“I Don’t Know Why I Should Use This App”: Holistic Analysis on User Engagement Challenges in Mobile Mental Health

Seungwan Jin[*]
Hanyang University
Seoul, Republic of Korea
seungwanjin@hanyang.ac.kr

Bogoan Kim[*]
Hanyang University
Seoul, Republic of Korea
bogoankim@hanyang.ac.kr

Kyungsik Han[†]
Hanyang University
Seoul, Republic of Korea
kyungsikhan@hanyang.ac.kr

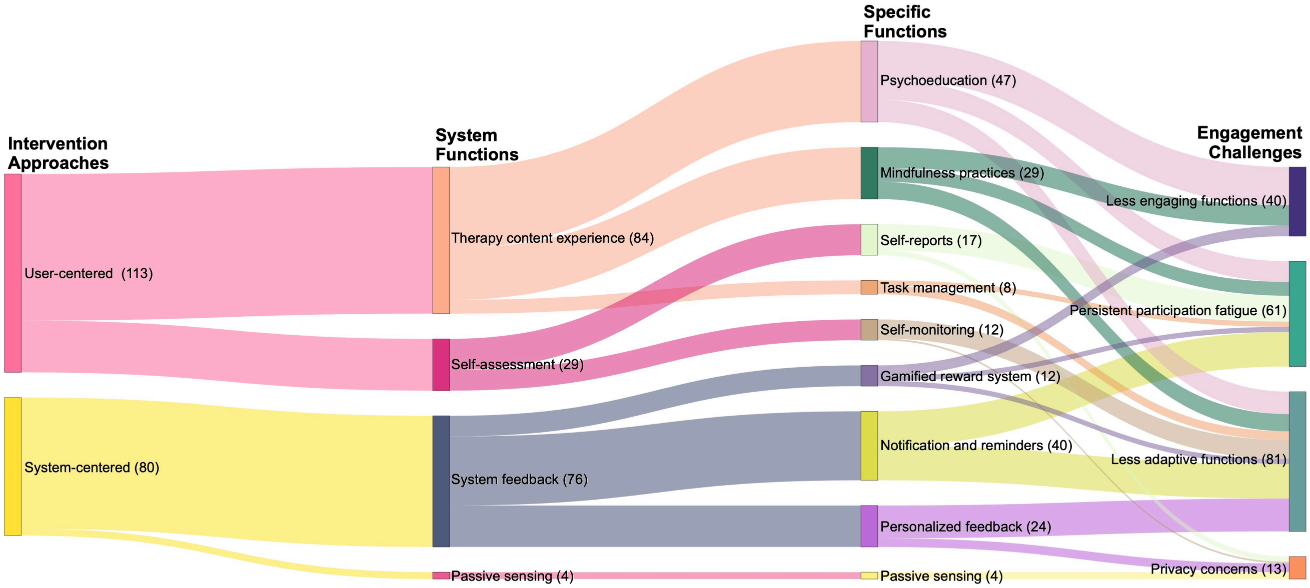

Figure 1: A Sankey diagram illustrating the analysis of 111 studies related to mobile mental health support. This diagram integrates multi-layered analyses of user- and system-centered intervention approaches to systematically reorganize functional elements and conceptually align engagement challenges, providing a holistic perspective on sustainable engagement.

Abstract

Over the past decade, mobile apps have been widely adopted as a digital intervention method for mental health support, offering scalable and accessible solutions to address the growing global mental health challenges. However, sustaining user engagement in real-world settings remains a major challenge in the development of these applications. This study systematically examines factors that hinder user engagement in existing mobile mental health support systems through a scoping review of the literature. After an initial identification of 1,267 papers, we conducted a final analysis of 111 empirical studies using mobile app-based mental health support systems. The study investigates the main factors that negatively affect user engagement from user and system perspectives. Based on these findings, we propose guidelines for enhancing user engagement and structuring personalized emotional interaction design along three dimensions: adaptive, continuous, and multimodal interactions. Furthermore, we discuss the potential for integration with advanced AI methods (e.g., LLM-based AI agents) as a way to achieve these design implications and suggestions. Our results provide critical insights for enhancing long-term user engagement in the development of future mental health support systems.

CCS Concepts

• **Human-centered computing → Ubiquitous and mobile computing**.

Keywords

mobile mental health, user engagement, scoping review, large language model

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[*]Both authors contributed equally to this research.
[†]Corresponding author

CHI ’25, Yokohama, Japan

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1 Introduction

As mental health well-being emerges as a critical global issue [72, 94, 95, 128, 147, 205], improving access to mental health care and developing effective intervention methods have become crucial. Various digital mental health interventions (e.g., Internet-based cognitive behavioral therapy, telepsychiatry, digital mood tracking) have been proposed to complement and extend traditional mental health services. In particular, Mental Health Apps (MHAs) take advantage of the capabilities of smartphones to provide personalized mental health services by incorporating explicit (e.g., user-generated content) and implicit (e.g., behavioral logs) information along with users' psychological profiles, states, and interaction patterns [52, 61, 85, 86, 189, 192, 195].

An important consideration is that MHAs are highly dependent on user engagement [20, 193]. Thus, maintaining clinically recommended levels of user engagement has emerged as a primary challenge for these systems [58, 104]. Users with mental health problems often experience difficulties such as lack of motivation [197], decreased concentration [180], and challenges in forming new routines [118], which can hinder consistent system use [87, 113]. Moreover, given the chronic nature of mental health problems, temporary engagement is insufficient for long-term symptom management and relapse prevention [62, 213]. Therefore, sustained user engagement in MHAs goes beyond mere app usage rates and becomes a pivotal factor in determining the continuity and effectiveness of treatment [38, 132], directly impacting users' treatment outcomes and quality of life [63].

Several studies have conducted systematic literature reviews on the topic of sustained user engagement with mobile-based mental health support systems [114, 178]. These studies have focused on identifying challenges related to sustained user engagement but have not considered the relationship between user engagement and the analysis of specific functions of the systems. Such an examination could more effectively identify the underlying causes of barriers to engagement. In addition, these studies have not discussed potential solutions to the identified challenges from both user- and system-centered perspectives. Perhaps for this reason, there is currently no comprehensive literature review that explores practical strategies, including the use of advanced artificial intelligence approaches such as large language models (LLMs), which have shown remarkable performance in various domains, to improve the features and design of existing MHAs.

With this motivation, this study conducts a scoping review to systematically examine existing approaches to enhancing user engagement in MHAs and to comprehensively analyze factors that hinder sustained engagement. To ensure consistency in our literature review, we view user engagement based on established conceptualizations in key previous studies [50, 51, 74, 91, 92, 135, 143, 144, 153], as an integrated concept that encompasses behavioral, cognitive, and emotional components, all of which interact dynamically over time. This definition goes beyond simple behavioral metrics (e.g., frequency or duration of use) by also considering the user's sense of meaning, goal-oriented thinking, and emotional attachments formed through interaction with technology. In particular, engagement is understood as a dynamic process that gradually evolves, starting from initial, sporadic interest at the early stages of technology adoption to more stable immersion and emotional attachment. Furthermore, we view personalization as the systematic customization of mobile mental health support systems based on explicit methods (e.g., user-provided information) and implicit methods (e.g., behavioral data analysis) to align with users' psychological profiles, states, and interaction patterns [86].

Recognizing the challenges posed by the absence of standardized metrics for measuring engagement [141, 194], we did not attempt to quantitatively compare engagement levels across mental health support systems. Instead, we identified recurring themes and challenges related to user engagement based on findings or discussions explicitly reported in the reviewed studies. Through an iterative process of discussion and analysis, we systematically analyzed the engagement challenges highlighted in each study. This approach allowed us to comprehensively discuss the specific factors that hinder user engagement in the context of each study without attempting to directly compare engagement levels across the studies.

Our review identified two primary approaches—user and system-centered—to user engagement in mobile mental health, and based on these approaches, we present and discuss challenges and strategies to mitigate these challenges with the goal of identifying design directions for effective mental health support systems in the field of HCI. Our research questions are as follows:

- RQ1: What are the barriers to sustained user engagement in MHAs, and how do they manifest in user- and system-centered approaches?
- RQ2: What research directions can effectively address the barriers to engagement identified in user- and system-centered approaches?

While many studies have focused on developing technologies, designing systems, and conducting design research to answer these questions, they often fail to provide or do not consider a holistic approach to addressing the issue of sustainable user engagement. Existing research tends to focus on isolated aspects of the problem without providing a comprehensive framework that integrates user- and system-centered perspectives. This study aims to provide specific insights into these research questions through a literature review. In doing so, we expect to provide a more comprehensive understanding of how to design effective mental health support systems that promote sustained user engagement.

We initially identified 1,267 relevant papers. Through a rigorous selection process, we narrowed the scope to 111 empirical studies that collected participation data from MHAs. Our analysis revealed key challenges to sustained user engagement from both user and system perspectives. Key factors identified include: (1) persistent participation fatigue, (2) less engaging functions, (3) privacy concerns, and (4) less adaptive functions (see Figure 1).

A notable phenomenon identified in our extensive review is a tension between users (e.g., patients), who need to use the system continuously, and MHPs (mental health professionals), who need to innovate intervention design while adhering to the theoretical foundations of treatment. To mitigate this tension, we propose a highly feasible scenario that highlights the need for personalized emotional interaction design to enhance users' intrinsic motivation to use the system in three key dimensions: (1) *adaptability*, (2) *continuity*, and (3) *multimodality*. These design dimensions allow for a balanced approach that promotes sustained user engagement while maintaining fidelity to researchers' theoretical foundations.

Given the capabilities of large language models (LLMs), the integration of LLMs into MHAs can provide significant advances in addressing many of the identified challenges, reflecting evolving requirements in scenarios, and maintaining the balance between theoretical foundations and sustained user engagement. By leveraging their extensive contextual understanding, LLMs can accurately detect subtle changes in users' psychological and emotional states and dynamically adjust intervention strategies accordingly [211]. This capability enhances the level of personalization, enabling interactions that go beyond simple question-and-answer exchanges to foster deeper and more meaningful engagement that ultimately drives intrinsic motivation. As a result, LLMs help fill critical gaps in existing digital therapeutic paradigms by strengthening the cognitive and emotional alignment of interventions.

LLMs can be further developed into agents, providing an opportunity for an agent-based mental health support framework through integration with LLMs. Such integration has the potential to change the paradigm of mental health care across the entire spectrum, from preventive interventions to long-term management, by facilitating emotional connection through the personalized emotional interaction design. We propose research directions that HCI researchers should consider designing more participatory mental health support systems by bridging the gap between users and researchers through an agent-based mental health support framework.

