Toward an mHealth App for Early Detection of Relapse in Remitted Depressed Individuals: A Focus Group Study on User Requirements and Concerns

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Abstract

Background: Major depressive disorder is often a recurrent condition, with a high risk of relapse for remitted depressed individuals. Early detection of relapse is critical to improve clinical outcomes. mHealth (mobile health) technologies offer new opportunities for real-time monitoring and prevention of relapse, given that user requirements of the target population are effectively implemented.

Objective: This study investigated remitted depressed individuals' user requirements and concerns for an mHealth app aimed at monitoring depressive symptoms and detecting early signs of relapse through integrating both active ecological momentary assessment (EMA) data and passive data from the user's smartphone and smartwatch.

Methods: Three focus group discussions were conducted with 17 participants who had a history of depression but were in remission at the time of the study. Prior to the focus group, participants had gained some experience with an in-house designed EMA monitoring app, prompting questions regarding their mood multiple times throughout the day. During the focus groups, feedback and insights were gathered into participants' expectations, requirements, concerns, and attitudes toward a depression monitoring app. A thematic analysis was performed to identify recurring themes and subthemes, shedding light on the desired user experience and functionalities.

Results: We identified five main themes. Participants highlighted (1) a need for customization settings, particularly in terms of data collection and sharing, and frequency of self-assessments. They also valued (2) positivity in the app's design through positive reinforcement and journaling features. Additionally, participants emphasized (3) interventions to be the main motivator for adoption and long-term usage. More specifically, they wanted the app to foster self-awareness, self-reflection and insights and to offer support during deteriorations in mental health. Furthermore, participants deemed (4) transparency in data use and machine learning predictions essential for building trust. Participants required these functionalities to bear (5) the user burdens of self-monitoring. Key concerns were for passive monitoring to cause a privacy burden and for active monitoring to raise an emotional burden.

Conclusions: Considering the vulnerability of potential users, caution is warranted in the design of an mHealth app for depression relapse prevention. Users' requirements for customization, positivity, interventions, and transparency must be addressed, while minimizing both the emotional and privacy burden. Carefully balancing these design elements is crucial to ensure adoption and long-term user engagement.

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Introduction

Major depressive disorder is a debilitating condition that is associated with tremendous personal suffering and substantial societal costs [1, 2]. It is the most prevalent of all mental disorders [3]. Moreover, its prevalence is increasing over time [4] and it is often a recurrent or even chronic disorder [5]. Despite the availability of pharmacological and behavioral treatments that can be quite effective in the acute phase, the risk of relapse remains high for remitted depressed individuals [6-8], with depressive remission being defined as the asymptomatic state after a depressive episode [9].

A key difficulty in the treatment of depression, is that there appears to be both a treatment gap [10] and lag [11]. That is, many patients–even those who have previously sought treatment for depression [12]–only seek help when depressive symptoms become severe [13] or persist for a longer period of time [14]. A common reason for depressed people to avoid or delay seeking treatment is wanting to manage the mood problem oneself, without the help of a professional [15]. Additionally, stigma around mental illness remains a barrier for seeking treatment [12-14, 16, 17]. Mental health care accessibility factors can also play a role in delayed help-seeking, such as long waiting times [16] and high costs of help [17]. Regardless of the reason for delayed treatment, it is often harmful to patients. Recovery rates decline while the risk of persistence increases if patients do not start treatment within the first few months after the manifestation of an episode [18]. Early intervention is paramount. Therefore, scholars and practitioners have recently broadened their scope of attention and focus on preventing the onset of depression, especially among remitted depressed individuals [19-23]. Of key importance to such prevention is predicting *if* and *when* there will be a novel depressive episode.

In this realm, recent innovations in mHealth or mobile health, ie, the application of mobile technologies for healthcare services [24], are promising for mental health follow-up. The ubiquity of affordable smartphones and–to a lesser extent–smartwatches, makes mHealth increasingly accessible to patients. These remote measurement technologies enable healthcare providers to flexibly gather real-time daily life measurements in patients' natural context, as opposed to collecting retrospective measurements during examinations at the clinic. mHealth technology also provides opportunities for empowerment by fostering self-management. mHealth apps might have less stigma associated with them, lowering the barrier for adoption. Furthermore, most review papers conclude that mHealth interventions are promising in terms of cost-effectiveness as well, especially for depression management [25-28].

The landscape of depression management apps largely consists of functionalities providing therapeutic support, intervention, treatment, and psychoeducation, followed by tracking of mood, behavior, or thoughts and symptom management [29-31]. In contrast to the myriad of therapeutic apps currently available in the marketplace, this study focuses on an mHealth app for prevention through monitoring depressive symptoms. More specifically, it is about a future app that captures and

feeds both active and passive data sources into a personalized machine learning model, being trained for just-in-time detection of early warning signs that are associated with depression relapse. Active data is gathered through ecological momentary assessment (EMA) questionnaires, gauging users' feelings, behavior and context. Passive data is sourced from the user's smartphone and smartwatch. Passive data tracking via these mobile devices is increasingly relevant for mental health care as it can be used for digital phenotyping. Defined as the "moment-by-moment quantification of the individual-level human phenotype in-situ using data from smartphones and other personal digital devices" [32], digital phenotyping could be a fruitful approach to identifying symptoms and early signals of relapse [33, 34]. Furthermore, recent technological advancements in predictive algorithms, machine learning techniques and artificial intelligence can facilitate making sense of the unprecedented amounts of granular passive data [35] and pave the way toward personalized preventive care [36]. Especially smartphones are well suited for digital phenotyping due to their worldwide adoption and users' engagement with them. Although mobile sensing through smartphones has not yet lived up to its promise [37], enriching the smartphone data with smartwatch sensor data and the real-time interaction with self-reported data through EMA is worth exploring [38].

