MUBS: A Personalized Recommender System for Behavioral Activation in Mental Health

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ABSTRACT
Depression is a leading cause of disability worldwide, which has inspired the design of mobile health (mHealth) applications for disease monitoring, prediction, and diagnosis. Less mHealth research has, however, focused on the treatment of depressive disorders. Clinical evidence shows that depressive symptoms can be reduced through a behavior change method known as Behavioral Activation (BA). This paper presents MUBS; a smartphone-based system for BA, which specifically contributes a personalized content-based activity recommendation model using a unique list of validated activities. An 8-week feasibility study with 17 depressive patients provided detailed insight into how MUBS provided inspiration and motivation for planning and engaging in more pleasant activities, thereby facilitating the core components of BA. Based on this study, the paper discusses how recommender technology can be used in the design of mHealth technology for BA.

Author Keywords
Depression; Recommendation; Behavioral Activation; Planning; Activities; Well-being; Smartphone; Mental health

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

INTRODUCTION
According to the World Health Organization (WHO), depression is a leading cause of disease burden [41]. One out of five may experience a depressive episode during their lifetime [43] and without proper treatment, there is a substantially increased lifetime risk of suicide [19]. Despite these consequences, only one out of four receive adequate treatment [42]. This broad treatment gap, especially in low- and middle-income countries [43], is caused by factors such as a lack of trained professionals, help-seeking stigma, and a high cost of treatment [40]. The World Psychiatric Association and the Lancet Psychiatry Commission have recently argued that a drastic change in mental healthcare is needed and suggest a major penetration of digital technology into psychiatry as one possible solution, which they refer to as *Digital Psychiatry* [7].

These challenges have inspired research into computer technology for mental health. A recent review of the last ten years of ubiquitous computing research in mental health identified 46 systems for mental health [6], and a review of papers published in the HCI community, identified 139 published papers with more than 50% of those published in the last two years [48]. The majority of these studies involve smartphone-based technology as it provides possibilities of measuring sensor data, and use machine learning techniques to detect changes related to mental health conditions and provide personalized feedback [50]. The majority of these systems have, however, focused on mobile sensing, disease prediction, and clinical assessment (i.e., diagnosis). Intervention-focused research has most commonly employed Cognitive Behavioral Therapy (CBT) as the choice of treatment methodology [6]. However, the Behavioral Activation (BA) component of CBT has repeatedly been found to have the same positive effect as full CBT for the treatment of depressive symptoms [9]. Compared to CBT, BA is simpler to administer and use, and has shown a significant effect on the reduction of depressive symptoms [14]. The main approach in BA is to reduce depressive symptoms by engaging in – or 'activating' – pleasant activities.

This paper presents the design and clinical feasibility of MUBS, which is a smartphone-based recommender system for the treatment of depressive symptoms. Adhering to the principles of BA therapy, MUBS aims to reinstate pleasant ac-

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tivities back into the lives of patients diagnosed with a mental disorder characterized by depressive symptoms.

MUBS utilizes a content-based (CB) probabilistic technique with a catalog of 384 pleasant activities in order to recommend activities personalized to the individual user. MUBS was designed following a user-centered design process, focusing on HCI research principles to target typical barriers for adoption (e.g., burden and usability) [20]. There is a specific design focus on personalization in both the usage of MUBS as well as the feedback on recommended activities, as insufficient personalization is the main perceived barrier to adoption [34]. An 8-week feasibility study with 17 clinically diagnosed patients was conducted, investigating detailed qualitative data on the usefulness and usability of MUBS. In summary, the main contributions of this paper are twofold:

1. It presents MUBS as a smartphone-based system supporting BA treatment of depressive symptoms, which implements a unique CB probabilistic recommender algorithm for personalized recommendations of activities. This recommender system utilizes a unique catalog of 384 positive activities.
2. A qualitative feasibility study of MUBS provides detailed insights into how smartphone-based BA recommender systems can assist in the treatment of mental health and thereby become a key component in realizing Digital Psychiatry.

