imagined DMHI served a similar role to trusted peers and

significant others - as a resource to draw attention to symptoms, offer solutions, and keep them accountable. The social nature of behavior change and goal setting has been observed in prior HCI studies [2, 56] and studies specifically focused on the self-management of depression [10, 11]. However, here it seems that patients imagined the DMHI providing opportunities for self-guided reflection and action based on the collection of data. From the participants' perspectives, recording and reflecting on these small steps had the potential to reinforce self-efficacy and prevent them from feeling like they were "wasting time." Notably, this inclination to set intentions and pursue activities that were pleasurable or provided a sense of accomplishment during periods of high symptomology, aligns with behavioral activation - an empirically supported treatment that teaches patients to monitor mood and daily activities to identify things that bring them pleasure to increase positive interactions, and to increase those activities [22]. Treatment plans for behavioral activation are goal-focused, highly customizable and among the key components are monitoring and scheduling pleasurable activities. However, because the types of activities that were pleasurable, and supportive, to participants shifted with ebbs and flows in their symptoms, DMHIs incorporating behavioral activation should be tailored to users' symptom presentations.

In sum, our findings suggest that during periods of mental health maintenance (low symptomology), patients may find more value in engaging with patterns surfaced from sensor data, while during periods of active symptom management, their needs would be better met through a DMHI providing guidance over education. There are at least two key design implications for the self-management DMHI for patients with depression and anxiety. The DMHI would need to: (1) accommodate shifts in needs over time and in response to symptoms and (2) identify and support personalized goals, activities, and feedback.

5.1.2 Using smartphone and wearable sensor data to accommodating shifts in needs over time and in response to symptoms load.

—Smartphone and wearable sensor data may be particularly useful to detect shifts in needs over time. As our interviews highlight, symptom presentation was characterized by different needs including shifts in what activities, levels of support, and goals (e.g., monitoring, learning, activating) were desired and perceived to be most useful. Importantly, the ways in which smartphone sensor data could facilitate these needs also differed. In digital mental health, sensor data has typically been used to send users insights during periods of poor health in an effort to empower them to make changes that support health and well-being. In most cases, these data are then summarized and displayed back to users as an association or correlation to mental health status. Counter-intuitively, however, behavioral markers from sensor data were perceived to be *most valued* by participants when they were maintaining mental health. Indeed, our participants described that in past experiences with self-tracking technologies, direct feedback from sensor data was not appreciated during periods of active symptom management, in part, because the user was already acutely aware of the behavioral markers sensors often capture (e.g., sleep, exercise). Feedback generated by sensor data was also perceived to be out of reach and outside of their immediate control because decreased motivation, fatigue, and anxiety made it more difficult for users to engage in activities, like physical activity. This is consistent with a trend in the broader literature around how the

feedback users receive from self-tracking technologies can be discouraging to users who have chronic conditions and are engaging in symptom management [3, 65].

While the mismatches in data that automated self-tracking systems commonly capture and participants' individual needs and goals are unsurprising, here we find that mismatches are particularly problematic during periods when users are actively managing symptoms and in need of the most support. This underscores the potential importance of reconsidering the role of sensor data in DMHIs for this population based on the data's utility in periods of high versus low symptomology. For example, sensor data may be particularly helpful to deliver feedback and visualizations when users are maintaining their mental health, but play a less prominent role when they are actively managing symptoms. Because sensor data are dynamic by nature, they also provide opportunities to detect changes in behavioral markers related to mental health which can automatically signal the need for a different configuration of the DMHI content or functionality, or a new protocol to support user needs. If these shifts cannot be feasibly detected purely through sensing, DMHIs nonetheless need to strike an appropriate balance between passive and active tracking to reduce participant burden while enabling accurate detection [15]. To identify ways design could address the challenges we identified a need for tools to support personalization and an evolution in needs [29, 88].

5.1.3 Identifying and supporting personalized goals, activities, and feedback.

—The HCI community has discussed approaches to elicit personalized activities and goals from technology users, as well as how to support users' evolving goals over time. While there has been extensive conversation and consideration of these topics, we still have many mental health self-tracking technologies that fail to meet user needs, and, in some cases, that exacerbate user symptoms [28, 29, 46]. We believe this may be, in part, because our orientation and efforts around DMHIs have largely been focused on their value to track and predict symptoms, with less attention to how they can support individuals to pursue activities of value in their daily life.