mHealth apps have been said to be promising in preventing depression [39-41] or at least in preventing the transition from minor to severe depressive symptoms [42]. Nevertheless, the majority of mHealth app users try an app only once [43, 44]. mHealth trials suffer high dropout rates, giving clues for real-life adoption problems [45]. Additionally, there is room for improvement when it comes to long-term engagement [35]. For the population with a history of depression in particular, the lack of motivation and behavioral avoidance inherent to the mood disorder [46] might pose a major challenge to engagement and retention [47]. Research already shows that the implementation of mHealth tools in routine mental health care often does not meet expectations [48]. Certain challenges are hindering successful implementation of mHealth in practice. mHealth tools need to be accepted by patients and they need to meet their expectations and preferences. Additionally, they need to be appropriate in addressing patients' mental health disorder. These challenges can be overcome by applying user-centric design principles to make sure the app is usable and aligned with end users' needs and expectations, and to ensure future adoption [49].

Hence, we conducted focus group discussions to explore (1) the user requirements and concerns of remitted depressed individuals for (2) a prevention and early relapse detection app (3) based on both active and passive data collection. This is different from existing research, which has primarily focused on (1) the preferences of currently depressed individuals for (2) interventional apps (3) based on active data collection. In this paper, we gauged attitudes of people in remission toward self-tracking. A major question was to what extent these individuals are open to the idea of monitoring early warnings signs of relapse. We assessed the role technology can play in this regard. We investigated adoption intention and participants' preferences regarding the app and its functionalities. We examined the differences between active and passive monitoring in terms of privacy and other user burdens. Thematic analysis revealed five main themes (ie, customization, positivity, interventions, transparency, and user burden) representing the different requirements and concerns participants voiced regarding a prevention tool, the design of which should carefully consider an equilibrium between both.

Methods

Participants

Three focus group discussions with remitted depressed participants were conducted. Most participants were recruited through social media by means of a flyer informing them about the study. The inclusion criteria were: (1) ≥ 18 years, (2) Dutch speaking, (3) in possession of an Android smartphone, and (iv) having experienced a depressive episode in the past, from which they were

recovered at the time of the study. It is important to note that prior experiences with depression were self-reported and no further clinical screening was carried out by the researchers. Research, however, indicates high accuracy in self-diagnosis for commonly occurring mental disorders, such as depression [50]. Other participants were recruited via a previous study on online cognitive control training for depression relapse prevention. These participants had already been screened for depressive symptoms in the past. This study was approved by the Ghent University Department of Political and Social Sciences ethics committee (2024-05).

The sample of 17 participants consisted of 3 men and 14 women, aged 21 to 49 years old (mean 27.7, SD 6.8 years). All participants were Caucasian. It should be noted that our sample did not reflect the general population, as under recruitment of ethnic minorities is a well-known issue in mental health research [51]. The fact that the sample was predominantly female is a prevalent self-selection bias in this kind of research [47, 52-57]. This is not necessarily problematic, as females experience higher risk of onset of depression, longer duration of episodes, and a tendency for higher risk of recurrence [58]. Women also find it easier to confide in others about psychological problems and therefore are more likely to seek help by attending health care services and receive diagnoses for mental health problems [59]. Females may thus form a target population likely to adopt an app that monitors depression relapse. The sample also consisted mainly of people in their twenties, which can be explained by the first recruitment method through a social media channel linked to the university.

Materials

The app used in this study is not commercially available and is currently in development by a consortium of research partners, named DEDICAT ("DEpression's DIgital foreCAsting Tool"). The app captures both active (EMA) and passive (smartphone and smartwatch data) data sources. EMA is a monitoring strategy to assess users' feelings, behavior and context in real time in natural settings, thus maximizing ecological validity while avoiding retrospective recall [60, 61]. Smartphone data contains phone usage patterns (eg, screen time per app), revealing a user's digital footprint. Additionally, smartphones include a multitude of sensors (eg, accelerometers, GPS location sensors, light and proximity sensors), providing detailed measurements about users' daily life and their environment. Similarly, smartwatches capture physiological, behavioral and contextual data (eg, heart rate, step count) in a non-invasive and continuous way. While the active data is self-reported and subjective, the passive data is automatic and objective. In the future, these data sources will be fed into a personalized machine learning model aimed at early detection of depression relapse.

A few days prior to the focus group, participants were requested to download a version of this app that only triggered the EMA questionnaires. No passive data was tracked from participants. Six times throughout the day, the app sent a notification at a random time to prompt mood questions (eg, "Right now, I'm feeling excited") (Multimedia Appendix 1). If the questionnaire was not completed within fifteen minutes, a reminder notification was sent. The EMA data was not stored and was deleted immediately. The purpose of this preparation was merely to provide participants with an accurate experience with a monitoring app.

Procedure

The three face-to-face focus group discussions took place in the research facility in Ghent, Belgium from February to March of 2024. These groups consisted of 2, 7 and 8 participants respectively. The number of participants in the first group was limited due to an unexpectedly high number of no-shows. The size of the group, however, did not affect the quality of the interview. After having read and signed an informed consent form, the audio-recording started and participants were interviewed for approximately one hour and a half, for which they received a financial compensation. The interview started with an explanation of the study rationale and the purpose of the app. By means of a semi-structured interview, feedback and insights were then gathered by probing into participants'

expectations, needs, requirements, concerns, and attitudes toward a depression monitoring app.

