Personalizing Mental Health: A Feasibility Study of a Mobile Behavioral Activation Tool for Depressed Patients

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ABSTRACT

Behavioral Activation (BA) psychotherapy for depression typically applies paper-based activity planning and registration. This is cumbersome, subject to recall bias, and provides limited support for personalized reflection on individual activity patterns. This paper presents MORIBUS; a smartphone tool for BA to be used in therapy. It provides a simple way of planning and registering activities, and their immediate emotional impact. Through visual analytic tools, the patient gains personalized insight into own behavior. We examined the feasibility of MORIBUS in a 4-week study including seven patients diagnosed with depression. The study revealed individual differences in BA patterns. We discuss the implications of these findings and argue for the necessity of automatic but still personalized technology.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; • **Applied computing → Health care information systems**; *Life and medical sciences*; *Psychology*;

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KEYWORDS

Depression, Smartphone, Behavioral Activation, Planning, Activity sampling, Mental health, Personalization

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1 INTRODUCTION

Of all mental disorders, depression has the highest prevalence of 6.9% [37]. This large patient group imposes a significant societal liability with re-admissions, lost productivity, and mortality [34]. Treatment typically consists of a combination of pharmacotherapy and psychotherapy [24]. The most widely used psychotherapy for depression and many other mental disorders is Cognitive Behavioral Therapy (CBT) [11], that includes Behavioral Activation (BA), which is a more straightforward therapy approach focusing entirely on changing behavior [20]. Recent studies have shown BA as an efficient and cost-effective psychotherapy approach for depression [5, 27]. However, despite the advances in therapeutic methods BA still relies on paper-based, and face-to-face, therapy. This does not scale well with the increasing number of patients and the limited availability of trained therapists.

In recent years, there has been a growing interest in the design of technologies for mental health. Examples include depression [22, 36], bipolar disorder (BD) [3], schizophrenia [4, 35], ADHD [9, 26], anxiety [8], and sleep disorders [10] Many of these studies use smartphone technology (mHealth) for collecting passive sensor data and Ecological Momentary Assessments (EMAs), i.e., prompt users in their everyday environment. This yields a powerful combination for studying behavior and for behavioral change interventions [25, 32].

However, in a recent review of 117 CBT and BA apps, Huguet et al. [12] finds that there is a "low level of adherence to the core ingredients of the CBT/BA models" and concludes that "the utility of these CBT/BA apps are questionable". Hence, the current literature seems to question mHealth BA as a standalone treatment option for clinical patients.

This paper presents MORIBUS, which was designed as a blended treatment option to support BA for therapists treating patients with depression. MORIBUS is designed to help the patient and the therapist to construct a diary of daily activities and rate their mood, accomplishment perception, and pleasure during these activities as well as provide personal insights and sense-making through a visual tool. As such, MORIBUS makes it possible for less-trained clinical personnel including nurses and psychology trainees, to assist in BA therapy. The paper also reports on a small feasibility study of MORIBUS involving seven depressive patients over a period of four weeks. The purpose of this study was twofold; (i) to assess the usability and usefulness of MORIBUS by real patients, and (ii) to collect subjective as well as contextual data from patients in order to better understand the relationship between activities and in what context they are done. The latter is relevant for therapists – and the individual patient – to get a better insight into the relationship between activities and their effect on mood and management of the depressive symptoms. Finally, the paper discusses the implication for the design of mental health technology for BA.

In summary, the paper contributes to two main findings: First, the study demonstrates the specific and useful case of using mHealth technology for BA therapy. Second, via qualitative and quantitative analysis of highly different usage patterns, we find that the design of this technology helps to preserve anonymity and personalization in use.

2 BACKGROUND AND RELATED WORK

CBT has shown to be as effective as pharmacotherapy in depression [1] and provides long-term protection against relapse. However, CBT is time-consuming and its effectiveness is dependent on the skills of psychological therapists, who are expensive to train and employ [27].

Behavioral Activation

BA is a simpler psychological treatment than CBT, with a focus on activity-monitoring, scheduling, and regulation of daily routines.

The treatment plan for BA starts with the patient reporting his/her activity every hour for several weeks [14]. This is done using a paper-based weekly diary detailing activities like, "going for a walk", or "coffee with mum". Each activity is provided with a score on '*mastery*' (i.e., the level of perceived accomplishment) and '*pleasure*' (i.e., how enjoyable the activity felt). Together with a therapist, the patient then identifies activities that reinforce healthy behavior [14]. The insight is then used to plan activities for the following week.