Goal directed self-tracking is an approach that focuses on matching user goals with the underlying data collected by self-tracking tools and can easily be used to encourage users in pursuit of behavioral activation [88]. This approach was developed in the context of migraine management, which like depression and anxiety, is often a chronic condition requiring periods of maintenance and active symptom management. Migraine experiences are also highly variable between individuals, and symptoms can be triggered by physical, psychological or emotional factors making personalized treatment necessary. To address the complexity underlying chronic illnesses, goal-directed self-tracking suggests that tools should be designed to recommend what, when, and how to track goals based on what is already known about the condition, while also being flexible enough to support users in tracking activities or behavioral markers that they find to be most useful. Giving the user agency over the types of data they track (e.g., activities, symptoms, moods, sleep), and when, may help address some of the between-participant variability we observed.

Interestingly, in studies of migraine management, Schroeder and colleagues [88] found that user goals typically fell into three main categories: to learn about symptoms, to predict symptoms, or to monitor symptoms. Each of these goal categories was associated with a

different level of granularity and effort in tracking activities. Based on these findings, a prototype was developed with question-based prompting as well as a “help me” button scaffold users in the goal-setting process by suggesting specific behavioral markers to track based on whether the user’s goal was to learn, predict, or monitor symptoms. Because what was perceived to be supportive by our participants during periods of active versus management would likely require different ways of capturing and aggregating data, a similar model could assist users in personalizing the self-tracking technology for their unique mental health symptoms. For example, based on our participants’ comments, a range of continuous data describing patterns and enabling users to learn about correlates to mental health over a longer time frame may be more desirable when participants are maintaining mental health and interested in monitoring, which is similar to the feedback they’d receive from Fitbit and smartwatch applications.

By contrast, during periods of active management, users may prefer a simple checklist of activities or tasks to be completed in pursuit of accomplishment, or enjoyment. The DMHI could make suggestions aligned with a behavioral activation approach, but ultimately allow users to make their own selections based on their desired outcome. Most importantly, sensor data can play a key role in re-configuring the technology to meet the changing needs of the user.

Though personalization is often desired, it often requires heavy effort from users. One way to simplify such a system may be through semi-automated tracking [15]. Similar to what some of our participants described in their use of technologies for physical health, a wrist wearable could automatically prompt the user to do some valued activity (e.g., painting) and detect how much time was spent on that activity. In this way, the user would only need to manually input how they felt after completing the activity, reducing the burden of tracking without compromising on data quantity or quality. Alternatively, in line with prior work, participants of our study described utilizing their peer support system to suggest activities for them to do during periods of high symptomology, suggesting that it may be feasible for those that have a close network to depend on [11].

In sum, using a goal-oriented self-tracking approach to the design of DMHIs can increase the level of personalization, and a semi-automated approach can balance manual efforts with passive tracking to ensure the burden on the user is manageable. This approach affords great flexibility as the DMHI could come with suggested parameters that can be modified based on user needs, or the user could walk through the set-up with their healthcare provider.

5.2 Stepped Care Service Needs

In the prior section, we discussed meeting participants’ needs through designing a self-guided intervention, which is a natural first step in a stepped care model of treatment delivery since it is scalable and requires no, or little, resources from healthcare systems. However, our participants described symptoms that affected motivation and ability to engage in activities that they know are useful to their mental health maintenance. This, coupled with the longstanding concerns around DMHI engagement [93], make it imperative for us, as designers and researchers, to explore ways of supporting user engagement with treatment. HCI researchers have typically approached issues of engagement through identifying unmet

user needs and evaluating the usability and usefulness of a tool. However, as we reflected on our participants' experiences and how to best address their needs, it became clear that it is likely not enough to design a tool for self-management, without also considering ways of sharing insights with a care supporter. In the clinical literature, it is common to consider technologies as services rather than products [74], which require additional support for delivery and sustainment. When it comes to DMHIs within HCI however, there has been little attention on what additional support may be needed to ensure engagement with the DMHI in the wild.