The interviews were transcribed verbatim and pseudonymized, after which a thematic analysis was carried out [62]. Transcripts were coded in NVivo using an inductive approach. Themes and subthemes were identified at the semantic level by iteratively deriving and refining the codes against the data. The criteria of what counts as a theme were a combination of the importance of the theme in terms of answering the research question and the prevalence of the theme, that is, the number of interviews it appeared in and the number of participants that brought it up. In the latter sense, themes are repeated patterns of meaning [62]. Finally, the active role of the researchers' judgement, their assumptions and theoretical backgrounds in determining themes should be acknowledged.

Results

The five main themes resulting from the thematic analysis and the relationships between them are visualized in a thematic map (Figure 1). The ovals depict the main themes, while the rounded rectangles represent the subthemes. The (sub)themes with a white background represent what participants require in an mHealth app, whereas the (sub)themes with a grey background depict their concerns. Many of the topics discussed within themes are interconnected with other themes. The double-headed arrows visualize which requirements balance out which concerns. Each theme is outlined below and is illustrated with a few quotes from participants (Multimedia Appendix 2).
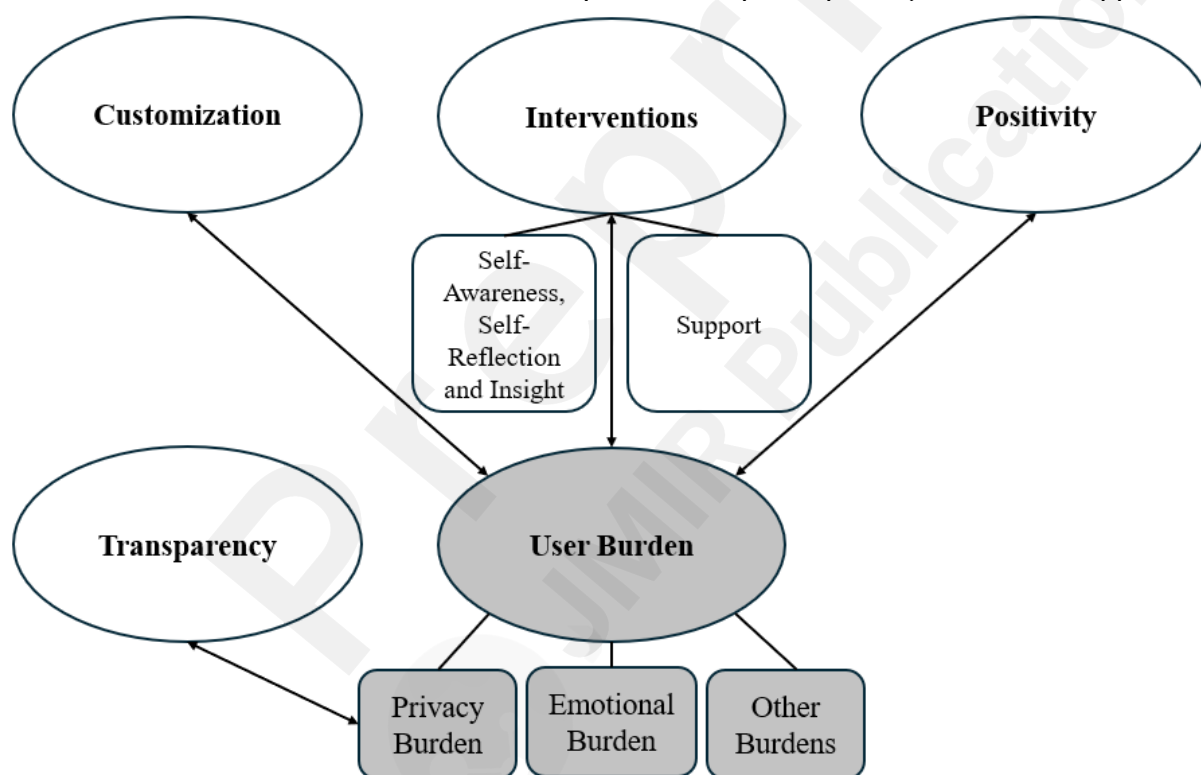

Figure 1: Thematic map of the five main themes: customization, interventions, positivity, transparency, and user burden.

Customization

The customization theme consistently appeared across all interviews and was echoed by numerous participants. The need for customization was apparent in multiple aspects of design; (1) data and privacy issues, (2) the EMA questionnaires, and (3) the feedback functionalities.

Participants wanted to customize which data parameters are tracked by the app. Such a customization feature would allow users to disable certain parameters they deem sensitive. Furthermore, they wished to configure whether the data would be shared with their mental health care provider(s) or

not, and if so, which mental health care provider would see which data parameters at what time. Participants preferred to decide for themselves whether and when to contact their mental health care provider in case of early detection of a relapse in depression.

Another topic of customization was related to the EMA questionnaires and the possibilities for feedback (eg, on tracked mood, sleep, or physical activity). Participants wanted to configure the frequency of the questionnaires. Next to the frequency, some liked to configure the timings of the questionnaires as well, whereas others embraced the random character in which the notifications appeared. These configurations would allow users to embed the usage of the app into their daily life– for example, shifts and breaks at work–and would allow them to decide how often and when they are confronted with questions asking about their emotional state. With regard to the content of those questions, participants expressed the need to provide context by linking mood and daily life activities. This functionality would allow for more personalized feedback, which in turn would provide the user with more valuable insights. However, a considerable number of participants preferred not to see any feedback at all to prevent adverse emotional effects–demonstrating the need for customization of feedback functionalities.

Positivity

Participants made it clear that they wanted 'positivity' to be included in an mHealth app and that design efforts should be directed toward establishing (1) a positive user experience, and (2) positive reinforcement and affirmation. An interesting observation here is that participants alluded to the importance of the app being more than just a relapse monitor; they saw opportunities for prevention. Participants mentioned, for example, that the app should also include (3) journaling functionalities.