Multiple paper-based surveys have created ratings for hundreds of daily activities, determining whether they promote or harm emotional states [15]. For example, seeing old friends is consistently judged as a highly pleasant activity. A meta-analysis of 17 positive activity scheduling interventions for depression (N=1,109 subjects) found that it improves depressive symptoms relative to placebo controls [7]. Another study of 2,480 hours of self-reported activities showed that across all patients, movement-related and social activities were associated with the highest pleasure score [29].

However, gaining this insight has only been possible by meticulous transcription of thousands of hours of paper-based diaries and it is only accessible by research-active therapists. Hence, this insight is in no way conveyable to the individual patient or his/her therapist to be used in everyday clinical practice. Moreover, these studies are very generic and operate on a statistical level rather than individual level; while movement-related activities may in general improve on depression, they are not necessarily suitable for all patients. Therefore, patients need much more personalized technology, which can provide overall guidance taken from the general findings. This will help them and their therapist to identify and plan specific activities that have the biggest impact on reducing depressive symptoms.

Mobile Health for Mental Health

A number of mHealth applications for mental health have been presented in the research literature. These include applications that support different types of therapy approaches like CBT [6], Dialectical Behavior Therapy (DBT) [28, 30], and BA [16, 17]. The most relevant prior systems to this research are the 'BA Application' [16, 17] and the Mobile Sensing and Support (MOSS) system [33].

The purpose of the 'BA Application' is to make it easy for depressed patients to remember and register important behaviors in order to increase everyday activation. The app features a database of 54 pre-made activities (e.g., 'Get ready in the morning' or 'Eat breakfast') as well as support for patients to add their own. When an activity is completed, the patient can register this in the app and add a short reflection. Statistics and summaries of activity frequency and reflections are available in the app. A randomized controlled trial (RCT) of the 'BA Application' has compared full behavioral treatment (n=46) including ten face-to-face therapy sessions with a so-called 'blended treatment' (n=47) that combine four face-to-face therapy sessions with the use of the app [16]. The study found significant improvements in both groups, but could not establish any difference between the blended treatment and full BA treatment. Due to the reduced number of face-to-face therapy sessions, the mHealth blended treatment approach could possibly treat twice as many patients.

The MOSS system collects context-sensitive sensor information that is classified into general context features (e.g., time-at-home, physical activity, social activity), which then is used to provide context-aware interventions derived from four categories of pre-defined activities (physical activity, social activity, mindfulness, and relaxation). A non-randomized, single-arm study (N=12) of MOSS showed a significant drop in depressive symptoms over an eight week period.

In line with the finding from the 'BA Application' study, MORIBUS is designed to be used as part of a blended treatment setup. However, compared to the 'BA Application' and MOSS, the design of MORIBUS has been extended to support more detailed activity planning and registration, as well as visual analytic tools for the patient and therapist to investigate data.

3 MORIBUS DESIGN

MORIBUS was designed by an interdisciplinary team of psychiatrists (n=3), clinical psychologist (n=1), computer scientists (n=2), biomedical engineers (n=1), mobile app designers and developers (n=2), as well as two patients suffering from depression. The design was grounded on the paper-based BA therapy method [20], which is currently used in the clinic by the involved clinical psychologist.

MORIBUS was designed to be part of the clinical treatment of depressed patients and to replace the paper-based forms. As such, the overall design goals of the app was to: (i) be able to plan and register activities, and their corresponding mastery and pleasure on an hourly basis; (ii) collect data on planned and executed activities together with context information such as time, location, and mood; (iii) provide visual analytic tools that give the patient and the therapist insights into the relationship between mood, activities, pleasure, and mastery.

Design Methods and Findings

The design team was meeting biweekly for a 7 month period. The meetings followed guidelines from the Patient-Clinician-Designer framework (PCD) [19], with questions concerning adoption, acceptance, and sustained use were assessed through discussions and creation of paper-based mockups and prototypes. The mockups were actively co-created with patients and clinicians. The final design of MORIBUS (Figure 1) supports the following main BA elements:

Activity planning and registration. Planning of activities was designed similar to the paper-based BA schema using a calendar week view (Figure 1B). Details on an activity's timing, category, and textual description are provided on the activity details page (Figure 1D). An activity can be planned by selecting an activity category, as adopted from [29]. The patients had the option to specify the activity in the text box, or select from a list of well-known positive activities [18, 23].