The main contributions of this study are as follows:

- Through an extensive literature review, we analyze factors that hinder sustained user engagement in mental health support from *both user and system perspectives*, and discuss directions for enhancing user-system interactions.
- We propose three dimensions of *personalized emotional user-system interaction design* to enhance sustained user engagement: (1) adaptive, (2) continuous, and (3) multimodal interactions, and highlight the potential for improved interactions through integration with LLMs.
- We explore the opportunities and risks associated with the agent-based mental health support framework that integrates LLMs with MHAs, drawing on insights from HCI, MHPs, and AI disciplines.

2 Background

2.1 Definition of User Engagement

User engagement is a dynamic, multifaceted construct that extends beyond mere program usage. It encompasses active user participation, commitment, and interaction with systems, reflecting both behavioral metrics and subjective experiences. In mental health interventions, engagement involves not only program adherence but also active interaction with features, personal change efforts, and support from therapeutic relationships [50].

In digital behavior change interventions (DBCIs), engagement integrates behavioral dimensions, such as frequency, duration, and depth of use, and experiential dimensions, such as attention, interest, and emotional responses. These dimensions emphasize the dynamic and evolving nature of engagement, which varies across individuals and adapts over time [153]. Engagement can be further categorized as a trait (a user's inherent tendency to be immersed in activities [174]), a state (context-dependent immersion at a specific moment [26, 48, 143]), or a process (the continuous evolution of user interaction over time [143, 144]) [51].

Engagement can also be defined by behavioral, cognitive, and emotional components, again highlighting its multidimensional nature. Behavioral engagement reflects the frequency and ease of integrating technology into daily life. Cognitive engagement includes users' recognition of the value of the system and their mental effort investment, while emotional engagement captures the satisfaction and positive emotions experienced during interaction. These components work together to shape overall engagement, emphasizing that it is not just a measure of usage, but a reflection of meaningful user experiences [91, 92]. By viewing engagement as an evolving, multidimensional construct, researchers and practitioners can design adaptive and context-sensitive interventions.

It is also important to note that engagement should be understood as a holistic and fluctuating phenomenon that evolves over time. Quantitative indicators such as frequency and duration of use complement qualitative dimensions such as perceived usefulness, satisfaction, and emotional connectedness. The interplay of these factors highlights engagement as a process that adapts to changing user needs and circumstances, requiring systems to incorporate re-engagement mechanisms, such as personalized notifications or adaptive content [74].

Building on the concepts of engagement reviewed above, we define user engagement as an integrated concept that encompasses behavioral, cognitive, and emotional components, viewing these three elements as part of a dynamic process involving temporal changes. This integrated and evolving conceptualization of engagement moves beyond fragmented approaches and provides a systematic understanding of how to refine design and intervention strategies to foster sustainable user engagement.

2.2 Digital Mental Health Support: Potential and Engagement in MHAs

Mental illness is one of the most urgent global healthcare problems, and its prevalence has accelerated during the COVID-19 pandemic [146, 158, 162, 170, 191, 202, 206], putting additional strain on traditional healthcare systems as they struggle to meet the increased demand for mental health services [54, 134]. As a complement to traditional mental health services, digital device-based mental health support has gained attention as a potential solution to overcome these barriers [10, 11, 61, 62, 77, 96, 97, 133, 161]. The use of mobile devices such as smartphones, which are widely available and highly connected, can serve as a primary digital platform for traditional mental health care, supplementing in-person therapy sessions that often rely on paper-based workbooks and assignments [17, 61].

Smartphones provide an accessible and scalable way to deliver evidence-based psychotherapy protocols to those in need. Smartphone-based mental health interventions have been demonstrated to be effective in addressing various mental health issues (e.g., depression, anxiety, stress) [61]. These apps provide mental health support to users by integrating various therapeutic approaches, such as Cognitive Behavioral Therapy (CBT), mindfulness, and behavioral activation. However, utilizing management techniques offered by MHAs (e.g., psychoeducation, task completion, experiencing therapeutic content) or evaluating and recording one's condition requires physical and mental effort, making it challenging to sustain user engagement over time [114, 138].

Various strategies have been explored to overcome these challenges and increase user engagement. These strategies include gamification [115, 124, 165], features that support social interaction [53, 90, 183], personalized interventions [55, 109, 203], condition monitoring [102, 131], and feedback systems [33, 88, 139]. In general, these systems reward or provide feedback to users for their behaviors, foster social interaction environments, provide information about physical conditions, remind users to perform certain tasks, help users monitor and visualize their behaviors, and encourage healthier actions or behaviors. However, our review shows that most apps still highly struggle with low user retention rates once they are released [20, 37, 56, 64, 78, 84, 114, 121, 123, 193].

2.3 Review of Factors Hindering User Engagement with MHAs

Previous studies have identified various barriers to user engagement in MHAs, including: (1) Technical and usability challenges, (2) Personalization and content issues, (3) Emotional, psychological, and social barriers, (4) Privacy, security, and trust concerns, and (5) Mental health condition-specific challenges.

2.3.1 Technical and usability challenges. Technical performance issues—such as frequent app crashes, errors, unexpected data loss, excessive memory usage, slow execution speeds, and inconsistent data synchronization across devices—undermine the user experience and make sustained engagement difficult [3, 13, 14, 27, 149, 172, 185, 190, 207]. Additionally, usability flaws, such as complex and non-intuitive interfaces, cluttered home screens, inefficient menu structures, and insufficient guidance in the early stage of use, discourage active user engagement [7, 50, 93, 142, 173].

2.3.2 Personalization and content issues. To enhance user engagement, providing personalized services is essential. However, many apps provide static and generic content that does not adequately reflect users' cultural backgrounds, contexts, and preferences. The lack of adaptive content and personalized interfaces has been identified as a critical issue [13, 14, 27, 34, 50, 142, 173, 185, 194]. Apps often fail to track and reflect users' current experiences and detailed state changes, and their design is not user-centered, offering limited functionality for customization based on individual needs [142, 172, 185]. In addition, low quality, generic and impractical information, repetitive and uninspiring text-based content, lack of multimedia elements, a mix of non-evidence-based features, and lack of core functions to address specific mental health issues reduce interest and immersion [149, 173]. In particular, adolescents demand engaging and interactive content, such as gamified elements, images, videos, and audio. If these demands are not met, the likelihood of early disengagement increases significantly [93].

2.3.3 Emotional, psychological, and social barriers. Apps that fail to provide sufficient emotional support or practical assistance to alleviate psychological distress often fail to be perceived as valuable resources, leading to user disengagement [42]. For example, if an app cannot offer timely emotional support during stress, users may lose trust and abandon it. A lack of opportunities for interaction with professionals or peers, as well as the absence of community-based features, can foster isolation, significantly reducing long-term engagement [42, 50]. This is particularly critical when users expect human-like interaction and emotional connections but find these missing in the app experience. Failure to address user needs during crises, such as providing immediate and reliable responses, has also been identified as a significant engagement barrier [194].

2.3.4 Privacy, security, and trust concerns. Privacy and security concerns—such as the inadequate resolution of security issues, lack of password settings, opaque privacy policies, default public data settings, and extra costs for private modes—undermine user trust [7, 27, 34, 142, 173, 185, 194, 207]. Furthermore, limited accessibility on certain devices or platforms, unmet initial expectations after download, and discomfort during the onboarding process often lead to early user dropout [3, 149, 207]. Lack of available professionals or customer support to resolve issues, lack of endorsements from credible organizations or authoritative bodies, lack of transparency in data usage, excessive ads or spam, inadequate long-term user retention strategies, and fatigue from repetitive patterns further erode trust and satisfaction with the app [71, 149, 160, 173].

2.3.5 Mental health condition-specific challenges. Mental health conditions can cause irregularities in user engagement patterns. Users with depression may find it difficult to use apps due to low energy and lack of motivation [8, 27, 50, 142, 160, 196]. Complex or non-intuitive interfaces can exacerbate stress for users with anxiety, leading them to avoid using technology. Furthermore, users with anxiety may experience non-continuous periods of use due to life events or improvements in their mental state [14, 27]. Users with schizophrenia tend to exhibit a sharp decline in usage frequency after initial engagement, which may be due to doubts about the purpose of the app. During manic episodes, users may enter excessive positive emotions or display highly variable emotional changes, resulting in irregular usage patterns [34]. Additionally, users experiencing intense negative emotions may avoid using the app or fail to record their emotions, resulting in inconsistent usage [172].

Analyzing the barriers to user engagement by comprehensively considering both the functions of MHAs and user perceptions is essential for fundamental improvements. In this study, we conduct a scoping review to systematically identify barriers to user engagement in MHAs from a comprehensive perspective. Additionally, we discuss design insights for a feasible and implementable conceptual framework that can promote user engagement by leveraging advanced AI methodologies such as LLM-based generative AI agents.

3 Method

To comprehensively examine MHAs, our review includes a wide range of studies that vary in their target mental health problems, theoretical foundations, user engagement strategies, and methodological approaches. In this section, we describe the scope of our review, the criteria for paper selection and the search strategies used. Our approach follows the methodology of a scoping review. To ensure high standards in the search, selection process, and reporting of our

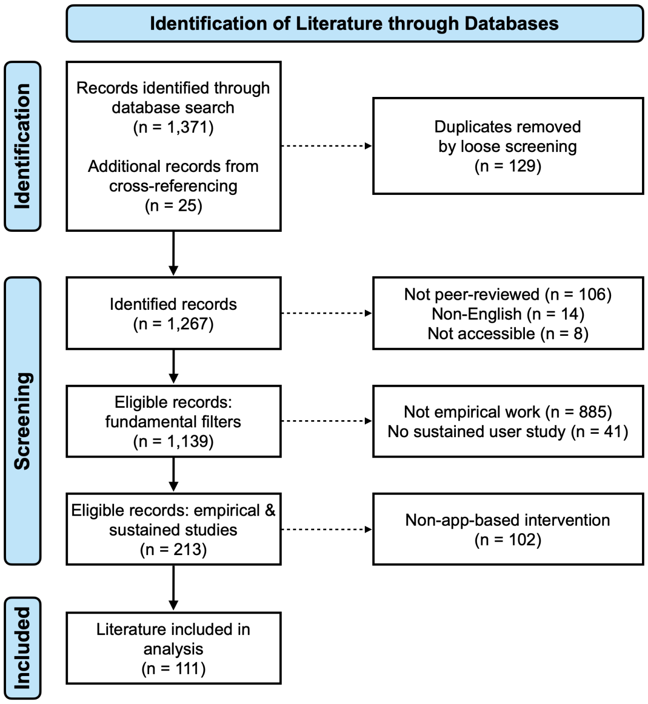

Figure 2: PRISMA Flow diagram of the literature selection process for the scoping review.

findings, we have adhered to the PRISMA-ScR guidelines [198], an extension of PRISMA specifically designed for scoping reviews. We have followed the PRISMA 2020 checklist [150] to guide our review process and reporting. Detailed information on our methodology and review process can be found in the supplementary materials.