With respect to a positive user experience, participants sought the ability to customize what the app looks like. The idea of choosing between a few options of themes was put forward in every focus group. Themes consist of a combination of colors, visuals, fonts and shapes that are consistently applied throughout the app. Participants expressed explicit interest in themes with more vivid color palettes, next to the default light and dark theme, as colors were said to represent positivity. What participants also meant with a positive user experience, is that the app does not look clinical, dull or depressing.

To prevent this, some participants proposed implementing positive reinforcement via gamification into the app. Gamification refers to enhancing an app with game-like elements to keep users engaged and motivated. Whereas some participants enthusiastically suggested creative ideas for gamification features, other participants thought of gamification as something inappropriate or immature that would make the app less suitable. Participants did, however, agree on the omission of one particular gamification feature: the streak. A streak is a consecutive series of actions performed without interruption. They are used to incentivize users to maintain consistent usage. Multiple anecdotes were given on how the loss of a streak in other apps caused demotivation, disengagement or even triggered them to stop using the app altogether.

What did appeal to participants in terms of gamification, was the potential for positive reinforcement through game rewards, without the risk of punishment. As one participant put it; "*We are already far too hard on ourselves*[1]", implying that the app should reflect mildness and forgivingness. A self-monitoring app that is flexible and forgiving after non-compliance would cultivate self-compassion [53]. An example of a reward is a motivational, positive or appreciative message after having completed an EMA questionnaire. Finishing tasks would be more rewarding when receiving such messages. Participants proposed to have the principles of positive reinforcement and affirmation implemented in the feedback functionality as well. More importantly, they wanted such encouraging messages regardless of whether the feedback indicates that the user's mental health remains stable, improves, or deteriorates.

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[1] Female, 31 years old (ID22)

Other functionalities proposed by participants were related to journaling, such as a gratitude journal and the possibility to write down positive events of the day or week. What appealed to them was the ability and encouragement to think about and share positivity. This would make for a more positive user experience. In turn, a weekly feedback overview could bring back gratitude and positive events to the user and could therefore serve as a reminder of the positivity during the week. The features mentioned above were desired by participants because of their potential to facilitate a more positive outlook on life.

Interventions

In every focus group, participants came up with ideas for functionalities that we categorized as possible interventions that an mHealth app could offer. The content of this theme is twofold. In return for personal data and consistent efforts to comply with EMA questionnaires, participants would want both (1) self-awareness, self-reflection, insight *and* (2) support during times when their mental health deteriorates.

Self-Awareness, Self-Reflection and Insight

Participants were interested in gaining self-awareness, self-reflection, and insights from their tracked data. They preferred feedback to be displayed in the form of weekly overviews of the monitored mental health parameters. It would be even more interesting to them if they were able to link their monitored mood with activities in the EMA questionnaires. This idea of adding context to mood experiences was echoed in every focus group. Participants believed that bringing back this relationship to the user in the feedback overviews could lead to the detection of patterns and help them get to know themselves. They expected the feedback to provide insight into their triggers, coping mechanisms, self-care activities and the activities that bring them energy. Even more so, they believed it could lead to action points or motivation for behavior change, upon learning what they felt when they were doing certain activities or when they were around certain people. When asked what appeals most to participants or what would be a motivator for adoption and long-term use of the app, the main answer boiled down to the valuable insights that the app could offer. Participants stated that for weekly feedback overviews to promote self-awareness, self-reflection and insight, the language use cannot be stigmatizing. Furthermore, they require the language to be subordinate to the user's feelings and to be carefully formulated to avoid triggering self-fulfilling prophecies. Finally, they want the app to be honest about the accuracy of its results and predictions.

Support

In addition to gaining self-awareness, self-reflection and insight, participants expressed a need for the app to provide support during difficult times. Participants proposed a few functionalities to support them in case the machine learning model would detect a decline in mental health. Since the app would collect a myriad of data anyway, participants would prefer to see this with an explanation and some examples. In their view, realizing and understanding the situation are the first steps in coping with it. Participants argued that a difficult time is often accompanied by a drop in self-reliance. Self-reliance refers to trusting and relying on one's own capabilities, judgements, and efforts without excessive reliance on others. Since self-reliance is less evident during more vulnerable periods, they saw opportunities for personalized support beyond merely follow-up. An example they gave is that the app could display personalized tips. By providing the user with their own coping mechanisms or self-care activities, the app would primarily focus on self-reliance by supporting the users' resilience. According to participants, this advice would act empowering and would be more accessible than a visit to their mental health care provider. However, in case the problems persist, participants would like the app to advise them to contact their mental health care provider. Should they, however, feel an immediate need for a conversation in anticipation of a consultation with a professional, a help page in the app could provide an accessible way for them to

contact a mental health care service. The participants argued that during visits with their mental health care provider, the feedback overviews could also act as conversation material. A few participants mentioned that the link between mood and activities is especially relevant here because it would help to overcome potential recall biases. For example, it can be challenging to remember what one did last week when one indicated low mood in the EMA questionnaire. Related to this, as one participant pointed out, the EMA questionnaires could potentially replace journals that mental health professionals ask them to keep.

Participants argued that they can recognize a relapse in themselves. However, some saw the potential of an mHealth app recognizing it in a timelier manner [47]. This early warning sign could lead them to consult their mental health care provider *sooner* than they would without the support of an app. Another way the interventions could prove useful in their lives–as indicated by one participant–is by bridging the waiting time until the visit with their mental health care provider. In the meantime, there would be something to hold on to.

Transparency

Participants requested transparency regarding (1) the data monitoring and (2) the explainability of the machine learning model. They required information on what data parameters would be tracked, where they would be stored, and who would be able to access the data. A better understanding was needed of why certain data parameters would be monitored and how they link to mental health. The more sensitive the data parameter, the greater their need to understand this link. If the benefit would be explained to them, participants said they would have a less reluctant attitude. Participants also demanded transparency regarding the timeframe during which data would be monitored before they could expect any meaningful feedback.