The main page (Figure 1A) shows the daily plan of activities, including a visualization of the activities into the seven categories. Registration and rating of activities can also be done from the main page. Timely registration is supported via notifications; when an activity is planned to end, the user is notified to enter mastery and pleasure scores (7-point Likert scale). If no activity is planned, the notification would ask the user what s/he has been doing for the last hour and take her/him to the activity details page (Figure 1D).

Mood tracking. Daily mood tracking was designed using a 5-point Likert scale from 'Extremely bad' (-3) to 'Good' (1). Biweekly assessment of depression and well-being were done by the Patient Health Questionnaire (PHQ-8) and Well-being Index (WHO-5), respectively. All of these assessments were accessible from the menu.

Statistics and insights. A core design goal for the patients and therapist was to support personalized insight into the self-reported data, in particular, the relationship between activities and mastery, pleasure, and mood ratings. For example, during a design session, one patient stated that: *"I would like to click [points on the daily mood graph] and see what I did on this day, since I was so well"*. He further draws a simple bar chart to illustrate how he scored pleasure for specific activities, which later became the bar chart in Figure 1C. Another patient wanted to associate his mood with the number of different activities done: "*I would like to have the different activities color-coded on a week view, but not too many different colors, then I can see if there is a skewed color distribution for some of the days, and how I felt that day*". This input was turned into the color coding in the calendar and the pie chart, which illustrates the distribution of the activities planned.

Implementation

MORIBUS was implemented using Xamarin (v. 2.3.4.244) as a cross-platform mobile app targeting both iOS and Android. It uses the Sensus (v. 13.3.0) mobile sensing framework for passive data collection, anonymization, and storing [38]. MORIBUS was designed as a fully anonymous app to comply with the European Union (EU) Data Protection Directive. Via Sensus' anonymization support, all personal data was anonymized and stored in Amazon Web Services (AWS) located in the EU. The data was only associated with a unique