3.1 Inclusion Criteria and Scope

This review included studies that met the following criteria:

(1) Studies must be peer-reviewed, published in academic journals or conference proceedings, retrievable, and written in English. We excluded non-peer-reviewed, short, non-English, or inaccessible papers.
(2) Selected studies should be empirical, involving direct research with human participants. We excluded studies that relied solely on simulation data, focused exclusively on technical aspects without considering human interaction, or were limited to short-term or intermittent user sessions. While acknowledging the value of qualitative research, including prototype evaluations, our review prioritized studies that allowed participants to freely use the system continuously for a specified duration. We also excluded theoretical papers without supporting user-based empirical evidence.
(3) This review focused on studies that used mobile apps as interventions for mental health support. We limited our scope to mobile apps because of their widespread use and accessibility. While acknowledging the contributions of other platforms, our review specifically examines mobile app-based interventions to maintain a focused scope of analysis.

To identify relevant studies within our research scope, we used the following keyword combinations in our database search. These keywords were applied to titles and abstracts to cover various aspects of MHAs. The search terms in our strategy are as follows:

- Mobile technology: mobil* OR app* OR mhealth OR smartphone* OR m-health OR system*
- Mental health: mental health OR stress OR depress* OR anxi* OR mental illness OR mental disorder*

3.2 Search and Selection Process

We implemented a three-phase search process to identify relevant papers. The first phase, which began on August 1^{st}, 2023, focused on scope definition and preliminary literature exploration. We queried Google Scholar and the prominent HCI conference proceedings, including ACM CHI, CSCW, and IMWUT. The second phase, beginning on September 5^{th}, 2023, expanded the search to include additional databases such as ACM Digital Library, IEEE Xplore, and Scopus for comprehensive coverage. The final phase, from November 22^{nd}, 2023, to early May 2024, involved a reference list review of previously identified papers to uncover additional relevant studies.

This process yielded a total of 1,396 papers, reduced to 1,267 after removing duplicates. A single coder excluded non-peer-reviewed, inaccessible, and non-English papers. For the second and third inclusion criteria, two coders independently reviewed all remaining papers, achieving Krippendorff's alpha of .86. This approach aligns with recommended practices for establishing intercoder reliability in qualitative research [105, 106]. In cases of disagreement, we employed a multi-step consensus process that includes articulation of rationales, in-depth review of the papers, and discussion based on predefined criteria. A third coder was consulted to make final decisions, ensuring coding consistency and reliability when necessary. Ultimately, 111 papers were included in the final analysis.

Details of the selection process are in the supplementary material, *Inclusion Criteria Summary*, which includes a comprehensive list of all 1,267 papers, along with inclusion and exclusion decisions at each step. The PRISMA flow diagram in Figure 2 further illustrates the literature selection process.

3.3 Data Extraction and Coding Procedure

First, we performed thematic coding of the *main content* explicitly mentioned in the reviewed studies on MHAs to derive *specific functions* (Tables 1 and 2) that represent the core features of MHAs (e.g., personalized feedback). The *main content* describes the tasks or activities users perform when using these features (e.g., progress tracking). Through a thorough examination of app descriptions, user interactions, and study results, we identified recurring themes and concepts, achieving a high level of inter-rater agreement (Fleiss' Kappa = 0.75−0.84, *mean* = 0.80). Based on these thematically derived categories, we performed a bottom-up analysis to create higher-level groupings for two categories: *system functions* and *intervention approaches*. Specifically, the findings identified in *specific functions* were organized into broader *system functions*, such as feedback systems or data collection features. These *system functions* were then grouped into user-centered and system-centered *intervention approaches*, reflecting the level of user involvement and system automation, respectively.

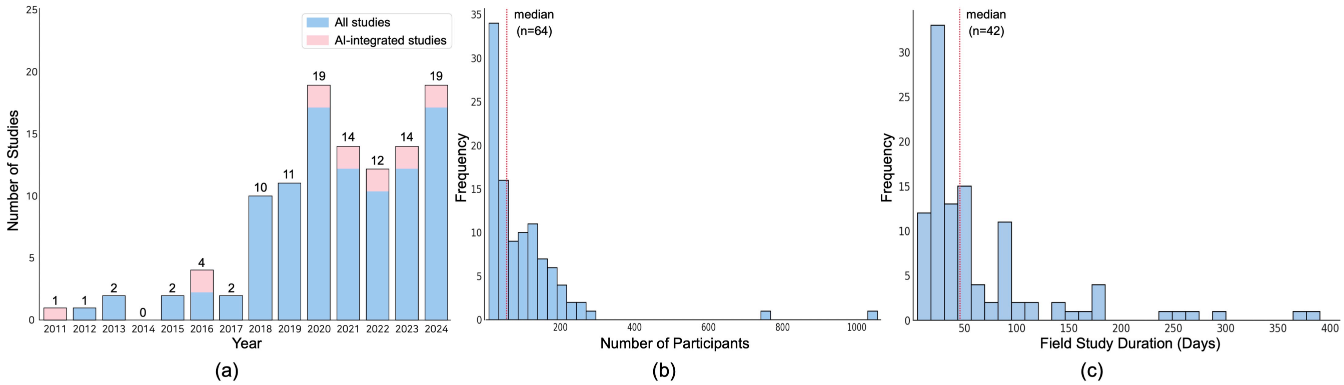

Figure 3: Key characteristics of the analyzed studies of mobile app-based mental health support systems. (a) shows the temporal distribution of research, including AI-integrated studies; (b) shows the distribution of the number of participants involved in field studies across the analyzed studies; (c) illustrates the distribution of the duration of field studies (in days).

Next, we performed thematic coding of the *specific functions* based on user-centered and system-centered intervention perspectives to identify *engagement-promoting features* within each perspective (Fleiss' Kappa = 0.77–0.83, *mean* = 0.79). From user-centered approaches, we derived *Integrated self-management features promoting sustained engagement* and *Complex feature combinations targeting holistic engagement* (Section 4.2.1). Meanwhile, from system-centered approaches, we identified *Personalized mental health support through data-driven features* and *Adaptive features enhancing personalized mental health support* (Section 4.2.2). From the findings and discussions explicitly related to user engagement in the reviewed studies, we derived *sustained engagement barriers* based on *engagement-promoting features* from both user-centered and system-centered perspectives (Fleiss' Kappa = 0.77–0.85, *mean* = 0.81). Through a bottom-up analysis, we finally identified four *engagement challenges*. The derivation of *sustained engagement barriers* and *engagement challenges* is illustrated in (Figure 4).

To visually represent the relationships and frequency of the analysis results, we used a Sankey diagram (Figure 1). While the process of deriving engagement-promoting features from the *main content* and identifying the four *engagement challenges* is extensive and not suitable for inclusion in the Sankey diagram, we structured these details using Tables 1 and 2 and Figure 4. The specific details are provided in Sections 4.2 and 4.3, and the coding results are documented in the supplementary material, "Final Analysis of 111 Studies."

4 Results

We present our analysis of 111 empirical studies, conducted by three experts in HCI, mobile computing, and digital healthcare. We examine the characteristics of research environments and participant samples in Section 4.1, analyze MHA functions categorized into user-centered and system-centered approaches in Section 4.2, and present identified user engagement challenges in Section 4.3. Figure 1 provides an overview of these findings, with many functions of MHAs represented across multiple categories due to their multi-functional characteristics. Our analysis in Section 4.2 focuses on functions and content most relevant to user engagement, exploring key themes in user-centered (Section 4.2.1) and system-centered (Section 4.2.2) approaches. Finally, Section 4.3 builds upon these insights to discuss the challenges in user engagement.

4.1 Study and Sample Characteristics

Of the 111 empirical studies analyzed, all were field studies employing MHAs. Figure 3-(a) illustrates the temporal distribution of the research, with 80.36% conducted between 2019 and 2024. Fifteen studies (13.39%), mostly after 2020, incorporated AI technologies, including machine learning and LLMs. The most commonly targeted mental health conditions were stress (n = 40), depression (n = 29), and anxiety (n = 17), followed by comorbid conditions (i.e., anxiety and depression; n = 13) and post-traumatic stress disorder (PTSD; n = 6). Other target conditions (n = 7) included bipolar disorder, schizoaffective disorder, and substance abuse. Regarding number of participants, four studies with open-access app distribution showed exceptionally large sample sizes (range: 619-13,421, median = 4,438) [25, 58, 157, 188]. As shown in Figure 3-(b), the remaining studies had 7 to 1,056 participants (median = 64, mean = 99, SD = 133). The duration of MHA interventions varied from 5 to 390 days, with an average of approximately 68 days (Figure 3-(c); median = 42, SD = 72).

4.2 Mental Health Support System Functions

In this section, we analyze MHA functions, categorizing them into user-centered and system-centered approaches based on intervention methods. This categorization builds upon the independent thematic analysis and bottom-up approach described in Section 3.3, where specific functions and their main content were identified and conceptually aligned into these two approaches. User-centered approaches require active use of therapeutic content and self-assessment tasks, while system-centered approaches encompass automated interactions and data collection features. Tables 1 and 2 present the classification of these functions based on an analysis of 111 papers using MHAs.

4.2.1 User-centered approaches. User-centered approaches were categorized based on the nature of user interaction and classified into therapy content experience and self-assessment. Therapy content experience involves engaging with mental health treatment or support content, while self-assessment focuses on observing or evaluating one's own condition. Among the analyzed items, 85 (74%) were therapy content experience, and 30 (26%) were self-assessment. Table 1 provides an overview of user-centered approaches. Therapy content experience consists of three main categories: psychoeducation (e.g., mood disorder facts, coping strategies, stress management), mindfulness practices (e.g., guided meditation, deep breathing exercises, body scan), and task management techniques (e.g., goal-setting, time management, priority lists). Self-assessment features include self-monitoring tools (e.g., mood tracking, sleep logs, symptom logs) and self-report measures (e.g., depression scales, anxiety inventories, quality of life assessments). Based on these categorizations, we identified two key findings: (1) integrated self-management features that promote sustained engagement and (2) complex feature combinations that target holistic engagement.