Participants claimed that machine learning in general is non-transparent and therefore requested more explanation on how the machine learning model would work. This was said to help them in deciding whether to trust or distrust the algorithm [54]. As opposed to a lengthy and tedious mandatory read at installation of the app, participants would like to have explanations displayed little by little where relevant and upon request. Progressive disclosure–where additional explanation is provided on demand–could therefore meet participants' need for transparency in intelligent systems [63]. In case the system would detect a decline in mental health, participants would like to know why, in the form of an explanation, preferably with some examples unveiling which parameters are most crucial in their case. When it comes to the language used in the explanations, they would like the accuracy of the predictions to be communicated honestly and transparently. This way, the participants would have access to sufficient information to decide for themselves whether to trust the system and whether they can rely on the technology.

User Burden

The four main themes mentioned above can be seen as antidotes for this theme. The user burden theme contains three subthemes: (1) privacy burden, (2) emotional burden, and (3) other burdens. We classified the user burdens into subthemes according to an existing user burden scale [64].

Privacy Burden

A repeated observation across the focus groups was that participants raised privacy concerns. The privacy burden is defined as a system's risk of revealing information about a user that they would prefer not to share [64]. As discussed in the customization theme, participants would like to configure which parameters would be tracked by the mHealth app. They also expected an option to put in personal preferences regarding whether to allow sharing data with mental health care providers. Among the most sensitive data to share, according to participants, would be location. They indicated resistance to allowing an app to track their phone usage per app category (eg, social media,

gaming, communication, etc.) as well, but to a lesser extent than their location. Participants considered location very personal, as it reveals a lot about one's daily life. Furthermore, not everyone was convinced of the link between passive data (ie, smartphone and smartwatch data) and mental health monitoring. Participants viewed passive data as more burdensome in terms of privacy to have tracked compared to active data (ie, EMA questionnaires on mood), which they deemed more relevant for monitoring mental health. The initiative of a mental health care provider would, however, increase trust and credibility in the system, enhancing participants' intention to use it [65]. Participants would expect benefits in return for tracking and sharing data to make the privacy burden more fair. In other words, they would seek a balance between the data they would 'give' and what would be in it for them. Examples of benefits expected by participants were positive affirmations, customization settings, a highly personalized detection model, self-awareness, self-reflection and insight based on personalized feedback, personalized intervention by the app in case of hard times, and personalized help from a mental health care provider based on the tracked data.

Emotional Burden

Another subtheme of user burden is the emotional burden, which is defined as a system's risk of making the user feel bad or unnecessarily worry [64]. Participants warned about potential detrimental side effects of (1) the EMA questionnaires and (2) the feedback overviews. Based on the experience that participants had gained with EMA before the focus group, they talked about the psychological influences it had on them. Even though the questionnaire was balanced in terms of measuring positive (eg, "Right now, I'm feeling satisfied") and negative affect (eg, "Right now, I'm feeling down"), a lot of participants stated that the introspection for filling in the questionnaire made them feel worse than before. They personally focused primarily on the negative emotions that were asked, even after the interviewers reminded them of the fact that positive emotions were gauged as well. Indeed, individuals remitted from a depressive disorder have a stronger attentional bias toward negative adjectives (eg, worthless), compared to a never depressed comparison group [66].

Participants in the focus groups warned about the downside effect of the confrontation with these questions multiple times a day on their mental well-being. The EMA questions forced them to think about how they were feeling, while they might otherwise not have thought about their mood. This had caused some participants to start ruminating about why they were feeling a certain way. Finally, some participants indicated that the EMA questionnaires fed preoccupation with having (had) depression. Filling in the questions triggered an unwanted reminder of a challenging time in their life. They compared it to visiting their psychologist, and how they wound down these visits or stopped them altogether when their mental health started to improve again. Similarly, those participants stated that they would install and use the app in times when they feel depressed. Consequently, they would delete the app again whenever they feel better.

Participants also worried about the emotional burden of feedback that the app could display to the user. Participants were inclined to envision feedback in the more negative scenarios, for example, displaying a downward trend in mood over the last week. Confrontation with this kind of feedback could also trigger rumination and would cause participants to be worried about a downward spiral due to a self-fulfilling prophecy. The latter would occur when the user would internalize this feedback. A participant explained that feedback stating a deterioration in sleep quality could cause trouble sleeping, which might otherwise not have occurred without seeing said feedback. To prevent any potential self-fulfilling prophecies, some participants indicated that they would like to have the option not to see any feedback at all. Seeing their own feedback would trigger anxiety, especially if they are alone at that moment. They proposed that only their mental health care provider would be able to see the feedback and would interpret and explain it to them during a consultation. However, not everyone shared this opinion, as others would worry that their mental health care provider would confront them with their data and feedback. This discrepancy in participants' requirements once again proves the need for customization in the design of mHealth apps.

Other Burdens

The last subtheme of user burden is 'other burdens'. It is an umbrella term for all other practical difficulties that participants brought forward. The following types of burdens were mentioned in the focus groups: (1) time burden, (2) social burden, (3) mental burden, and (4) access burden [64]. The time burden refers to the frequent use of the system due to the EMA data collection. Many participants indicated that filling in a questionnaire daily or multiple times a day is too burdensome. It was often not compatible with their work, education, or daily life in general [47]. The social burden applies to the difficulty or inappropriateness to respond to the EMA notifications in social settings. Those notifications also distracted them from what they are doing, resulting in a mental burden. Lastly, the access burden refers to the incompatibility of filling out EMA questionnaires and wearing a smartwatch in certain jobs. For example, nurses are not allowed to wear a smartwatch [eg, 47], or some company policies prohibit employees from carrying a smartphone with them during their shift. Also, participants working in jobs that involve a fixed timetable (eg, a teacher) or jobs that involve consultations with people (eg, a psychologist) were not able to fill in a questionnaire at any time of the day. Many of these issues could be mitigated by customization settings that would allow the user to choose the frequency and timings of notifications.