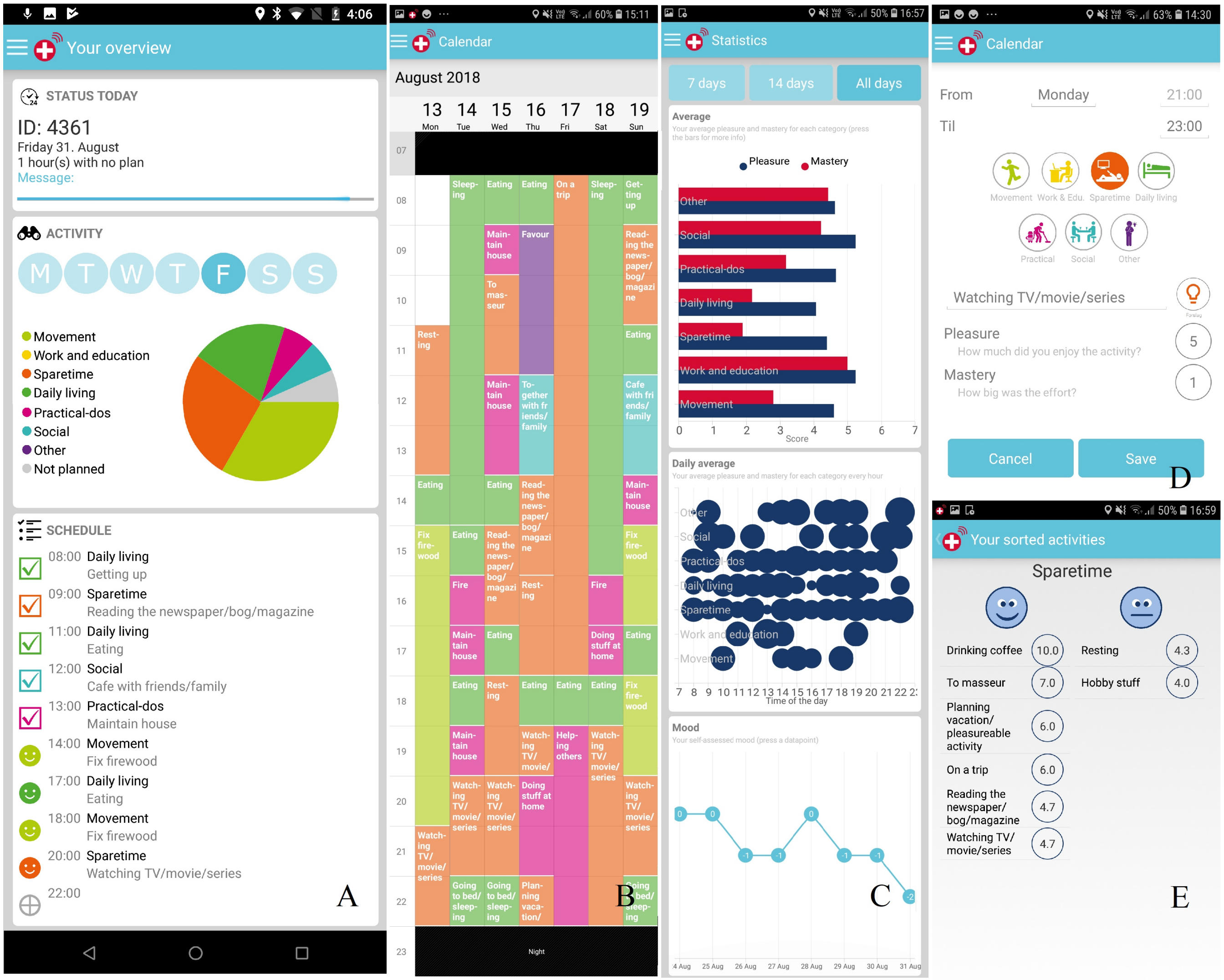

Figure 1: MORIBUS user interfaces showing data from P82: A) The *home screen* shows planned activities for a day. At the top is a pie chart summarizing activities according to activity categories and at the bottom a temporal list of scheduled activities. B) The *calendar* used for activity planning and to get an overview of the week. C) The *visual analytic page*, summarizing all historical data. The bar chart displays the average score of mastery (red) and pleasure (blue) for each activity category. The bubble chart shows the average pleasure score for each activity category across time. The line graph displays the reported mood scores over time. D) The *activity details* page, is used both for planning an activity as well as for rating. E) The *insight page* showing the relationship between the activity category and the pleasure rating. In this example, drinking coffee was the most pleasurable spare time activity, while resting and hobby activities were below the average.

four-digit PIN which is generated during app installation. The PIN is shown to the user on the front page as illustrated in Figure 1A.

4 FEASIBILITY STUDY OF MORIBUS

As argued by Klasnja et al. [13], when in the early stages of design or when evaluating novel technologies, "a deep understanding of the *how* and *why* of the system use by its target users should be a central goal for evaluations of systems for health behavior change". Thus, following best practices in health-related research in HCI, a non-clinical, single-arm feasibility study of MORIBUS was conducted in order to obtain a detailed understanding of how it could support BA therapy for depressive patients. Specifically, the following two things were investigated; (i) what is the usability and usefulness of MORIBUS prior to any clinical trial; (ii) since MORIBUS is a personal health technology [2], we wanted to investigate how it supports a more personal and individual BA approach. Note, however, that in order to evaluate MORIBUS on the real target group of patients and to assess its feasibility in future clinical implementation, this study deliberately had strict inclusion criteria of only including patients with a mood disorder and recent depressive episodes.

Recruitment

The research protocol was reviewed and approved by the Committee on Health Research Ethics of the Capital Region of Denmark (j. 17018289). Recruitment was done in two clinics. Users received information written as a Q&A document, available both as a flyer and online. Inclusion criteria were; (i) being diagnosed with either a unipolar disorder (UD) or bipolar disorder (BD); (ii) previous or current enrollment in BA or CBT therapy; (iii) experiencing at least one depressive episode within the last year. We used a rolling recruitment strategy throughout six months. Fifteen patients were interested and met the inclusion criteria. Only eight patients signed the informed consent and had the app installed, due to reasons including lack of financial compensation, participating in other research studies, or privacy concerns. One patient dropped out of the study, with the reason that the app misplaced activities in the calendar view.