BACKGROUND AND RELATED WORK

Depression is characterized by periods of inactivity, lack of motivation, and a feeling of hopelessness and guilt. Due to its problem-solving technique, CBT is one of the most efficient and successful psychotherapeutic methods for the treatment of depression [21]. Lewinsohn [33] and Jacobson et al. [25] have, however, demonstrated that the behavioral component of CBT – what they refer to as Behavioral Activation (BA) – accomplished equivalent results as the well-practiced full CBT and is comparable to pharmacotherapy in the treatment of depression [14]. These results are remarkable considering that BA is a more straightforward approach, requiring less consultation time, and can be delivered by junior mental health workers with less intensive and costly training [45]. In BA, the patient fills out a paper-based activity diary for several weeks. Each activity is provided a 'mastery' (i.e., *the level of perceived accomplishment*) and 'pleasure' (i.e., *how enjoyable the activity felt*) score. Together with a therapist, patients identify past activities that reinforced healthy behavior and are then assisted to schedule and re-engage in pleasant activities, resulting in less negative, depressive behavior.

The success of CBT and BA in the treatment of mental health has contributed to an increasing number of mobile health (mHealth) applications for mental health, both in research and commercially (see [48] for a review). Many of these technologies have been subject to non-randomized feasibility studies, showing a significant reduction in depressive symptoms. For example, Deady et al. [11] developed the HEADGEAR app to reduce depressive symptoms through a 30-day challenge program. Each day, 84 participants received a BA task (i.e., a mindfulness exercise, activity planning, or goal-setting). Fuller-Tyszkiewicz et al. [17] created a self-guided app (BLUEWATCH) to improve well-being for people with depression. It used the patient-reported mood survey data to provide feedback messages regarding when to engage in the app contents. The content included psychoeducational and BA activities such as creating to-do lists and monitoring daily activities. Qualitative analyses after the 12-week usage of the app demonstrated positive usability. Dahne et al. [10] developed a BA app, APTÍVATE!, where the user associate values across five life areas. Examples of values would be: "*Have family dinners twice a week*" or "*Call my children three times a week*". Through a daily calendar, the user scheduled and kept track of the activities, and was able to associate activities with daily mood. They used a badge reward system to motivate continued use. On average, the non-clinical users completed 21.73 activities with a 50% retention rate after eight weeks use.

Findings from the studies highlighted should be cautiously interpreted, as the target group was non-clinical users that exhibit different behavior than clinically diagnosed users [46]. Furthermore, the studies did not include support to identify positive activities to schedule and reengage in. To inspire positive activities, the BA APPLICATION [36] included a database of 54 pre-made activities (e.g., "*Clean at least 15 min*", or "*Take a walk with a friend*"). The goal of the app was to make it easy for patients to remember and register behaviors, thereby increasing everyday activities. An 8-week randomized controlled trial (RCT) study with clinical patients reported a significant clinical effect. MORIBUS [47] was designed to mimic the paper-based BA activity diary [32] while adding personalized visual analytic feedback to the patient. A 4-week single-arm feasibility study with eight clinical patients showed that visualizations concerning 'pleasure' and 'mastery' scores from enacted activities were highly valued as insights towards future behavior. The MOSS app [54] implemented activity recommendations based on context. By collecting context information such as location and steps, it recommended specific activities every six hours, such as "*Look at yourself and smile for at least 20 seconds*". These recommendations were within four categories; physical activity, social activity, mindfulness, and relaxation. Ratings from the user were the sole determining feature on what activity to recommend within each category. As such, no knowledge concerning the content or purpose of an activity is used in the recommender algorithm. An 8-week non-randomized single-arm study involving 12 non-diagnosed participants of MOSS showed a drop in depressive symptoms.