Our participants' willingness to share data with their providers opens up opportunities to design for providers' (or other care supporters') access to data to support user engagement if more intensive intervention is indicated. In this case, rather than designing new technologies, we argue that this requires designing new services - which we call "wraparound services" - since they are meant to support the patient in using, and interpreting data from, the intervention with the ultimate goal of increasing clinical gains. In the sections to follow, we outline an opportunity for HCI researchers to extend design thinking to infrastructure needs and wraparound services and see this extension in thinking as critical to improve real-world use of technologies.

5.2.1 Wraparound Services.—Wraparound services originated in community-based mental health programs as a way to meet the complex needs of children in treatment and their families [9, 96]. Over the years, wraparound services have come to refer to services that support the client in attending and getting the most out of treatment, including transportation, childcare, and legal services, for example. Thinking about wraparounds in the DMHI context may help shift focus from an individual level - designing and evaluating a product for an individual/population - to a systems level which considers strengths and challenges individuals are presented with, which may ultimately impact their ability to use and reap benefit from a technology. For example, participants were particularly concerned about the interpretability of DMHI data, and imagined that their provider could help provide them with a critical translation of data into actionable feedback. In this way, the provider may become part of the DMHI, an additional service needed to ensure clinical gains.

Studies in the clinical sciences literature have consistently found that DMHIs are more efficacious at improving mental health outcomes when they involve low-intensity human support [44, 57]. We argue that by considering the *design of services as adjuncts to technologies*, researchers may be better able to serve the communities and populations that they design for, in the contexts where the technology is meant to be deployed. We briefly define low-intensity coaching as one example of a valuable wraparound service, that could be used as a "step-up" from self-management, and could increase data interpretability and communication channels within primary care. Then we discuss implications for this focus and feasibility moving forward.

5.2.2 Low-intensity Coaching.—Low-intensity coaching is to facilitate the use of a supportive technology and provide the user with a sense of accountability. Coaching protocols vary, but often involve a motivational interviewing approach with goal setting and encouragement that accounts for the uniqueness of patient needs [4, 53, 67, 89]. Coaches

help patients translate findings into actions and serve as a source of motivation and escalate patients to higher levels of care. They also work with the patient to develop a set of tasks or activities in support of reaching their goals and can monitor data to detect a need to shift goals to make them more manageable, and adapt feedback so it is more meaningful, when symptoms increased [1]. This is most often enabled with a coach facing tool (e.g., a portal) that provides coaches with incoming data and diagnostics. Being able to discuss mental health and receive feedback from a provider was appreciated by participants in our study. Designing technologies that enable two-way communication and passive monitoring can enable both self-management and clinical monitoring to prevent symptoms worsening and potentially acute need for visits.

5.2.3 Challenges and Future Directions.—If we are to make a difference in mental health conditions at a population level, and reduce burden on an overtaxed healthcare system, we must think more deeply about the infrastructure needed to deliver evidence-based resources in a way that is expeditious and efficacious. DMHIs offer a potential solution but to make measureable gains we will need to address issues that come with DMHIs, including engagement [68]. Low-intensity coaching works well to improve engagement, and is feasible, in research environments as evidenced through many trials with different coaching protocols. Coaches often receive minimal training on the technology and strategies to increase engagement, troubleshoot, motivate users and identify barriers to use. Hiring an external coach, however, comes at a cost and may not be practical as a first step in care within primary care settings. Indeed, designing for intervention deployment in primary care settings is a challenge since digital tools rarely fit within providers' existing workflows and require extra labor, training, and personnel. We suggest that using a completely self-guided self-management intervention as a first step in primary care, and supported self-management with low-intensity coaching as a next step for patients who do not respond, may be more feasible.

Dissemination strategies must also be at the forefront of designers' minds in DMHI. One barrier to implementing DMHIs more broadly is that they are not yet reimbursable. Indeed, most DMHIs are on a direct-to-consumer payment model, requiring users to subscribe to the service [81], which limits the user base to those who can afford the service [89]. Proper implementation within primary care would likely require users to pay for services, or for broader structural changes. Payment models that are more similar to traditional healthcare interventions, with reimbursement for human-in-the loop time would make these interventions more accessible and scalable. Additionally this would resolve some of the issues with integrating DMHIs in healthcare settings, since this would provide some financial incentive for training in DMHI and enable clinicians to bill for their time [8, 71].