Procedures

Each patient was instructed to use MORIBUS for four weeks. Two meetings were held with the patients; one at the beginning and one at the end. In the first meeting we gave a thorough explanation of the app and how to use it for BA planning and registration. Afterward, the patient read and signed the informed consent, and we helped to install the app on their smartphone (29% Android users). We carefully explained to them that the data collection was done entirely anonymously and was only linked to the PIN code. They were informed that no one (including their therapist) would have access to the data during the study. We did, however, encourage the patient to share the data on their phone with their therapist, just like they would do with the paper-based schemes. Lastly, we collected demographic information.

In the second meeting, patients did a semi-structured exit survey containing; (i) a Post-Study System Usability Questionnaire (PSSUQ), (ii) a questionnaire on clinical feasibility consisting of 16 questions divided into five categories (see Figure 2), (iii) an eight question interview targeting the usefulness of MORIBUS. Patients were not compensated for their participation. We gathered all data from AWS once the last exit survey was conducted. The data were processed in MATLAB (R2017A).

5 RESULTS

Overall, we present data from seven patients (4 females, 3 males, 21-63 years old with average age of $M = 43.00$, $SD = 19.59$). While all patients contributed to the qualitative data, we only consider quantitative data from six patient (data from P21 was lost[1]). In total, 1,684 activities across 140 days were collected. Overall study compliance was 71% (140/196) as calculated by the number of days that activities were registered or rated within the entire study duration. A summary of the collected data is given in Table 1.

Table 1: Summary statistics of the collected data: C: Study compliance; Act: number of registered activities; List: the percentage of activities that were picked from the predefined list; Rated: The number of rated activities; Delay: Response time (hours) from the activity ends; Mood: Mood entries

ID	*C.*	*Act (List %)*	*Rated*	*Delay (h)*	*Mood (N)*
P13	96%	452 (2%)	430/430	5.83	34
P82	75%	234 (54%)	216/214	8.26	33
P88	100%	236 (81%)	234/234	1.19	29
P92	61%	255 (5%)	251/249	6.43	17
P83	96%	415 (2%)	413/412	3.05	1
P46	71%	87 (5%)	65/65	3.75	0

Usability

The overall PSSUQ score (M±SD = 2.76 ± 1.08) and the three sub-scores achieved a positive usability score (neutral = 3, and 1 representing highest level of usability and satisfaction). For the overall usability the patients agreed on the statements: *"I felt safe using this system"* (60% strongly agreed, 40% agreed), and *"It was easy to get-to-know the system"* (40% strongly agreed, 20% agreed, 40% neutral). On the other side, the patients disagreed more on statements such as: *"I was capable of efficiently completing tasks and scenarios with the help of this system"* (20% strongly disagree, 40% disagree, 40% neutral), and *"I think that I could quickly become productive by using this system"* (40% agreed, 20% neutral, 40% disagree).

Participants rated information as being easy to understand and find (80% agree, 20% neutral). The worse score on interface quality (M±SD = 2.93 ± 0.80) was mainly related to the question: *"The system has all the functionality I expect"* (20% agreed, 40% neutral, 40% disagreed). When asking the patients, they stated that there were limited self-assessment options such as tracking the amount of sleep. Some patients

[1]No data was stored on AWS for P21, even though all patients claimed to have had wifi connection at various times during the study, which was necessary for data upload.

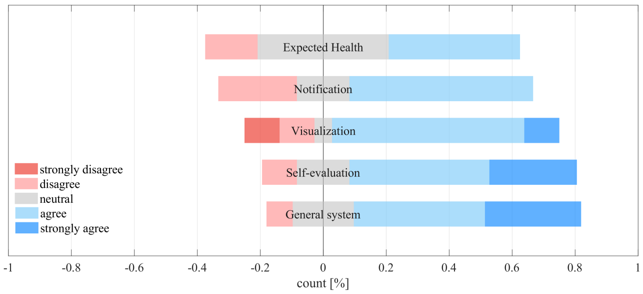

Figure 2: Feasibility: 16 questions in five categories

were also asking for a more efficient activity registration approach.

Feasibility

From the qualitative questionnaire (Figure 2) and the interviews, patients reported that they found MORIBUS useful for BA. For example, patients generally agreed to the following statements: *"The system improved my attention on my condition"* (33.3% strongly agree, 50% agree, 16.7% neutral); *"The system made it easier to fill-out activities compared to the paper-version"* (33.3% strongly agree, 16.7% agree, 50% neutral); moreover, *"It was easy for me to always have the system with me"* (66.7% strongly agree, 33.3% agree). P21 directly compared MORIBUS with the other paper-based method and commented that

> *"I have my phone on me more often than the paper [schema]. I also checked [my activities on] my phone more often than on paper."* [P21]

Patients highlighted the benefits of using their phone instead of paper.