Discussion

This paper presents a focus group study with remitted depressed individuals on requirements and concerns related to the design of an mHealth app for early detection of depression relapse. Participants provided feedback on an mHealth app that would capture both active EMA data and passive sensing data from the user's smartphone and smartwatch. The aim of this app in development is to feed all data into a personalized machine learning model, being trained for just-in-time detection of depression relapse. In general, five main themes were identified by means of a thematic analysis: customization, positivity, interventions, transparency, and user burden. Whereas the first four themes reveal participants' requirements of the mHealth app's design and functionalities, the fifth and last theme covers their concerns regarding the use of such an app. The five main themes are discussed below.

Firstly, participants emphasized the need for customization in several areas of design: data and privacy settings, the EMA questionnaires, and the feedback functionalities. Configuring what data parameters would be tracked and who they would be shared with and when, would allow participants to maintain control over their data. This would mitigate the privacy burden for them. The assumption of ownership over one's own data and the choice of sharing it with clinicians is in line with previous studies [52, 67, 68]. Participants expected functionalities to customize the timing and frequency of the EMA notifications to alleviate the time, social, mental, and access burden by embedding the usage of the app seamlessly into their daily routines. This confirms the findings of many previous studies stressing users' need for customization of the timing [67] and frequency of self-assessments [52, 53, 55, 69, 70]. The same functionalities would also address the emotional burden by allowing participants to decide how often and when they would be confronted with questions asking about their emotional state that could potentially trigger rumination. An important remark here is that from a psychometric point of view, customization in terms of timescales can lead to significantly different conclusions [71-74]. From the perspective of training a machine learning model, sufficient EMA data is needed as well to generate accurate predictions. Another example given by participants of how customization could address the emotional burden was a feature to opt-out of seeing one's own feedback overviews. This was said to prevent adverse emotional side effects. Allowing users to select or deselect specific visualizations in a dynamic feedback interface might provide an even better solution [55]. The importance of customization settings cannot be overstated as insufficient personalization is a perceived barrier to using mHealth apps for depression [75] and one of the main reasons for disliking the use of apps for mental health in general [65].

A second main finding is that participants preferred an app to display and encourage positivity. Since depression is associated with biased attention to negative information [76-78], participants might require positivity in an app to compensate for this information processing bias. According to them, a positive user experience can be established through colorful visuals, thereby avoiding clinical or monotonous aesthetics [55, 79]. Additionally, participants suggested to direct design efforts toward positive reinforcement and affirmation, in the form of rewards. This can be a motivational, positive or appreciative message after having completed an EMA questionnaire. Previous studies suggested rewarding users for their efforts with advice and compliments [67] or encouragement messages [53]. Other functionalities proposed by participants–such as gratitude journaling and the possibility to write down positive events of the day or week–are inspired by positive psychology. This field of psychology is about positive subjective experiences: well-being, contentment, and satisfaction in the past; flow and happiness in the present; and hope and optimism for the future [80]. Positive psychology interventions such as writing down good things in life or cultivating gratitude have the ability to–at least temporarily–decrease depressive symptoms [81]. Researchers provided ample empirical support in favor of positive psychology practices alleviating depressive symptoms and enhancing well-being [82-85]. Furthermore, positive psychology strategies can act as a prevention mechanism, by helping to build resilience and coping capabilities that reduce relapses in the treatment of depression [86].

The third finding is that participants required interventions to be the focal point in the app's design. This is interesting since participants were in remission and we clearly stated that the app would aim at mere monitoring and follow-up. The importance of interventions cannot be overlooked as it was said to be the main motivator for long-term use of the app. In exchange for accepting a certain degree of user burden, participants would expect benefits in addition to early relapse detection. Those benefits can come in the form of self-awareness, self-reflection and insight, or support during difficult times. Linking mood with context was deemed crucial for obtaining meaningful feedback. Contextual data can be gathered through a smartwatch [87] or through EMA diaries. It is important for the latter to include (social) contextual factors next to symptoms [52, 67, 69, 88]. Combining mood with context is key to reflect on emotional patterns and to detect triggers to mood changes [57, 89]. Participants of previous studies agreed that the act of self-monitoring in itself and the feedback based on this data can result in self-awareness, self-reflection, insight, and behavior change [47, 52-55, 57, 67, 88-91]. Increased self-awareness is expected to help in self-assessing whether they need to reach out for help from others or not [53].

During periods of mental health decline, participants would want the app to provide them with support. In line with previous studies, they would like the app to display personalized tips and coping strategies [53, 70]. In another study, patients put forward the suggestion to have the system alert their clinician in case of a significant change in symptom levels [67]. They liked the idea of the alerts triggering personalized therapeutic advice. However, the study also highlighted clinicians' points of view, stating that they were hesitant of the possibility of receiving alerts. Alerts would make them worry about patient safety. The clinicians were also concerned about an increased burden of responsibility, given their time constraints. A more realistic way in which the app can offer support in difficult times is by referring the user to professional help. Participants also saw value in having the feedback overviews serve as a starting point for dialogue with mental health care providers. Another way in which feedback can help according to them is in overcoming the recall bias, especially if significant time has passed since a prior appointment [53, 55]. EMA-derived feedback can provide a more reliable overview of how patients have felt since the previous session compared to directly asking the patient. This is because the latter is often influenced by current mood [67]. Overall, feedback overviews were expected to improve communication with clinicians [47, 52] and make time spent with them more efficient [57].