Integrated self-management features promoting sustained engagement. Our scoping review revealed that MHAs implement strategic combinations of features to encourage consistent self-management of mental health. This design approach is based on the understanding that the efficacy of clinically-based app content is realized through repeated user interaction. For instance, the integration of *stress literacy* from *Psychoeducation* features and *stress trigger and response log* from *Self-reports* emerged as a significant combination, prompting users to continuously track stressors and document their responses. This integrated approach was designed to enhance users' understanding of their stress patterns and reinforce ongoing self-management through regular recording and reflection. Furthermore, we observed frequent pairing of *sensory focus* from *Mindfulness Practices* with *goal setting* from *Task Management*, serving as a primary method for guiding users through a structured framework for recurrent self-assessment and management. This combination was found to encourage users to focus on the present moment while working towards mental health objectives, thereby promoting sustained use of the app.

These findings indicate that MHAs are designed to promote sustained self-regulation by integrating diverse features that encourage users to continuously monitor and improve their mental health. This strategic approach aims to support long-term engagement by going beyond simple information provision to foster consistent, active participation in self-regulatory practices.

Complex feature combinations targeting holistic engagement. We observed that many MHAs incorporate complex combinations of features designed to foster holistic engagement across emotional, physical, and social dimensions. These features aim to provide users with a comprehensive approach to mental well-being by addressing multiple aspects of their experience. For instance, we observed the integration of *social awareness* from *Self-monitoring* features with tools that track and reflect on emotional states, such as the real-time monitoring of a spouse's stress levels and emotional states [183]. This combination encourages users to not only monitor their own emotions, but also to be aware of the emotional states of important people in their lives. By fostering this awareness, these features cultivate emotional connection and shared reflection, increasing engagement with both personal and relational emotional well-being. We also found that the *body-mind connection* from *Mindfulness Practices* is often combined with physical exercises that link movement with sensory or emotional experience. These exercises are designed to help users understand how their physical states influence their mental health, encouraging mindfulness through this interaction. Furthermore, combinations of *goal setting* from *Task Management* with physical and emotional monitoring tools were observed, providing users with a structured framework for setting mental health goals while regularly assessing their progress.

These complex feature combinations reflect MHAs' efforts to provide a multi-faceted experience that interacts with users on emotional, physical, and social levels to promote a more comprehensive approach to mental well-being.

4.2.2 System-centered approaches. When categorizing system-centered approaches based on how the system interacts with the user, we classified them into System feedback, which provides the system's response according to the user's state or environment, and Passive sensing, which continuously collects user data. An overview of the system-centered approaches is explained in Table 2. System feedback and Passive sensing were observed in 76 (95%) and 4 (5%) systems, respectively. Most studies considered System feedback, which includes specific functions, including personalized feedback (e.g., tailored mood insights, personalized coping recommendations, custom activity suggestions), notifications and reminders (e.g., medication alerts, appointment reminders, self-care reminders), and gamified reward systems (e.g., achievement badges, progress streaks, narrative storylines). Passive sensing incorporates functions that collect information about the user's daily activities and mental health status by analyzing smartphone built-in sensors (e.g., accelerometer data, GPS location, ambient light) or usage patterns (e.g., screen time, app usage frequency, call logs). Two prominent themes emerged from this analysis: (1) personalized mental health support through data-driven features and (2) adaptive features that enhance personalized mental health support.

Personalized mental health support through data-driven features. The results highlight a prevalent trend among MHAs in utilizing data-driven features for personalized support. Analysis of the reviewed studies showed that these features predominantly aim to optimize engagement and improve mental health outcomes through tailored feedback. We found that *Personalized Feedback* frequently manifests as *stress management*, *emotional support*, and *app content recommendations*. Our review indicated that these tools typically analyze user activity patterns, reported mood states, and stress levels to provide tailored feedback, offering content most suited to each individual. For instance, users identified as having high-stress levels may receive customized stress management techniques [46], be provided with access to human coaching apps offering personalized support [36], or be offered content tailored to their specific interests [100]. This personalized approach was consistently observed to support user engagement by modifying content based on evolving mental health needs. Furthermore, our review observed the integration of *Passive Sensing* technologies in many MHAs. These apps often collect data such as movement patterns, location, or device usage without requiring direct user input. Our analysis

Table 1: Specific functions and their main content identified under user-centered approaches in mental health support mobile apps. Each function is categorized based on user-driven interactions and engagement.

Specific Function	Main Content (Themes and Definitions)	References
Psychoeducation	**Stress literacy**: Educational content focusing on stress mechanisms, personal trigger identification, and evidence-based management techniques, enhancing users' understanding of stress-related processes.	[18, 46, 65, 70, 89, 155, 171, 199], [28, 47, 49, 57, 188]
	Cognitive skills: Training modules aimed at improving mental processes like critical thinking, problem-solving, and decision-making, distinct from emotional or behavioral interventions.	[5, 24, 36, 39, 66, 81, 175, 186], [33, 102]
	Emotional awareness: Guidance and exercises aimed at helping users recognize, understand, and articulate their emotions, fostering improved emotional intelligence.	[4, 21, 76, 122, 156, 157, 201], [131, 139, 177]
	Resilience building: Strategies and activities designed to develop psychological adaptability, coping skills, and the ability to bounce back from adversity.	[2, 19, 43, 45, 59, 69, 73, 108]
	Condition-specific education: Targeted, in-depth information on particular mental health disorders, including symptoms, treatments, and management strategies.	[23, 68, 83, 115, 117, 130, 151], [40, 103, 116, 148, 169, 218]
	General mental health education: Comprehensive overview of mental health concepts, practices, and resources, providing a broad foundation of knowledge.	[152, 159, 179]
Mindfulness Practices	**Meditation practices**: Guided exercises and techniques for cultivating mental clarity, emotional balance, and present-moment awareness through focused attention.	[4, 5, 36, 39, 82, 107, 110, 156], [6, 29, 127, 145, 169, 187]
	Body-mind connection: Activities and information designed to help users understand the relationship between physical sensations and mental states.	[2, 45, 102, 116, 129, 136, 181, 199], [28, 212, 214, 215]
	Sensory focus: Structured activities that guide users to focus on specific sensory experiences, enhancing present-moment awareness.	[15, 43, 122, 131, 175, 188, 218]
	Metacognitive awareness exercises: Tasks and reflections that enhance users' ability to observe and understand their own thought processes and cognitive patterns.	[32, 35, 155, 184]
Task Management	**Daily planning**: Tools and features for organizing and structuring daily activities, routines, and schedules to promote mental health and productivity.	[19, 23, 45, 90, 133, 165]
	Goal setting: Functionalities that allow users to establish, track, and adjust personal objectives related to mental health and well-being.	[15, 32, 83, 117, 131, 151]
	Content scheduling: Systems for planning and managing the delivery of app content, ensuring timely and relevant information provision to users.	[18, 186]
	Event management: Functions for organizing, tracking, and preparing for significant life events or milestones that may impact mental health.	[53, 109, 140]
	Task structuring: Methods and tools for breaking down complex tasks or goals into smaller, manageable steps, reducing overwhelm and promoting achievement.	[5, 33, 49, 70, 159, 177]
Self-monitoring	**Mood tracking**: Tools and interfaces for recording, visualizing, and analyzing emotional states over time, enabling users to identify patterns and triggers.	[12, 15, 21, 39, 76, 108, 131, 157], [45, 88]
	Stress monitoring: Features designed to observe and measure stress levels through self-reporting or physiological data, helping users understand their stress patterns.	[46, 65, 109]
	Health behaviors: Tracking systems for monitoring lifestyle choices that affect mental health, such as sleep, exercise, and diet, to promote healthier habits.	[16, 19, 32]
	Progress visualization: Graphical representations and analytics of user advancement towards mental health goals, providing motivational feedback and insights.	[17, 52, 68, 89, 124, 151, 155], [43, 139, 165]
	Social awareness: Tools for monitoring and analyzing social interactions and their impact on mental well-being, fostering improved interpersonal relationships.	[80, 183]
	Clinical monitoring: Professional-grade tracking of symptoms, treatment effects, and overall mental health status, often used in conjunction with clinical care.	[99, 102, 130, 171]
Self-reports	**Mood and affect evaluation**: User-input assessments designed to capture emotional states, ranging from simple mood logging to more detailed affective patterns.	[12, 21, 68, 76, 80, 122, 163, 175], [22, 33, 49, 108, 131, 139, 148, 200]
	Stress trigger and response log: Structured documentation system for users to record specific stress-inducing situations and their psychological responses.	[36, 44, 65, 102, 109, 110, 171, 183]
	Activity and lifestyle logging: User-driven recording of daily habits, behaviors, and experiences that may impact mental health and well-being.	[16, 32, 88, 124, 136, 203]
	Health assessments: Holistic, structured questionnaires for evaluating various aspects of mental and physical well-being, often based on validated clinical measures.	[17, 19, 39, 46, 52, 69, 137, 157], [15, 24, 41, 43, 89, 127, 151, 155], [47, 166]
	Behavioral tasks: Assigned activities or challenges for users to complete and report on, designed to promote skill development or provide diagnostic information.	[58, 66, 81, 130, 165]

Table 2: Specific functions and their main content identified under system-centered approaches in mental health support mobile apps. Each function is categorized based on automated or system-driven processes.