> *"I don't want to bring pen and paper with me to register activities... and in front of people. But on the phone it is much more anonymous – people can't see what you use the phone for."* [P88].

A majority of the patients found the visual analytic tool useful and agreed on the statement: *"The visualizations made it easier for me to find patterns and meaning"* (66.6% agreed, 16.7% neutral, 16.7% strongly disagreed). For example, P83 understood the relation between her mood and the type of activities done: "*The circle-diagram, makes good sense to me.*", and a patient explained the benefits of using the circle-diagram to recall previous activities:

> "*"It was really nice to look at the circle plot [the pie-chart]. When I've had a hard day, I looked back on the previous day, and saw a big yellow portion [Work and Education] and then it made sense to me why I felt bad today"* [P88].

The visual analytic page was also used by the patients:

> "*Yes! It [the bubble chart] gave me an insight into when – during the day – I enjoyed training the most*" [P21]

> "*It is funny to look at the first graph... 'social' gave me more pleasure! Here I learned something. I thought I had more mastery in social...*" [P88]

Notifications were also found useful in remembering to fill in information on activity (hourly) and mood (daily) (66.7% agreed, 16.7% neutral, 16.7% disagreed). P82 explained:

> "*Yes. It was also one of the features I liked most, and is an advantage over the paper-version*" [P88].

Lastly, regarding health benefits, there was a more neutral opinion as to whether MORIBUS can be used independently of the therapy sessions, as illustrated in the mainly neutral response to the statement; *"By using the system, I can reduce behavior that is associated with lower mood"* (33.3% agreed, 50% neutral, 16.7% disagreed). This is, however also understandable since MORIBUS was designed to be part of a blended BA therapy sessions.

Behavioral Activation Patterns

Since activity planning and registration is core to BA therapy, we did a deeper analysis of the users' planning and registration patterns. Based on clinical experience, it is relevant to analyze; (i) the relationship between *pleasure and mastery*, (ii) the *type* (category) of activities done, and (iii) the *temporal* (i.e., when) and *spatial* (i.e., where) patterns of activity planning and registration.

Figure 3 plots the activity categories in a pleasure/mastery coordinate system, and illustrates quite individual patterns; (i) P92 have activities at the lower right corner of low mastery and high pleasure indicating that the patient is functioning well doing manageable activities; (ii) P83 shows minimal differences in mastery and pleasure across the categories; (iii) P46 uses less effort in practical related activities; (iv) P88 enjoys social activities most. When looking further into the individual activities of P88 it is revealed that passive activities (e.g., 'cinema' or 'watching TV') all have low mastery scores, whereas more active activities (e.g., 'homework' and 'meeting new people') have higher mastery scores.

Table 1 shows the numbers of activities picked from the standard list and the amount typed, i.e., provided with a text label. Overall, we find that most patients specified a label and did not just specify the activity category (1586/1684, 94%). However, as shown in Table 1, individual differences exist. For example, P13 only picked 2% from the list whereas P88 used 81%.

Figure 4 shows the overall distribution of activities within the seven activity categories for the six most active patients, confirming quite individual activity patterns. For instance,

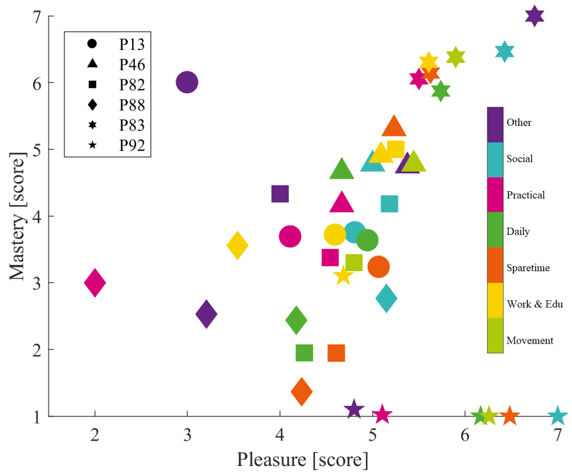

Figure 3: The average pleasure and mastery score of the activities within the seven categories for each participant.