As illustrated in Table 1, MUBS is designed to support all the major components of BA. It has been found that many smartphone-based technologies for mental health do not comply with, or implement support for, the core components of the state-of-art BA therapeutic models [23]. Hence, MUBS uniquely integrated support for symptoms and activity tracking, planning, reflection, inspiration, and recommendation. In terms of recommender technology, MUBS implements a novel CB activity recommendation algorithm, which can suggest novel activities personalized to the individual. Unlike Wahle et al. [54], knowledge of the *content* from prior enacted activities is used to estimate probabilities of enjoying other activities. The activities are based on a unique catalog of 384

	Smartphone applications						
BA Component	*BlueWatch [17]*	*Aptivate [10]*	*HeadGear [11]*	*BA app [36]*	*MOSS [54]*	*Moribus [47]*	**MUBS**
Activity planning		✓	✓	✓		✓	✓
Mood tracking	✓	✓	✓			✓	✓
Activity reflection		✓		✓	✓	✓	✓
Daily routines		✓					✓
Feedback/reward	✓	✓	✓	✓		✓	✓
Activity inspiration	✓	✓	✓	✓		✓	✓
Activity recommendation					✓		✓

Table 1. An overview of smartphone-based applications targeting BA and the various components of BA therapy.

pleasant activities specifically designed for this recommender technology. Apart from a unique design contribution, the study of MUBS will focus on the users' perception of BA enabling technology, and the role that personalized recommendations have for users living with a depressive disorder. These insights are lacking in prior studies where the focus lies on the clinical outcome, the model itself [27], or simply ineligible due to the design choice [55].

THE MUBS SYSTEM

The design of MUBS followed the user-centric methods recommended for affective disorders [48], involving clinicians and patients in all phases [7].

Design Methods and Goals

The design team consisted of an interdisciplinary set of clinical (psychiatrists, psychologists, and nurses) and technical (computer scientists, user experience (UX) designers, and biomedical engineers) professionals. All involved clinicians and patients had extensive experience with BA as a therapeutic method. In total, eight clinicians and four patients diagnosed with affective disorder (unipolar depression or bipolar disorder) were involved. The design activities included interviews of patients and clinicians, two design workshops, iterative prototyping, and a lab-based evaluation of the user interface design. The design process lasted for six months. The design activities resulted in a set of core design goals for a smartphone-based system supporting BA.

First and foremost, the design should support *activity tracking and registration* since this is core to the BA methodology. During the design process, several proposals for how to do this were explored, in particular how to register the 'mastery' and 'pleasure' levels used in BA. The BA approach recommends detailed hourly activity registration with 'mastery' and 'pleasure' scores, but the design process revealed that this was too cumbersome and demanding, and would not succeed in real-world usage. Instead, a novel approach was co-designed in which activity registration was reduced to only morning, afternoon, and evening, 'pleasure' was replaced by a simple 'thumbs-up/down' approach, and 'mastery' was predefined for each activity as a difficulty level between 1-3. In this way, activity registration was considerably simplified while still complying with the core BA methodology.

Second, the design should support *activity planning* – another core component of BA. Again, during the design process, it became apparent that activity planning should be straightforward. Hence, an initial idea of using a calendar (with detailed information on e.g., timing) was rejected in favor of a simple approach in which activities could be added 'somewhere during the day'. As pointed out by both clinicians and patients; even a simple thing like planning a bath in the morning could be a tremendously difficult task for a depressed person. Another feature in the system was the option to create a 'routine'. Being able to plan simple routines like having a bath each morning, go to sleep at 11 PM, or having a cup of coffee with a friend every Thursday afternoon, can help a patient to get back to a life with recurring pleasant activities.

Third, the system should *inspire* the patient to identify, plan, and perform healthy activities, which is a BA component generally supported by a therapist. The idea which arose during the design process was whether the system could assist in recommending activities, thereby inspiring healthy behavior. During the design process, two features were discussed to accommodate this; one was the design of a catalog of inspirational activities, and the second was to use a recommender algorithm, which could be trained to learn the patient's activity preferences and then propose personalized activities.