Specific Function	Main Content (Themes and Definition)	References
Personalized Feedback	**Emotional support**: Tailored responses and resources provided based on the user's reported emotional states, offering comfort and coping strategies.	[12, 58, 73, 80, 99, 163, 184], [45, 166]
	Stress management: Customized advice and techniques for handling stress, based on individual user data and reported stressors.	[17, 46, 55, 60, 100, 138, 171], [65, 88, 181]
	App content recommendations: Suggested materials, activities, or resources within the app, personalized based on user preferences, behavior, and progress.	[21, 36, 66, 89, 110, 136, 140, 165], [35, 41, 155, 187, 201]
	Progress tracking: Individualized updates and insights on goal advancement, highlighting achievements and areas for improvement.	[19, 33, 43, 69, 124, 159, 182, 209]
	Cognitive restructuring: Personalized guidance and exercises for identifying and reframing negative thought patterns, based on cognitive-behavioral principles.	[81, 122, 130, 139]
	Behavioral interventions: Targeted suggestions and strategies for modifying specific behaviors to improve mental health outcomes.	[40, 131, 151, 203]
	Professional support: Customized feedback, advice, or interventions provided by mental health professionals through the app platform.	[5, 22, 25, 68, 126, 156, 177, 199]
Notifications and Reminders	**Task reminders**: Alerts and notifications for scheduled activities, pending tasks, or user-set goals related to mental health management.	[17, 52, 60, 100, 122, 137, 168, 209], [19, 32, 66, 73, 129, 151, 201, 218], [33, 44, 45, 159, 177, 179, 187]
	Stress alerts: Proactive notifications based on detected or predicted high stress levels, offering timely support or intervention.	[41, 55, 108, 109, 183]
	Motivational messages: Encouraging prompts and affirmations designed to maintain user engagement and reinforce positive behaviors.	[16, 28, 59, 76, 103, 171, 199]
	Engagement boosters: Strategically timed notifications designed to increase app interaction and adherence to mental health programs.	[23, 30, 36, 68, 133, 136, 140], [35, 152]
	Health monitoring: Reminders for health-related activities, check-ins, or assessments to maintain consistent mental health monitoring and management.	[12, 21, 24, 69, 131, 145, 154, 182], [29, 40, 88, 148, 166, 214]
Gamified Reward System	**Achievement tracking**: Systems for monitoring, recognizing, and rewarding user progress in mental health-related activities and goals.	[2, 16, 124, 130, 139, 165, 177]
	Avatar customization: Options for users to create and modify personalized virtual representations, often tied to progress or achievements within the app.	[6, 59, 68, 154]
	Challenge systems: Gamified tasks or missions designed to promote engagement with mental health practices and app features.	[30, 41, 90, 115, 133, 140]
	Content unlocking: Progressive access to new features, information, or resources based on user activity and achievement, encouraging continued engagement.	[58, 110, 117]
	Virtual companion: An in-app character that guides users' mental health journey, providing support and encouragement through programmed interactions.	[127]
Passive Sensing	**Visual data**: Information collected through device cameras, such as facial expression analysis for mood detection, without active user input.	[137]
	Social and media data: Insights gathered from user's social media activity and content consumption patterns, providing context for mental state analysis.	[12, 22, 163, 168]
	App usage: Metrics on how and when the app is utilized, including frequency, duration, and feature engagement patterns.	[136, 209]
	Location sensors: Data on user's geographical positions and movements, providing context for behavior analysis and environmental influences on mental health.	[41, 80]
	External IoT sensors: Information collected from external devices, such as wearables or smart home devices, for comprehensive health monitoring.	[40, 55, 89, 155, 182, 183]
	Combined smartphone sensor and usage data: Integrated analysis of multi-modal data from the smartphone for holistic behavior assessment.	[43, 98, 100, 181, 200, 203]

showed that this information is primarily used to detect behavioral or emotional changes, enabling more accurate, contextual feedback. The integration of passive sensing was often reported to better align support with users' daily experiences, potentially enhancing the timeliness and effectiveness of interventions.

These data-driven features, as evidenced by our review, reflect a clear focus in MHA design on creating personalized and adaptive user experiences. Our findings indicate a strong trend toward using user data to deliver customized content and support that evolves as the user's mental health progresses.

Adaptive features enhancing personalized mental health support. Our analysis revealed that MHAs often include adaptive features designed to respond to users' changing needs. The analysis showed that *Personalized Feedback*, *Notifications and Reminders*, and *Gamified Reward System* are commonly used to enhance personalized mental health support. *Personalized Feedback*, often manifested as *progress tracking*, has emerged as a key component in many MHAs. These features typically assess users' mental health metrics, such as mood and stress levels, providing evolving feedback as users progress. *Stress alerts* were commonly implemented to prompt timely intervention. Our review found various types of stress alerts (e.g., predictions based on physiological responses [138], notifications triggered by long periods of uninterrupted work [55]). *Gamified Reward System* was frequently observed as a strategy to motivate consistent participation. Many MHAs offer progress badges or rewards (*achievement tracking*), with some incorporating *avatar customization* features that evolve based on user progress (e.g., character growth tied to daily activities [59], coin-based avatar modifications [154], or quiz rewards for psychoeducation content [68]) and narrative stroylines [58, 117], making the experience more engaging while adapting to users' changing goals.

These findings suggest a trend in MHA design toward personalized and contextualized support, with the goal of providing relevant and timely feedback based on users' changing mental health needs.

4.3 Identified User Engagement Challenges

We identify four major themes observed in both user-centered and system-centered functionalities from Section 4.2: (1) persistent participation fatigue, (2) less engaging functions, (3) privacy concerns, and (4) less adaptive functions. The first two themes were derived as major challenges from the findings in Section 4.2.1: (1) persistent participation fatigue emerged from Integrated self-management features promoting sustained engagement, and (2) less engaging functions were derived from Complex feature combinations targeting holistic engagement. The latter two themes were derived from Section 4.2.2: (3) privacy concerns emerged from Personalized mental health support through data-driven features, and (4) less adaptive functions were identified in Adaptive features that enhance personalized mental health support.

As summarized in Section 3.3, the four engagement challenges were identified through thematic coding and bottom-up analysis of specific functions based on both user- and system-centered approaches. While multiple *sustained engagement barriers* can be mapped from each identified *engagement-promoting feature*, Figure 4 highlights only the main mappings with arrows.

4.3.1 Theme 1: Persistent participation fatigue. Theme 1 presents an analysis of factors related to user fatigue observed in the literature as a result of continuous app use. Fatigue from sustained engagement may hinder user participation in MHAs that require consistent management and support, potentially reducing the effectiveness of the system's mental health support. Our analysis results identified two key themes: (1) the burden of continuous tasks and (2) time constraints on participation.

Burden of continuous tasks. The burden of continuous tasks refers to the psychological and temporal strain users experience when consistently engaging with an app, potentially leading to reduced engagement and diminished therapeutic efficacy. Repetitive activities, such as daily mood logging, regular meditation sessions, or ongoing symptom monitoring, can become burdensome over time. Lee et al. [109] reported that participants found it challenging to repeatedly enter events into the system without an auto-completion feature. In response, Neupane et al. [138] introduced text auto-completion and contextual visualizations to reduce user load. Despite these efforts, they observed that some participants still lost interest and withdrew from the study due to the ongoing demands of data entry. These findings highlight the critical need to address user burden in the design and implementation of mobile mental health support systems to maintain engagement and maximize therapeutic outcomes.

Time constraints on participation. This refers to the difficulty users face in allocating time for app use in their daily lives. Participants struggle with consistent and regular app use due to the absence of fixed moments to work with the app [154], busy schedules [60, 140], competing priority activities, and challenges in time management. Rohani et al. [165] found that patients with full-time jobs may have particular difficulty with daily planning and suggested that routine features that allow scheduling of recurring activities may be beneficial for this population.

4.3.2 Theme 2: Less engaging functions. Theme 2 analyzes the factors that lead to users not using features effectively. Less engaging functions contribute to high dropout rates, and even when users do engage with the system, low participation raises questions about the validity of the app's effectiveness.

Low attention. According to our review, previous studies have shown that certain features of mental health support systems sometimes fail to capture participants' attention. Reasons for this included failure to generate interest [44, 80], lack of understanding of the features [215], and low accessibility [25]. In the study by [44], the dropout rate for those who did not complete the intervention was approximately 95%. A common reason for dropout among these participants was forgetting to use the app, with another common reason being a loss of interest. The study in [201] found that approximately 22.9% of the intervention group did not use the app at all, indicating a lack of motivation or interest in using the app.

Monotonous design. Monotonous patterns [140], limited options, and tedious processes have been observed to cause users to disengage from the system [215]. Peuters et al. [154] found that while adolescents initially had high expectations for interactive

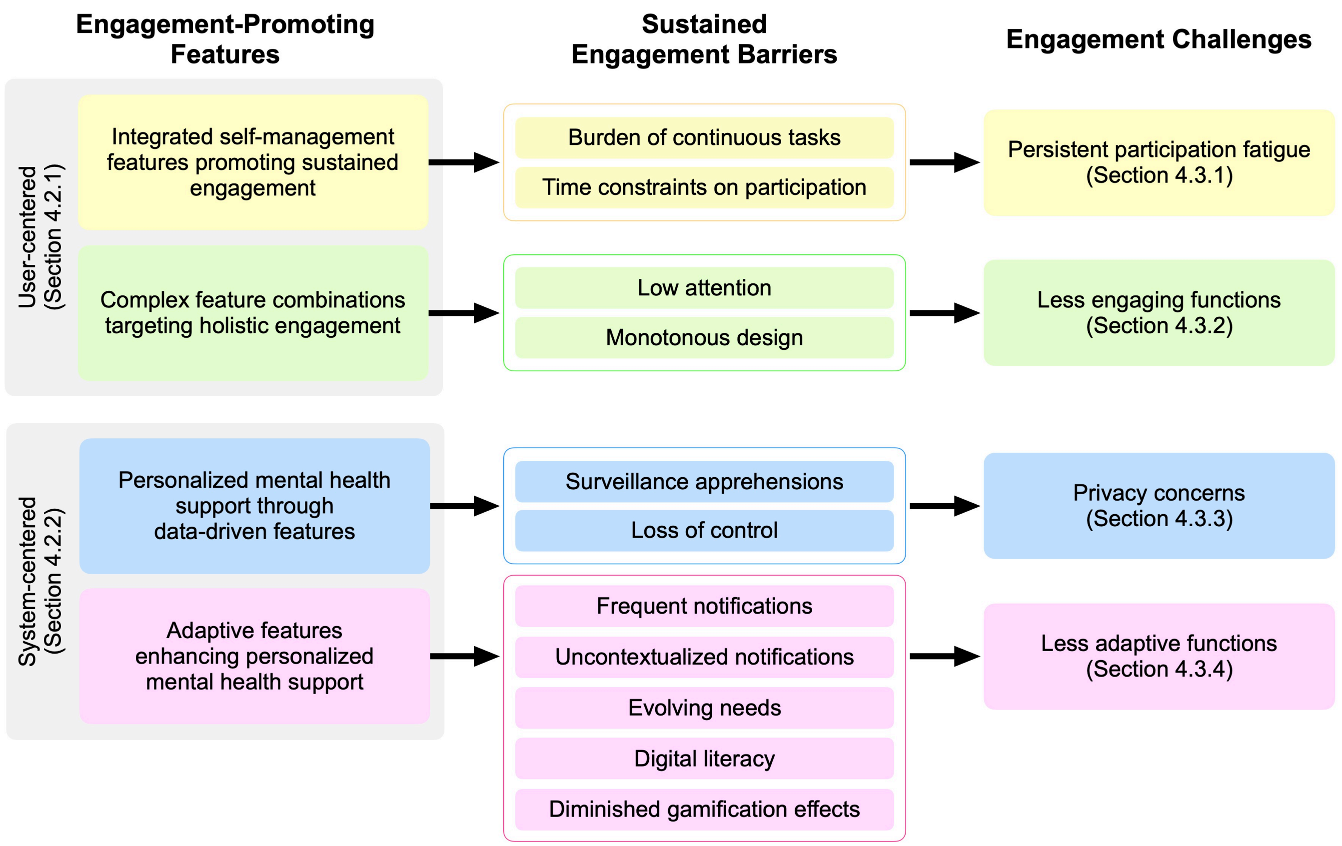

Figure 4: Thematic mapping of user engagement challenges in MHAs. This figure illustrates the progression from the key *engagement-promoting features* (Section 4.2) through *sustained engagement barriers* to the identified *engagement challenges* (Section 4.3). Compared to the Sankey diagram (Figure 1), this result contains thematic clusters derived from specific functions, from which elements of the barriers to sustaining engagement were organized and linked to challenges.