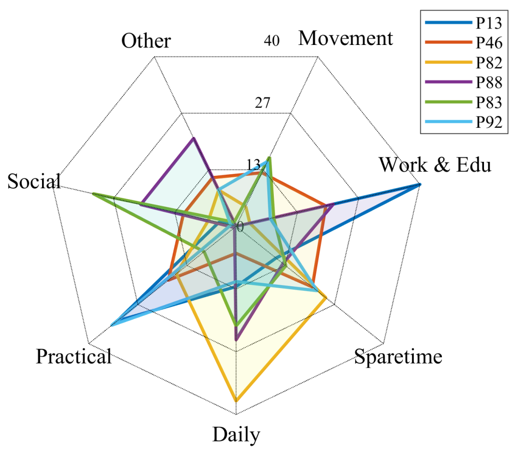

Figure 4: The distribution (%) of activities

even though 'movement' accounts for 6% of the activities across patients, P88 has no registered movement-related activities, P13 spends the most time doing work and practical activities, while P83 spends the majority of time in a social context.

Figure 5 illustrates the temporal pattern of *when* activity rating takes place as a function of the time that the registered activity ends. The dotted line represents registration right after the activity. The results show differences in registration patterns. For example, we found that P92 rated her activities more or less everyday around 10pm, whereas P88 and P83 to a larger degree follows the dotted line indicating ratings just after the activity was done. The blue distribution curve (on the right side of Figure 5) illustrates that activity registration across all patients was mainly done in the evening (8-12pm).

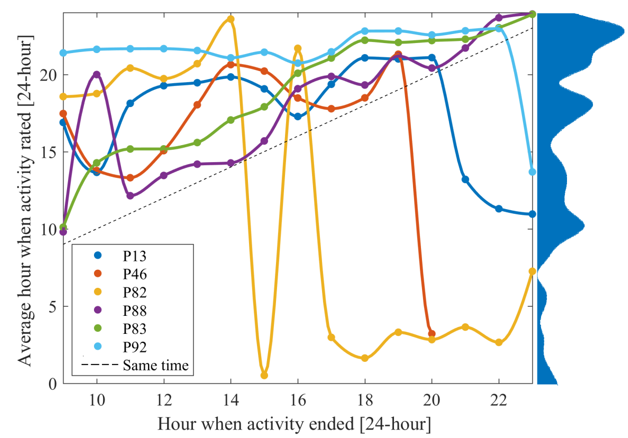

Figure 5: A shape-preserving pchip-interpolation of the average rating hour (24-hour) for the patients, with a blue distribution showing the amount of times an activity was rated across all patients as a function of time (24-hour). The dotted line represents current time, with points below representing the next day of rating.

The data also shows a wide variety in the spatial pattern of activity registration (relative to home). P88 was only home 43% of the time when registering activities, while both P83 and P82 registered all their activities at home.

6 DISCUSSION

The present study of MORIBUS helps us discuss three core questions in the design of technology for mental health: (i) What is the potential feasibility of such a system? (ii) What are the core usage patterns and how should these be supported? (iii) How should individual personalization be supported in these technologies?

Feasibility of MORIBUS

Patients in general stated that they prefer MORIBUS over the existing paper-based schemes. This is in line with prior research that patients, across all age groups, are positive towards using smartphones to monitor their mental health [31]. When looking at the usability scores, MORIBUS scores slightly over neutral. Taking into consideration that MORIBUS is designed for a rather cumbersome data entry task (detailed activity registration on an hourly basis), this score is, in our view, acceptable. Only a study with non-clinical users have investigated similar demanding registrations, however no usability score was provided [32].

In the qualitative questionnaire (Figure 2) and the interview, patients reported that they found MORIBUS useful for BA, especially the insight gained from the chart visualizations. Moreover, in the original design we anticipated that patients would mainly use the activity categories and only rarely add a label to the activity. Instead, when looking at the number of reported activities in Table 1, the patients did have high compliance in terms of reporting activities on a daily basis (ranging from 61% to 100%) and did plan and/or register a large number of activities on a detailed matter. Hence, we find that MORIBUS fulfills the design goal of providing a useful smartphone-based BA activity planning and registration approach, while recommending that such BA applications are designed for rich activity planning and registration.