Fourth, the system should be *rewarding*. This goal came from one of the patients who had designed a simple star collecting system where she would paint stars in her diary when she planned an activity; one star for an 'easy' activity, and three stars for a difficult one. Moreover – as she pointed out – difficulty level for an activity was never fixed; it would often change from day to day and depend on many things. All participants of the workshops – including clinicians – liked this idea, which was adopted as a more straightforward way to register 'mastery'.

Finally, the system should work *independently* of the clinic and the therapist, and be designed as a self-management tool for engaging the patient in BA. The system should inspire the patient to plan and track activities in-between therapy sessions or even when no longer in therapy. Hence, even though the system, of course, can be brought to and used during a clinical session, the main focus is to support self-efficacy.

All of the different design inputs and user interface sketches were carefully implemented in different versions of MUBS, which were presented and discussed with participants. At the end of the design process, a mature version of MUBS was put to the test in a lab-based UX evaluation applying traditional UX evaluation methods, including task-based evaluation, think-aloud, and usability ratings. All inputs were merged into the final version.

User Experience Design

The main user interface (UI) of MUBS is shown in Figure 1 and consists of five pages (A–E). The homepage (A) shows a daily weather forecast, step count, achieved 'difficulty level points', and a list of planned and completed activities. Planned activities are separated into three time slots; morning, afternoon, and evening. Daily mood ratings are automatically

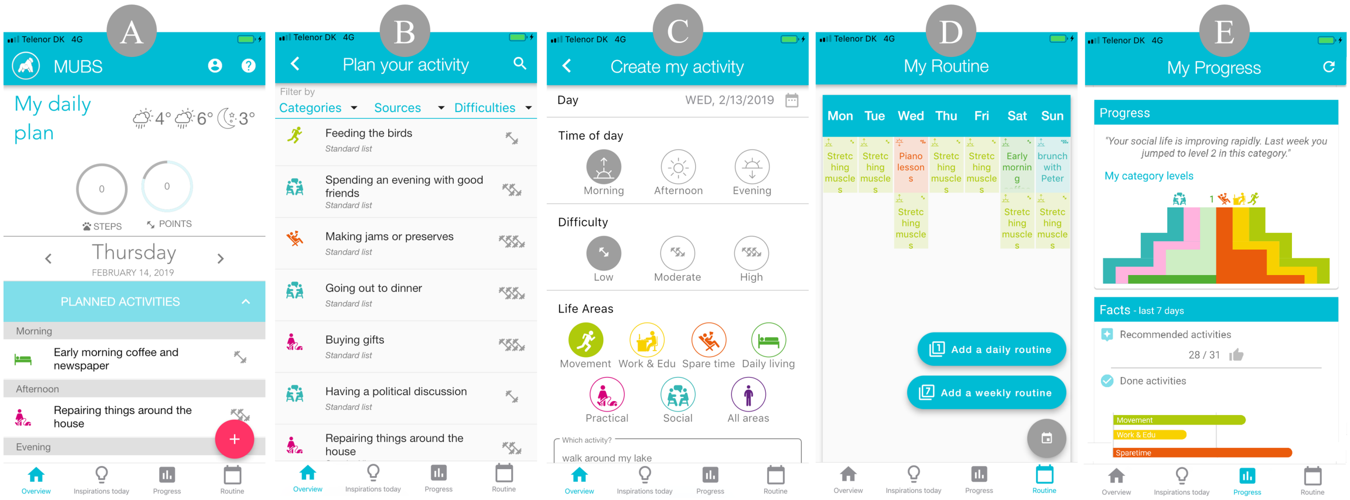

Figure 1. The MUBS mobile user interface. A) The *homepage* showing daily steps, points, and a list of planned and done activities. B) The *planning page* where activities are created, either by searching the activity catalog or by adding a personal activity. C) The *activity page* showing the details of an activity. D) The *routine page* that shows the recurring daily or weekly activities. E) The *progress page* with the pyramid showing points within each activity category and a bar chart with the number of completed activities within each category