chatbots, their failure to provide meaningful responses led to disappointment and low user engagement. This finding aligns with previous research [119], which similarly reported that chatbots' limited ability to provide personalized and context-appropriate responses led to decreased user satisfaction and engagement. Additionally, mental health support apps that utilize gamification must compete with existing entertainment mobile mental health channels. If these apps fail to capture the interest of adolescents more effectively than existing channels, it may result in low engagement.

4.3.3 Theme 3: Privacy concerns. Theme 3 presents an analysis of factors that hinder user engagement due to privacy concerns, which can have significant consequences for users, because violations can lead to the unintended or unauthorized disclosure of mental health information or personal data. Our analysis results identified two key themes: (1) surveillance apprehensions and (2) loss of control.

Surveillance apprehensions. According to Nepal et al. [137], participants expressed concerns about photographic data collection, focusing on privacy invasion, damage to self-esteem, the potential for inappropriate situations, and data security. Participants felt uncomfortable being watched or monitored, which led to a sense of intrusion into their personal space. Some participants were concerned about the possibility of being caught in uncomfortable moments in situations where photos were taken continuously. Despite awareness of the data protection measures, concerns about image security and storage persisted. According to a study by Wu et al. [209], which analyzed log data from smartphones, participants reported feeling uncomfortable with the system collecting information related to the time and location of app use. Kim et al. [100] partially mitigated participants' concerns about the security of log data by conducting a Q&A session during the introductory session of the user study. However, over time, there were instances where the explanatory effect of the initial session did not persist. In [22], some participants still expressed concerns about privacy and monitoring. One veteran reported feeling as if his emotions and activities were being monitored and described the discomfort of being constantly tracked by the app.

Loss of control. In [137], participants expressed concerns about the safety and storage of the images, even though they were aware of the study's data protection measures. In particular, they were concerned about not being able to review, approve, or delete the continuously captured photos and not knowing when the camera was active. This uncertainty about how the photos would appear or whether they might be embarrassing added to their discomfort.

4.3.4 Theme 4: Less adaptive functions. Theme 4 presents an analysis of the factors that hinder user engagement due to mental health support systems do not adequately respond to users' evolving needs and preferences. A lack of flexibility can result in systems that provide one-size-fits-all notifications or messages that do not take into account individual circumstances, leading to user frustration and reduced engagement. This section analyzes how static system designs can hinder user participation and highlights the need for more personalized and adaptive features to sustain user engagement. Our analysis identified five key themes: (1) frequent notifications, (2) uncontextualized notifications, (3) evolving needs, (4) digital literacy, and (5) diminished gamification effects.

Frequent notifications. Early research on mobile-based mental health support systems found that alerts effectively reminded users to perform tasks such as self-assessments, serving as a way to maintain user engagement [17]. Elvitigala et al. [55] discovered that participants who were motivated to use notifications for reassurance found that self-set reminders effectively managed their stress. Meanwhile, other participants who experienced stress tended to adjust notifications to reduce environmental stress or re-enable alarms once stress levels decreased. Doherty et al. [52] conducted the first longitudinal study to deploy a mobile app to self-report psychological well-being during prenatal care. They found that participants who perceived notification frequency as either too high or too low were less engaged with the system, as evidenced by fewer reports, than those who found the frequency appropriate.

Uncontextualized notifications. Huang et al. [80] observed that while trigger messages generally had a positive impact on participants, there was variation in preferences regarding message format and content. Some participants strongly disliked trigger messages and preferred to disable this feature entirely. In the study by Song et al. [183], excessive notifications that were out of context with the user's state also led to user dissatisfaction. These findings underscore the importance of allowing users to select preferred strategies or implementing context-sensitive strategies tailored to individual participants' circumstances.

Evolving needs. Previous studies have found that user attrition also occurs when mental health support systems fail to adapt to changes in users' conditions over time (e.g., app usage purposes, requirements) [209]. Børøsund et al. [28] notes that the predetermined 3-day waiting period before unlocking a new module in a multi-module mental health app failed to adapt to users' changing needs. Some participants responded that the long waiting period could lead to delaying the use of the app or even forgetting to use the app, and mentioned that they wanted to continue with new modules as soon as they felt able, especially when they started to feel tired. This suggests that the system needs to be more adaptable to users' changing conditions and needs.

Digital literacy. In the study [165], some patients found it challenging to interpret the hierarchical visualization and struggled to understand how to read it. This difficulty was not associated with a particular socioeconomic or educational background, but was more common among older patients. For instance, one participant mentioned that she was unfamiliar with technology, which contributed to her inability to comprehend the highly complex structure of the visualized report. Malek et al. [122] found that some participants experienced difficulties using the app without assistance, which was attributed to a lack of digital literacy. This highlights the importance of considering varying levels of comfort with technology when designing such interventions.

Diminished gamification effects. George et al. [68] found that if the difficulty level or requirements of a system do not match the user's abilities or preferences, it can hinder long-term engagement. A lack of adaptability in the app's progress to personal circumstances or abilities can also impact completion rates. According to the study in [2], 60% of participants felt that gamification elements (e.g., points, rewards, achievements) did not align with the philosophy of MHAs or mindfulness. Participants felt that the primary motivation for using the mindfulness app Oiva was its content and well-being effects, believing that true achievement comes from learning and self-improvement. This suggests that simply applying external reward systems is not enough to keep users engaged. If gamification elements are not organically integrated with the core purpose of the app and fail to tap into users' intrinsic motivation and sense of accomplishment, their impact may be limited. Participants indicated that the app's ability to align with intrinsic motivation (i.e., features that resonate with the users' genuine reasons for using the app) could be critical to sustaining engagement.

4.3.5 Others: Technical issues and unreported cases. Of the literature reviewed, 28 publications addressed barriers to user engagement only in terms of simple technical issues, while 35 publications did not explicitly mention them. Participants reported various technical issues and usability challenges with smart devices and apps that hindered user engagement across all functions. The short battery life of smartwatches was noted as a barrier on participation [138]. Intermittent Bluetooth connectivity problems between smartwatches and devices were also reported, negatively impacting the user experience and contributing to lower System Usability Scale (SUS) scores for some participants [55]. App bugs and errors were identified as additional major challenges for users, impacting the overall performance and reliability of the apps [17]. Some participants experienced problems with WiFi accessibility issues and data overages. Specifically, some participants reported being unable to access to WiFi at any time during the day, which limited their app use [171]. Lastly, technical errors and difficulties in navigating content were reported in chatbot interactions, creating additional barriers for users engaging with these systems [156]. These technical issues and usability challenges in various aspects of smart device and app usage were found to impede user engagement and overall satisfaction with the technology.

4.4 Summary

In Sections 4.2 and 4.3, we systematically investigated and analyzed issues related to sustained user engagement based on specific features of mental health support mobile apps. We identified four major themes and derived sub-themes for each. The analysis revealed that despite various features of existing mental health support systems that have been suggested to enhance user engagement, there is still ample room for improvement by considering both user-centered and system-centered designs. Additionally, key factors such as persistent participation fatigue from long-term app use and privacy concerns were identified as major issues.

An interesting finding appeared in Section 4.3, where many users struggled to maintain engagement due to the lack of intrinsic motivation to use the system. This suggests that there should be a distinction between users who need mental health support but lack intrinsic motivation to use the app, and those who use general commercial apps with self-motivated interest. The challenges posed by users' lack of intrinsic motivation can be seen as a point of tension between MHPs who require system use and the users themselves. This finding, which has not been reported in previous research, will be an important consideration in the effective design and implementation of sustainable mental health support systems.

In the next section, we will discuss possible research directions to mitigate the identified challenges and the technical and social approaches that can be considered for each direction.

5 Discussion

In this section, we identify the key challenges to user engagement in MHAs and propose strategies to address them. Section 5.1 examines user-centered and system-centered barriers, while Section 5.2 focuses on encouraging intrinsic motivation through a balanced design. We then present an AI-integrated conceptual framework in Section 5.3, explore flexible system adjustments in Section 5.4, and consider privacy and ethical implications in Sections 5.5 and 5.6. Finally, Section 5.7 summarizes the limitations of this review and offers directions for future research.

5.1 Holistic Perspective on Engagement Challenges and Intrinsic Motivation

Our findings are consistent with several aspects identified in previous reviews of MHAs. For instance, Hornstein et al. [79] demonstrated how rule-based personalization and passive sensing can enhance the personalization of the user experience and improve the effectiveness of system design. Stawarz et al. [185] also identified key barriers to sustained engagement in MHA design, such as privacy concerns, usability issues, and lack of clarity in data collection practices, which are consistent with the engagement challenges identified in our analysis. Furthermore, Torous et al. [194] highlighted that the lack of user trust due to poor data privacy and insufficient transparency significantly hinders engagement with MHAs. They further recommended integrating user engagement during the design and testing phases to bridge the gap between user expectations and app functionality.