The fourth and last requirement from participants was transparency concerning the data monitoring and the explainability of the machine learning model. Participants viewed transparency as an antidote

to the privacy burden. However, the literature is in disagreement regarding this relationship. For example, information-use transparency features–as requested by participants in the focus groups–inform users about how and for what purposes the acquired information is used [92]. While many authors have speculated that said transparency features alleviate privacy concerns, this assumption has not been empirically supported [93, 94]. Therefore, a dual effect is assumed. Whereas transparency as a signal of trustworthiness and fairness [95] can help to drive information disclosure [96], it can also make privacy hazards explicit and users reluctant to share sensitive information [97]. Transparency regarding the machine learning model can be addressed with explainable machine learning. By providing a transparent explanation for its results, reasoning, and predictions, this form of machine learning is made understandable for humans. Participants' requirement for transparency is aligned with literature. A qualitative study found that patients with bipolar disorder would like to see simple explanations of the data analysis behind the experience sampling feedback [52]. In another interesting study that measured stress by combining smartwatch and EMA data into a predictive algorithm, participants expressed a curiosity to understand how stress can be determined [54]. More specifically, they were interested in the relationship between certain data parameters and stress. Especially those participants that articulated distrust in the stress algorithm felt the need to identify the quality and reliability of the algorithm. In contrast to the dearth of studies that did not find an empirical relationship between transparency and privacy, participants in this study viewed transparency as essential for building trust and thereby reducing the perceived privacy burden.

Participants required customization, positivity, interventions, and transparency to bear the anticipated user burdens of mental health monitoring. The most prevalent user burdens highlighted by participants in this study were the privacy and emotional burden. Privacy concerns were related to the tracking and sharing of sensitive data. Other studies confirm that privacy concerns are among the biggest barriers to the use of apps for depression [47, 75], apps for mental illness [65], and health apps in general [98]. Given that the data would be highly personal, participants require it to be safely stored to protect their privacy [69]. Among the most personal data to track and share according to participants, would be location, which is known to be sensitive to share [47, 68, 99]. By extension, passive data tracking instilled more privacy concerns compared to active data. This finding fits seamlessly with earlier work on willingness and participation in passive mobile data collection [100, 101]. Even though active data collection requires more effort than passive tracking, users were more willing to agree to it, as it rendered them a greater sense of control over the content [102]. By consequence, the possibility for direct control over the passive data collection process–such as an option to temporarily switch off tracking–can lighten the privacy burden [103]. What might reduce the privacy burden even more, would be a functionality to specifically pick which data parameters to share and which not ahead of time (ie, à la carte consent). This functionality is exactly what was proposed by participants in this study.

Interestingly, however, privacy issues do not necessarily translate into poor adoption, as the literature describes a discrepancy between user attitudes and actual behavior. This is called the privacy paradox [104]. Despite reporting high privacy concerns, online users disclose private information, nonetheless. Among the possible explanations of the paradox are consumers lacking sufficient information to make informed privacy decisions, and in the case of sufficient information, they are likely to trade off privacy risks for possibly gained benefits [105-107]. The latter is also known as the privacy calculus theory [108, 109]. The theory holds in different contexts, including the context of mobile apps [110] and the Internet of Things environment [111]. As perceived benefits, users often expect a better personalized service [112, 113]. This is where the personalization-privacy paradox comes into play, stating that users pursue personalized services, yet the collection of personal information to provide such services raises privacy concerns [92, 114]. The personalization-privacy paradox is highly relevant in the mHealth context, where trust largely mediates the effects of perceived personalization and privacy concerns on adoption intention [115]. Participants in our focus groups indeed expected benefits in exchange for sharing personal information. Personalized services

were on top of the list, such as a highly personalized detection model, personalized feedback providing self-awareness, self-reflection and insight, personalized intervention during difficult times, and personalized help from a mental health care provider based on the tracked data.

In addition to privacy concerns, participants also feared the emotional burden of self-tracking. While frequent self-assessment and feedback is promising in terms of self-awareness, insights, and motivation for positive lifestyle choices, many authors also warned against emotionally adverse side effects. EMA assessments can be regarded as a continuous reminder of symptoms rather than what goes well, possibly resulting in preoccupation with mental illness [57] or symptom worsening [67]. Frequent confrontation with mood could impair the user's adaptive coping strategies, such as seeking distraction [52]. Interestingly, emotion tracking seems more burdensome for people prone to depressive symptoms [116, 117], especially since this population is known to have a greater focus on negative emotions [66]. It is, however, worth noting that participants underwent intense assessments, which is not the purpose for long-term usage of the app.

Participants were also cautious about the idea of seeing their own data and the psychological consequences of receiving said feedback. For example, some participants were anxious about negative feedback triggering self-fulfilling prophecies. The accuracy of feedback is also important, as suggestive or misleading feedback can lead to self-reported symptom worsening [118]. Similar to the findings of other studies, some participants in this study therefore proposed to reduce the emotional burden by having the EMA-derived feedback explained and interpreted by their mental health professional in person [52, 55, 57, 67, 90]. The main reason for preferring not to look at their own data would be to prevent anxiety [47] and rumination [54]. Rumination is characterized by repetitive negative thoughts and is related to a deterioration in mood over time [119]. Rumination is both a symptom of depression [120] and a risk factor for the onset, maintenance and recurrence of depressive episodes [6, 121]. Given the vulnerability of potential users, mental well-being related assessments and feedback should therefore be well considered and carefully designed to avoid doing harm or at least to minimize mood reactivity [54]. The emotional burden would make participants refrain from self-reporting during periods in remission, when they do not want to worry about their mental (ill) health [52]. This runs counter the idea of a relapse detection app, that can only work when users start monitoring in times of remission. Contrary to the scientific evidence that follow-up is valuable in relapse prevention [122-124], many participants stated that they would only consider self-monitoring in the presence of more severe depressive symptoms.