scheduled as an evening activity (not shown). When a planned activity is selected, it can be marked as 'done' and given a 'thumbs-up / down' rating (not shown). A new activity can be created via the red plus button, which gives two options; (i) a list containing the catalog of 384 enjoyable activities and previously completed activities (screen B), or (ii) fetch a list of 10 personalized recommended activities to chose from (not shown). Screen B shows the activity catalog. Each activity is labeled with a difficulty level (1–3 dumbbells) and is organized into activity categories. Each category has a unique icon and color used throughout the app. The list can be filtered by activity attributes (category, source, difficulty). Activities can be searched using the search icon. If the activity searched for does not exist, the user can create a new activity, as shown in screen C. Custom-made activities are saved in the catalog and available for later planning. The routine page (D) shows a schedule of re-occurring activities and provides a button for creating routine activities daily or weekly. The progress page (E) visualizes patient progress in two ways; (i) the pyramid illustrates progress according to the three difficulty levels divided into the activity categories – each step indicates the achievement of one difficulty level, and (ii) the bar chart showing the number of activities the patient has completed within each activity category.

Recommender Model

A multinomial Naive Bayes machine learning (ML) algorithm is used to implement the content-based (CB) recommender model in MUBS. The theoretical model has been explained and evaluated elsewhere [38]. Briefly, a CB model uses feature information of past rated items to suggest new items that have features favoring a positive rating [3]. In MUBS, a personalized model of a patient is built by storing activity features together with the rating provided by the patient once the activity is completed. The activity features are shown in Figure 1C and include time, the difficulty level, the activity category (e.g., 'movement'), and the content of the activity as a bag-of-words vector (e.g., 'walk', 'around', 'my', 'lake'). The rating is then used to estimate a likelihood function for each feature. If the patient tends to rate activities that contain the word 'walk' with a thumbs-up, the likelihood function for the feature word 'walk' will favor the thumbs-up class. The likelihood function improves as more activities are registered. By combining the likelihood function for all features of an activity, the recommender algorithm can estimate the posterior probability of an activity being rated as either thumbs-up or thumbs-down. When the patient looks for a recommendation, four previously completed activities, together with six novel activities with the largest posterior probability of receiving a thumbs-up is presented. In this way, the model is designed to recommend both well-known as well as novel activities to the patient, which aligns well with the BA approach.

Activity Catalog

The recommender system draws its recommendations from a unique catalog of 384 enjoyable activities. This catalog was created by combining activities from the Pleasant Event Schedule work of Lewinsohn & MacPhillamy [37] and Mørch and Rosenberg [39]. Each activity is categorized into one of six activity categories (movement, work & education, spare time, daily living, practical, social) and labeled with a default difficulty level. Labeling was conducted independently by two researchers, and any disagreement was discussed to ensure agreement. The catalog of labeled activities is available as a CSV file in the supplementary material to this paper.

Implementation

MUBS is available on both iOS and Android. It is implemented using Flutter (v1.2.2), which is a cross-platform development toolkit for building responsive, natively compiled applications for mobile phones from a single codebase. It uses a mobile sensing framework for the collection of the context data, including steps and weather information [5], and Google Firebase as a secure backend server.

FEASIBILITY STUDY

Following best practice in personal health technology research [28], a single-arm feasibility study was conducted in order to investigate the feasibility of MUBS, including its potential health benefits and patients' perceptions of its usefulness and usability. The study was reported to the Danish National Committee on Health Research Ethics and was exempted from ethical approval since BA is a well-established method applied in clinical practice (File no. H-19002943).

Participants and Recruitment

Recruitment of patients was carried out via clinician referral and self-referral through a national patient recruitment website. Inclusion criteria were; (i) clinically diagnosed with an affective disorder (unipolar or bipolar disorder), (ii) experienced recurrent depressive episodes, (iii) own a smartphone, and (iv) speak either Danish or English. Participants were compensated by a gift card corresponding to US$ 90 for the entire study, including the interviews. The gift card was handed out at the final interview.