This study provides a more comprehensive understanding of engagement challenges by conceptually aligning specific functions and user engagement under two overarching perspectives: "user-centered" and "system-centered." In doing so, the analysis aims to provide a more holistic understanding of these barriers. Going beyond a focus on specific features or technical improvements, the results of this study provide a systematic foundation for understanding how functional elements interact to shape the user experience, and for identifying the tensions and imbalances that emerge in the process. The significance of the study lies in its reinterpretation of the complex interplay between functional elements and engagement barriers within the framework. In other words, this study systematically addresses not just "what the problems are" but also "why these problems arise and how each factor interacts to influence the user experience."

This holistic perspective is closely related to the lack of intrinsic motivation, as discussed in Section 4.4. Rather than increasing intrinsic motivation by addressing an individual user's "lack of interest" or "indifference," we aim to explore how structural tensions and imbalances between user-centered and system-centered intervention strategies can hinder the development of intrinsic motivation. User-centered interventions (e.g., continuous self-reporting, goal setting, task performance) are primarily designed to encourage proactive user participation. However, such approaches tend to increase the behavioral and temporal burden on users in the long run. The more self-management tasks are required, the more users are likely to face the fundamental question, "Why should I continue this effort?" In situations where users merely respond to extrinsic demands, it becomes increasingly difficult for them to find intrinsic meaning or value in their actions.

On the other hand, system-centered interventions (e.g., automated feedback, data-driven personalization, passive sensing) aim to reduce effort while providing personalized support. However, overly automated or insufficiently nuanced system-centered approaches can lead to privacy concerns, out-of-context notifications, and less adaptive functionalities. These issues may cause users to feel that their needs, values, or life contexts are not adequately considered. This raises questions such as, "Does this app really understand my situation?" and "Why should I trust and integrate this system into my life?" Mechanistic responses that fail to adapt to individual contexts may weaken users' willingness to engage voluntarily, thus hindering the development of intrinsic motivation.

Intrinsic motivation is not simply a matter of providing information or functionality, but must be linked to a positive and personalized answer to the question, "What does this app mean to me?" Without a harmonious design between user-centered and system-centered strategies, users fail to internalize the fundamental reason ("Why should I use this app?"), making it difficult to sustain engagement. Building on the holistic perspective proposed in this study, in the following section, we aim to broaden the discourse on the lack of intrinsic motivation from an issue of individual characteristics to one that encompasses structural and contextual factors.

5.2 Enhancing Intrinsic Motivation to Sustain User Engagement

Research in HCI and digital mental health interventions suggests that adjusting individual features or making incremental usability improvements is insufficient to address engagement challenges fundamentally [11, 75]. Building on the holistic perspective in Section 5.1, in this section, we discuss strategies for strengthening intrinsic motivation, a critical factor for sustained user engagement in mobile mental health support systems. Enhancing intrinsic motivation requires a balanced, integrated approach that recognizes the value of both user- and system-centered strategies, while mitigating the tensions and imbalances that hinder users from internalizing the deeper reasons for continued app use.

According to Self-Determination Theory (SDT), intrinsic motivation thrives when three core psychological needs—autonomy, competence, and relatedness—are met [167]. User-centered approaches excel at supporting autonomy and competence by fostering self-directed actions such as goal setting, self-monitoring, and active participation in treatment. These strategies allow users to feel a sense of control over their mental health journey and recognize their growing capabilities. However, when these tasks become repetitive or overly burdensome, users may lose sight of the fundamental value behind their efforts. Over time, the experience can become a series of chores rather than a meaningful path to well-being, making it difficult for users to internalize the "why" of their engagement.

On the other hand, system-centered approaches reduce user effort and provide timely, data-driven support through automated feedback, passive sensing, and personalized recommendations. While these strategies enhance efficiency and relevance, they risk feeling impersonal, intrusive, or misaligned with users' life contexts if not implemented thoughtfully. Privacy concerns, irrelevant notifications, and a lack of truly empathetic responses may lead users to question whether the system truly understands their needs. This undermines the sense of relatedness—feeling understood, supported, and valued—that is essential for fostering intrinsic motivation.

An example of balancing user-centered and system-centered interventions is as follows: User-centered interventions continue to nurture autonomy and competence, but designers ensure that these tasks do not become overwhelming. For example, rather than requiring frequent self-reporting, the system might offer flexible participation schedules and celebrate small increments of progress, allowing users to see their efforts as personally meaningful growth opportunities rather than burdensome obligations. At the same time, system-centered elements can go beyond superficial personalization. By taking into account the user's emotional state, contextual factors, and personal values, the system can provide empathic, situationally appropriate responses. This could include offering comforting messages during stressful moments, suggesting a short relaxation exercise, or acknowledging a user's recent challenges. In doing so, the system not only reduces cognitive load but also increases the user's sense of being understood and supported.

This balance ensures that users see the app not just as a tool they "have to" use, but rather as a trusted partner in their mental health journey. This partnership resonates on both rational and emotional levels. For example, users see their actions as intrinsically meaningful because they set their own goals (autonomy), witness their gradual improvement (competence), and feel personally acknowledged and cared for (relatedness), aligning with SDT. Together, these conditions pave the way for intrinsic motivation to flourish, leading to more sustained, fulfilling engagement over time.

To enhance intrinsic motivation, it is essential to implement both user-centered and system-centered interventions that understand the dynamic state changes of users and reflect not only the current interaction context but also the history of past interactions. However, as identified through the literature review in this study, traditional functionalities have limitations in addressing these requirements. One potential solution to overcome these limitations is the adoption of LLM-based AI agents with memory capabilities [217]. These AI agents are capable of detecting subtle psychological and emotional changes in users, providing immediate, context-aware interventions, and facilitating continuous and coherent interactions informed by interaction history. Such advancements have the potential to transform the relationship between users and mental health support apps, moving from simple interactions to active engagement with the AI agent embedded in the app. As a result, users may come to perceive the app as a trusted partner or companion. This personalized experience enhances users' sense of autonomy and competence while simultaneously cultivating a profound sense of relatedness, ultimately strengthening intrinsic motivation.

5.3 Conceptual Framework Proposal

Sections 4 and 5.1 discussed the factors that hinder sustained user engagement in MHAs, highlighting a holistic perspective that these challenges cannot be addressed through functional improvements or usability enhancements alone. In particular, Sections 5.1 and 5.2 presented the importance of a balanced approach based on SDT, which highlights the need to satisfy users' autonomy, competence, and relatedness to enhance intrinsic motivation.

In this section, we propose an extended conceptual framework that integrates emotionally intelligent conversational AI agents into mobile mental health support systems that provide therapeutic content. The proposed framework highlights two important future research topics: (1) tension mitigation between end-users and mental health professionals (MHPs) and (2) the need for collaborative design between MHPs and HCI researchers. An overview of the proposed framework is illustrated in Figure 5, with detailed descriptions in Sections 5.3.1 and 5.3.2.

5.3.1 Interaction based on emotional support. In our findings, we focus on the importance of emotional support regarding users' sustained engagement with mental health support systems. In Section 4.2.2, the positive impact of emotional support through human coaching on app usage and treatment outcomes was observed. This suggests that emotional support contributes not only to temporary satisfaction but also to long-term behavior change and improved treatment effectiveness. In contrast, interactions with chatbots with low emotional intelligence were found to create negative perceptions among users, hindering sustained engagement.

Recent advances in LLM-based conversational AI agents, which combine retrieval-augmented generation (RAG) [111] and long-term memory (LTM) methods [219], enable interactions based on emotional support by not only providing information, but also recognizing users' emotions, empathizing with them, and offering personalized support. We highlight the need for future research on designing personalized emotional interaction using emotionally intelligent conversational AI agents as a way to bridge the perception gap between users and MHPs.

The elements of personalized emotional interaction are categorized into (1) adaptivity, (2) continuity, and (3) multimodality. First, *adaptivity* refers to the ability to interact LTM-augmented personalization [216] can be one possible approach. LTM-augmented AI agents can alleviate the challenges caused by less adaptive system functions by remembering, updating, and retrieving behaviors with the user to perform more user-friendly interactions. Second, *continuity* focuses on maintaining an ongoing relationship between

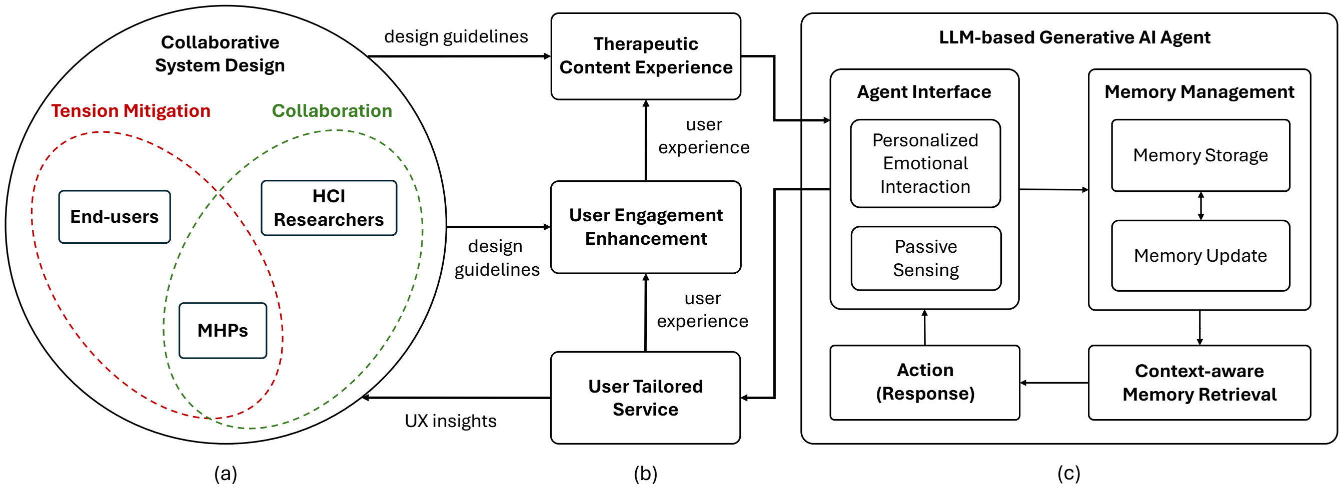

Figure 5: Key components of the proposed conceptual framework: (a) collaborative system design, (b) user experience, and (c) LLM-based generative AI agent. The collaborative system design aims to alleviate tensions and develop design guidelines through the collaboration of end users, HCI researchers, and MHPs. This framework, which includes an AI agent that provides interventions based on personalized emotional interactions and data analysis through passive sensing, contributes to enhancing the user experience with therapeutic content tailored to their needs, as well as improving user engagement.

the user and the system, which can be implemented through various continuous learning methods [112, 210]. Through continuous learning, AI agents can build a strong relationship with users, enhance context-aware interactions, and promote effective just-in-time adaptive intervention (JITAI). Lastly, *multimodality* refers to the modes of interaction between the user and the AI agent. Beyond text-centered interactions, the system may use other data modalities, such as images, to provide intuitive interactions according to the user's needs (e.g., time constraints, reluctance to verbally express) [208] or provide notifications or feedback based on the analysis of log data (e.g., app usage, wearable sensing data) [204] that reflect the user's ongoing state (e.g., emotions, state of activity).