Usage Patterns

Two main usage patterns were found in this study. First, in the opening interview all patients reported that they always carry the phone with them. Therefore – and following the BA guidelines – MORIBUS was designed under the assumption that patients would register activities at the time and place they were done. However, we found quite different patterns. Some patients preferred to allocate specific time slots at home to register activities, while others registered throughout the day. To the best of our knowledge, no prior research has done a detailed investigation of BA registration patterns on clinical samples. Therefore, it is still an open discussion whether our findings are influenced by the design, or by the nature of conducting studies in-the-wild.

Second, during the qualitative questionnaire (Figure 2) and the interview, patients reported that they found MORIBUS particularly useful due to the anonymity of using their own phone. This finding is in line with prior research on non-diagnosed patients, which may not have come to terms with their mental disorder [21].

The design implication of these usage patterns may be particularly relevant for the design of technology for mental health considering EMA for BA. A strict emphasis on *momentary* assessment could unfortunately turn out to miss data from patients that prefer to rate at home, later, or simply are unable to address the prompt due to current symptoms. Moreover, the design for 'non-stigmatizing' personal technology was highlighted from this study.

Personalization in Personal Health Technology

One of the main findings of our study of MORIBUS is the high degree of individual differences in how patients do BA. The textbook version of BA assumes (or instructs) that patients do activity planning and registration in one way and provides only one schema to do so (see e.g. Appendix 1 in [20]). However, our study – despite its limited number of participants – showed that activity patterns and their effect on pleasure and mastery are highly individual. The individual differences in the patterns in how patients do BA were observed along several dimensions. First, there was large individual difference regarding *which* activities were planned – ranging from selecting standard activities to creating highly personalized activities. Second, as shown in Figure 4 there is quite a difference in what *type* (i.e., category) of activities patients were doing. Third, as shown in Figure 5 and Table 1 we found individual difference as to *when* patients reflected on activities and *where* they did the planning and registration of activities.

This personal – rather than generic – insight into the relationship between activities and their effect on mood, pleasure, and mastery was designed into MORIBUS via the visual analytic page (Figure 1C). Here, the patient could click on an activity category and see what activities contributed to a high or low pleasure or mastery score. This personal insight was also found useful by the patients:

> "*Under the statistics [...], I found the most valuable tool to analyze my activities. It provides an understanding of which activities helps me, and which gives problems that I need to be aware of — or completely avoid.*" [P82]

The core design implication from this study is, therefore, that it is crucial to the design of activity tracking technology like MORIBUS to enable for highly individual and personalized activity planning and registration.

Limitations and Future Work

The three main limitations of this work was (i) the lack of a larger user-centered focus group during the design phase. A diverse demographic representation could have shed light on the different usage patterns that we observed, and have changed some of the design elements that was corroborated with only two patients. As an example the hourly notification feature - although positively received in our study sample - may negatively impact the users mood if they get reminded on unfulfilled activities. (ii) The limited number of participants who used MORIBUS in this study, and (iii) the lack of evaluating the use of MORIBUS in active therapy sessions. Therefore, the evidence for the feasibility of MORIBUS in clinical use is limited. Future work, therefore, includes deploying MORIBUS as part of clinical therapy in a clinical setting, while improving on its design based on the formative inputs from this study. Moreover, this study in no way claim to establish clinical evidence for the use of mHealth-based BA treatment, which would require a randomized clinical trial.

7 CONCLUSION

This paper presented the design and implementation of MORIBUS; a smartphone-based Behavioral Activation (BA) registration tool to be used in blended therapy sessions of depressed patients. MORIBUS has the advantage, over existing paper-based tools, of visualizing personal analytics derived from the registered activities.

In a small feasibility study, the patients reported benefits from using MORIBUS for personal behavioral activation in terms of activity planning and registration, and reported it as potentially useful in therapy sessions. They emphasized the importance of having MORIBUS on them wherever they went, while still being inconspicuous in the public space. Furthermore, they all commented on the benefits of gaining personalized insights via the visual tools. Analysis of the usage data and the semi-structured interviews with the patients revealed highly individual usage patterns both in terms of what type of activities to plan, the details of planning, and the spatial and temporal patterns in activity planning and registration.

The main design implications from this study are therefore to design both for simple and easy, as well as for detailed and individual activity planning and registration, and use this to provide visual analytics tools for obtaining a personal insight into the relationships between activities and depressive symptoms.

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