Procedure

The study ran for eight weeks, in line with the length of traditional BA treatment, and similar studies [2,10,31,54]. Patients who were enrolled were contacted by phone for an introduction to the study and the app. There was an option of a physical meeting, but none of the patients asked for this. Each patient was instructed to use MUBS daily and plan activities ahead of time. They installed the app and followed the in-app tutorial and guidelines, which included signing the informed consent form, adding demographic details, and filling in a Patient Health Questionnaire (PHQ)-8 questionnaire [30] of depressive symptoms.

At the end of the 8-week study period, each patient was invited for a closing meeting carried out face-to-face, by video call, or by phone according to the preference of the patient. At this meeting, a semi-structured interview was conducted asking questions on the usage of the app, including the adaptation of the app in daily life, handling of depressive symptoms, the role of the app during therapy sessions, and support for BA. Afterward, patients were asked to fill in a 5-point Likert scale questionnaire designed according to the Unified Theory of Acceptance and Use of Technology (UTAUT) methodology [53]. This questionnaire investigated future acceptance of MUBS by assessing the five core constructs of the UTAUT model; performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention to use. The full questionnaire is available as supplementary material.

Data Analysis

Interviews were audio-recorded and transcribed, and via an inductive thematic approach, two researchers used Braun & Clark's affinity diagramming approach [8] to discuss and categorize the quotes collaboratively.

We used Javascript to generate JSON files of the activity tracking stored in Firebase. Summary statistics describing the registered activities were calculated in Python (v. 3.7), and Matlab (v. R2018b) was used to model app usage across the study. We used a Linear Mixed-Effects (LME) model to capture the covariance within each patient. Control for individual variation among patients was carried out by adding random effects. Specifically, we were interested in knowing whether the fixed effect of time interacted with the change in app usage and whether there was any quadratic interaction. A combination of a simulated Likelihood Ratio test and inspection of the conditional residuals from the fitted models was used to determine the model specification.

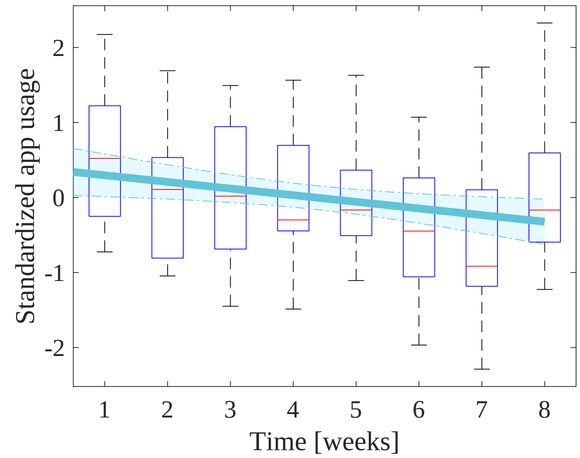

Figure 2. Normalized app usage over time is shown as a fitted LME model with a shaded confidence interval

RESULTS

We recruited 21 patients. Four dropped out before the end of the eight weeks. Demographic and clinical characteristics did not differ between the dropouts and the patients who completed the study as assessed by an independent sample t-test (Chi-square test for sex, occupation, and diagnosis). We report on the 17 patients who completed the study, which resulted in 2,895 planned activities in MUBS. An overview of the patient characteristics is shown in Table 2.

Usage

The second part of Table 2 shows different usage data for each patient, including daily usage. Overall, patients used MUBS 76% (SD= 15%) of the days during the 8-week study. We used the LME model to examine app usage, defined as the number of registered activities across the study period. Through the Likelihood Ratio test, the linear model was deemed a better fit. This was also verified through inspection of the residuals. An F ratio of $F(1,127) = -1.27, p = .21$ for the linear time interaction revealed no statistically significant trend ($\beta_1 = -0.67$, SD $= 0.53$). We controlled for the intercept (mean app usage) as a random-effect between patients. The patients showed consistent adherence to reporting and the creation of activities in MUBS. Figure 2 shows usage over the eight weeks, and the fitted model (blue line).