5.3.2 Collaborative design between HCI researchers and MHPs. Based on our Sankey diagram analysis, over 50% of the therapeutic content and the gamified reward system functions in mental health support systems were mapped to the challenging factors categorized as less engaging. Contrary to the expectations of MHPs, there were often features that users did not actively engage with, and users sometimes reported feeling bored or dissatisfied with design elements while using the mental health support systems. Attempts to evaluate therapeutic effects solely through an app should be approached with caution. Claims of therapeutic efficacy, particularly in situations of low user engagement, may raise questions about validity. Low engagement can limit the actual impact of the app, which in turn can affect the reliability of the results.

We recognize the difficulty in adhering to the theoretical foundations of treatment while also incorporating user-centered design innovations in the design phase of therapeutic content for MHAs. We emphasize the necessity of close collaboration between HCI researchers and MHPs from the system design phase to ensure that the content intended by MHPs for therapeutic purposes is effectively digitized and clinically impactful. Functionality improvements based on understanding the end-user's condition and needs could alleviate the challenges associated with the less engaging aspects of the content that users experience.

The widespread use of wearable devices that collect real-time health data (e.g., heart rate, physical activity, sleep patterns) makes them highly useful for continuously monitoring and predicting health status [125]. These data support the monitoring of mental health, early detection, and personalized psychological counseling, contributing to preventive psychiatry. Recently developed AI models, such as Health-LLM [101], combine powerful language comprehension and generation capabilities with rich health data from wearable sensors. These systems are designed to convert time-series sensor data into a format in which LLMs can understand and apply various prompting techniques and fine-tuning methods to personalized health predictions.

As identified in our review, the medical domain requires a high level of expertise and accuracy of LLMs' outputs, and the hallucination [1] or bias [67] of LLMs can lead to serious consequences. For this reason, the application of LLMs in the mental health domain has been limited. However, the vast knowledge base and flexible reasoning capabilities of LLMs show great potential in areas such as medical diagnosis, treatment planning, and summarizing medical information. While ethical issues such as data privacy and information bias remain important considerations in applying LLMs to healthcare, integrating advanced AI technologies with mental health support systems presents the possibility of increasing user engagement by providing personalized content. As more research is conducted to find the best way to use LLMs in the context of healthcare, and as we expect to see more reliable versions in the near future, our role as HCI researchers would be to find the best way to use them in terms of user engagement and sustainability.

We emphasize the need for research that overcomes the limitations of traditional mobile mental health interventions through collaborative user-participatory design between MHPs and HCI researchers, developing sustainable solutions that reflect interdisciplinary needs. By leveraging wearable devices and app usage data to analyze users' conditions and preferences, personalized intervention strategies can be developed. Collaboration between MHPs and HCI researchers strengthens interdisciplinary integration, facilitating the alignment of clinical and user-centered needs. Through collaborative research, researchers can develop mental health support systems that sufficiently reflect user needs, reduce noise in clinical effectiveness verification, and consider study designs that track clinical efficacy and user satisfaction over the long term. In this way, true effectiveness can be validated, and directions for continuous improvement can be identified. This comprehensive and long-term research approach could have the potential to contribute to the advancement of digital mental health support systems.

5.4 Flexible Environmental Adjustments for Enhancing User Engagement

As mentioned in Section 4.3.1, MHA users experienced fatigue while continuously performing tasks required by the app. This was mainly attributed to frequent notifications, the burden of ongoing task completion, and time constraints. Initially, notifications were effective in reminding users to engage in self-assessment activities; however, over time, they started to cause fatigue [109, 138]. Moreover, users struggled to find time to use the app in their daily lives due to busy schedules, competing priorities, and challenges in time management, particularly affecting those with full-time jobs [60, 140, 154, 165]. The burden of continuous task completion also emerged as a key factor. Activities such as daily mood tracking or repetitive meditation exercises caused fatigue over time [109]. Despite design improvements, such as the introduction of autocomplete features, problems with engagement persisted [138]. Thus, even if MHAs achieve clinically meaningful improvements (e.g., significant changes in clinical measures), the efficacy of those apps may be questionable if users disengage early.

These issues can be mitigated by providing flexibility to create, modify, and manage tasks within the app. However, while considering these system-centered improvements, it remains important to encourage users to engage with key app tasks and content designed by clinical experts, as individuals with mental health conditions still require guidance. In particular, individuals suffering from depression or anxiety may find it challenging to create an environment that helps self-improvement through the app on their own. One way to do this is to use a collaborative care model [19], in which multiple clinical professionals and caregivers work together to support the patient in a comprehensive treatment approach. This model can be integrated into the app, allowing caregivers to monitor task completion and outcomes and provide appropriate support as needed. While mobile apps are primarily designed for independent use, for users who struggle with environmental adaptations, the app must be flexible and responsive to their context in order to effectively support therapeutic content. This can help individuals with mental health conditions use MHAs effectively and facilitate improvements in targeted conditions.

5.5 Enhancing User Privacy: Integrating Literacy Education and Adaptive AI

We have identified privacy concerns among users of MHAs (Section 4.3.3). These concerns are particularly pronounced with *Self-reports* features and *Passive Sensing*. Users of MHAs experienced considerable discomfort compared to apps with other purposes, because they frequently recorded sensitive information such as current emotional states, stressors, and depressive symptoms. The anxiety associated with this discomfort stems from uncertainty about how recorded data will be used and shared [120, 176]. We have confirmed that researchers provided information about data collection and use in accordance with IRB guidelines and ethical standards [25, 44, 80, 215]. However, some users may not have fully understood this information or wanted additional explanation during the experiment. In particular, information about the scope and amount of data accessible to app developers or researchers may have seemed unclear from an end-user perspective. This ambiguity may leave users with vague fears about how automatically collected smartphone sensor and app usage data will be processed.

To address these concerns, it may be helpful to communicate the types of data the app will collect and how it will be user-friendly prior to study participation. However, as highlighted by Kim et al. [100], providing too much information or too much freedom of choice can lead to user resistance. Therefore, providing information as clearly and concisely as possible is crucial to foster trust without causing user discomfort. Additionally, providing concise and clear privacy education during the user onboarding process can be effective. Moreover, technologies such as Federated Learning [164] can train models directly on users' devices without transmitting personal data to a central server, thereby minimizing the risk of personal data leakage while improving model performance. Another approach, the concept of Unlearning [31], involves making models forget unintentionally included sensitive personal data or retraining them to adapt to new patterns instead of outdated information. This can help address privacy concerns while allowing models to continuously improve their performance by reflecting the latest data. These approaches can increase user engagement with MHAs by providing personalized services while protecting the privacy of user data.

5.6 Ethical Considerations in LLM Integration: Expert-Guided Safety Enhancements

We have found that LLM can raise ethical concerns, including the generation of false information or responses (Section 4.3.5). These ethical concerns may be further amplified as LLMs improve personalization based on user input and passively collected usage logs. In this regard, one study [199] reported that they did not apply LLMs to their conversational chatbot system to minimize potential ethical issues that patients may face. Another study [99] required MHPs to implement strict participant screening processes to mitigate ethical problems that might arise from LLM outputs (e.g., excluding those who scored high on suicide/self-harm risk scales). This study also temporarily suspended system use and reassessed participants who frequently raised sensitive issues during the research to determine whether they should continue to participate.

One possible way to address these ethical issues is to continuously improve LLM performance through Reinforcement Learning from Human Feedback (RLHF) [9] based on MHPs' input. This method reduces model prediction errors by incorporating expert feedback in both initial model training and real-time learning environments. It can also provide more reliable personalized support. In zero-shot or few-shot learning situations, prediction accuracy can be improved through prompts and output validation procedures predefined by MHPs. Particularly in sensitive situations, such as the detection of specific emotional states or mental crises, a system can be built to minimize prediction errors by applying RLHF together with prompt conditions predefined by MHPs. Through these techniques, LLM-based systems can provide safer and more reliable personalized support.

5.7 Limitations and Future Work

Although this study identified factors hindering user engagement with MHAs through a literature review, it cannot be assumed that these factors affect all users uniformly. Even with the same MHA, individual differences–such as personal preferences, underlying mental health conditions, cultural backgrounds, prior experiences, and levels of digital literacy–can lead to diverse patterns of engagement and motivation. For instance, the engagement barriers identified in this study (e.g., fatigue due to excessive self-reporting or lack of contextual personalization) reflect phenomena commonly reported in the reviewed studies but may not be universally applicable to all users. Nonetheless, recognizing these limitations serves as an important starting point for developing future MHA design and improvement strategies. More specifically, a multifaceted approach–incorporating personalized strategies that reflect individual user characteristics and latent variables, introducing intervention context-aware technologies, and strengthening long-term motivational factors–can enhance user engagement with MHAs.

6 Conclusion

We conducted a comprehensive scoping review to investigate the key functional components of MHAs and their corresponding user engagement challenges based on user-centered and system-centered approaches. Through a systematic analysis of 111 papers, we identified four key challenges that hinder sustained engagement: (1) persistent participation fatigue, (2) less engaging functions, (3) privacy concerns, and (4) less adaptive functions. Building upon these challenges, we discuss potential research directions and the technical and social approaches that should be considered within each direction to mitigate these issues. Specifically, we propose five future research directions: (1) interaction based on enhancing intrinsic motivation and emotional support, (2) collaborative design between HCI researchers and MHPs, (3) flexible environmental adjustments for enhancing user engagement, (4) enhancing user privacy, and (5) ethical considerations in LLM integration. These research directions aim to support personalized emotional interactions centered on three elements – adaptivity, continuity, and multimodality – thereby enhancing long-term user engagement and system effectiveness.

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