Another way to make coaching financially viable at scale may be to use a paraprofessional model of service delivery like the crisis textline or to have other supportive peers or family members serve as coaches. Crisis lines are able to support millions of people in crisis year after year through volunteers who provide basic support and safety planning to individuals who call and/or text in [40]. Interactions through crisis lines are also typically under 30 minutes, and crisis counselors keep a detailed record of each call which they can then reference for repeat callers. Low-intensity coaching similarly requires very minimal contact

with users but potentially over a longer period of time (e.g., several months). A related opportunity that may fit within patients existing self-management of systems, could be for patients to elect an individual in their life to serve as a coach, or offer check-ins as a way to stay on track towards their mental health practices and goals. Other studies in HCI have similarly discussed the value of peers and other social actors for behavior change, and have offered solutions such as “peer-sourcing” or peer-driven planning where peers provide direct feedback on strategies for change. [2, 56]. Given that participants in our study mentioned that family members and significant others were frequently a source of accountability for them in symptom management, this may have significant potential. In sum, leveraging a model like crisis line or peer-based support for DMHIs meant to bridge a gap in healthcare services, may have significant potential.

We have suggested that in order for the HCI community to make an impact on real-world mental health conditions we need to think more about building low-intensity digital treatment options into existing services, and, as part of this, developing services that enhance technology use and provide more intensive support if, or when, indicated. In many ways, how to do this effectively in the current environment is an open question but one that the HCI community has a stake in, and is well-positioned to contribute meaningfully to. Facilitating engagement with technologies will likely require creating novel pathways to share with providers, and structural changes. We offer low-intensity coaching as one service that can enhance engagement and potentially be integrated into healthcare systems as a stepped care option. Future work will need to extend these conjectures to get input from clinical stakeholders to determine the ways in which they would like to, or could feasibility, be involved in the use of DMHIs at this point of care.

6 LIMITATIONS

This study has several limitations. While we attempted to recruit a representative sample from primary care, we recognize that those who engage in research may still have been more motivated than individuals who choose not to engage in research. We also have relatively small ($n=10$) and predominantly female sample, which is common in mental health research, but speaks to the need to better engage male-identified patients. It may be necessary to tailor recruitment language to male audiences or to pause recruitment of female participants and leave recruitment open to male participants longer in future studies. Additionally, our sample endorsed relatively low symptomology at the time of enrollment and most did not have prior experience receiving clinical mental health care. Though this can be a strength in that it enabled them to reflect retrospectively on periods of more symptomology with the mental health literacy of the general population, it is also possible that a sample with greater symptom severity or the experience of clinically effective mental health treatment methods would endorse different needs. Finally, while we discuss design for the primary care context we focused exclusively on patient perspectives. Provider perspectives should be explored in future work.

7 CONCLUSION

In this study, we interviewed 10 individuals with symptoms of depression and anxiety as identified through primary care. We aimed to understand how a self-tracking technology may fill a gap in care by providing support to individuals who are not treatment engaged, in the period between diagnosis and treatment, where many get lost. We used a stepped care framework as inspiration for the delivery model – where a self-management technology could be augmented by additional supports to deliver evidence-based support in the most efficacious and expeditious way. Based on our participants’ experiences of managing mental health symptoms, we argued that the way HCI has typically approached, and designed, sensing technologies for affective symptoms (depression, anxiety), in particular, does not closely align with this population’s needs. What became clear in our conversations with participants was the need to design for their complex needs in a more nuanced way. To do so, we argue that this may mean reconsidering the use of sensor data within DMHIs, and thinking more deeply about the additional services that might be needed to properly augment DMHIs, and have a lasting impact on mental health overtime. We describe implications for design drawing from both clinical and HCI literatures.

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CCS CONCEPTS

- Human-centered computing;

Table 1:

Participant demographics. PHQ9 scores of 5, 10, 15, and 20 represent cutpoints for mild, moderate, moderately severe and severe depression, respectively. GAD7 scores of 5, 10, and 15 represent cutpoints for mild, moderate, and severe anxiety, respectively.

P#	Age	Gender	Race	PHQ9	GAD7
1	22	F	More than one race	8	13
2	24	F	White	4	11
3	26	F	White	8	6
4	25	F	American Indian or Alaskan Native	11	16
5	26	F	American Indian or Alaskan Native	14	10
6	26	M	Asian	2	NA
7	17	F	African American or Black	8	8
8	31	F	Asian	2	5
9	55	F	African American or Black	4	2
10	42	M	Asian	4	1

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