To conclude, this study underscores the importance of designing mHealth apps for depression relapse detection that carefully balance requirements and concerns [47]. More specifically, their design should include customization, positivity, interventions, and transparency while minimizing the privacy and emotional user burden. According to participants, active data collection was most burdensome emotionally, while passive tracking would mainly contribute to the privacy burden. Whereas externalizing tracking by moving from user-driven to more technology-driven, automated data collection has potential to reduce the emotional burden, it would likely aggravate the privacy burden. Passive mood monitoring will only become clinically useful if patients are open to learning about its potential, tolerate it, and perceive it to be helpful. Participants required certain functionalities to be willing to bear both burdens of self-monitoring. Only then can mHealth apps start to be widely adopted and effective. Taking into account the vulnerability of the potential end users, caution is warranted in the design of mHealth apps. Our findings reiterate other authors' call for designer responsibility in the mHealth landscape, especially since researchers have yet to unravel the complicated relationship between the usage of emerging technologies and mental well-being.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Details of the EMA questionnaire.

Multimedia Appendix 2

Quotes from participants per theme.

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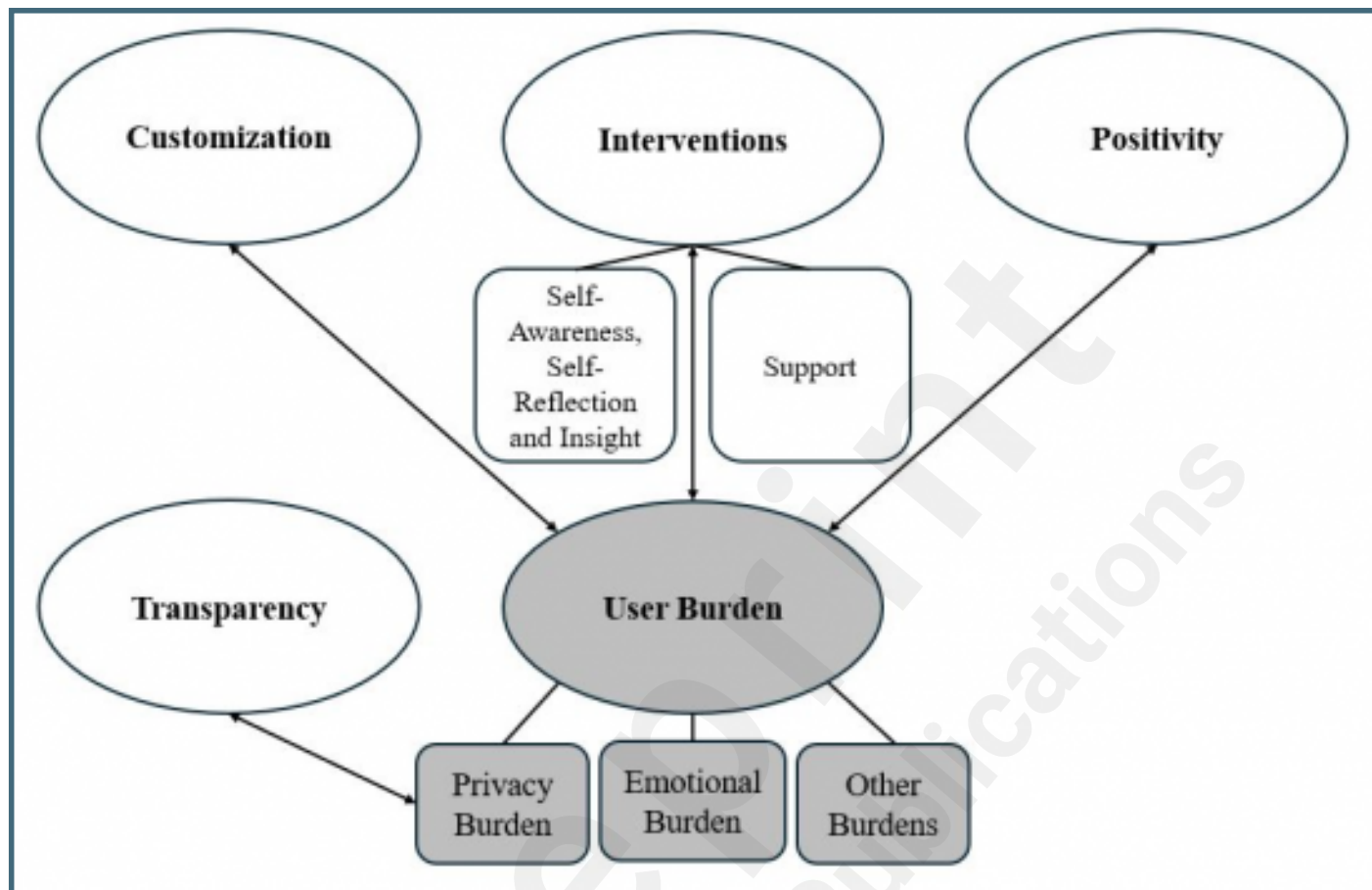
Abbreviations

EMA: ecological momentary assessment
mHealth: mobile health

Supplementary Files

Figures

Thematic map of the five main themes: customization, interventions, positivity, transparency, and user burden.

Multimedia Appendixes

Details of the EMA questionnaire.
URL: http://asset.jmir.pub/assets/86c324c51a0b5ce0f37b67796245c90f.docx

Quotes from participants per theme.
URL: http://asset.jmir.pub/assets/4cc900552de9f7383ee75aa321bafb1b.docx