Future Acceptance

The UTAUT questionnaire measured patients' agreement with 27 statements on a 5-point Likert scale from strongly disagree

Table 2. Participants in the study. First section: demographic information. UD: Unipolar Depression, BD: Bipolar Disorder, OCD: Obsessive-Compulsive Disorder, BL: Borderline, C = Clinic, O = Online. Second section: Usage data. The total amount of completed activities (act), where the list represents the catalog of 384 activities. Edited, indicates the number of chosen activities that were edited in difficulty. Daily Usage is the fraction of days with registered activities over the study period. Third section: clinical information. The depressive level at the start of the study

ID	*Sex*	*Age*	*Occupation*	*Diagnosis*	*Recruitment*	*Total act*	*M daily act*	*From list (%)*	*Recommended (%)*	*Edited (%)*	*Planned (%)*	*Routine (%)*	*Daily usage (%)*	*Init. depression (PHQ-8)*
P1	F	41	Unemployed	UD	O	194	3.18±0.50	59	2	5	29	0	64	Moderately severe (18)
P2	M	44	Unemployed	BD	C	32	1.40±0.94	3	0	0	79	0	95	Moderately severe (19)
P3	F	28	Full time	UD	O	161	2.68±1.16	12	2	20	43	61	63	None-minimal (3)
P4	M	43	Full time	BD	C	259	3.45±1.50	84	0	3	33	57	81	Mild (6)
P5	F	50	Part time	UD	O	61	1.65±0.89	92	7	0	1	0	95	Mild (8)
P6	F	25	Student	UD	O	126	3.86±3.52	73	19	12	79	42	89	Moderate (10)
P7	F	27	Unemployed	UD	O	80	1.43±0.66	75	4	0	70	51	90	None-minimal (4)
P8	F	22	Student	BD	O	121	1.48±0.71	77	17	1	83	85	93	Moderate (10)
P9	F	33	Unemployed	UD, OCD	C	527	7.75±1.77	74	0	2	45	70	99	Moderate (13)
P10	F	27	Student	UD, anxiety	O	90	1.96±0.29	1	0	0	8	0	90	None-minimal (4)
P11	M	56	Unemployed	BD	C	224	3.11±1.06	75	1	0	43	0	70	None-minimal (2)
P12	F	33	Student	UD	O	79	1.20±0.40	29	5	0	34	16	44	Mild (6)
P13	F	28	Student	BD	O	103	3.81±1.52	64	0	11	43	87	96	Mild (7)
P14	F	30	Part time	UD	O	339	4.65±1.29	77	7	6	38	23	96	Mild (5)
P15	F	29	Unemployed	BD	C	133	2.39±0.90	44	1	3	54	2	83	Severe (22)
P16	F	28	Full time	UD, anxiety	O	114	2.43±0.68	97	0	0	58	66	30	Moderately severe (15)
P17	F	20	Student	UD, BL	O	252	4.45±1.94	10	0	0	77	3	93	Moderately severe (19)
M		33.17				170	3.00	62	4	4	54	9	76	
SD		10.00				123	1.65	30	6	6	24	20	15	

to strongly agree. We averaged the scale count from statements within each of the five core dimensions of the UTAUT model. Figure 3 shows the resulting diverging stacked bar chart.

Regarding performance – or health – expectancy, a majority of patients believed that using MUBS would help attain gains in health. For example, 75% of patients agreed to the statement that "*using MUBS would help me reach my health goals of reducing depressive symptoms*".

Regarding effort expectancy, a majority of patients also expected MUBS to be easy to use. For example, 77% of the patients agreed to the statement: "*I would find MUBS easy to use*". Since MUBS was designed to be used independently of close clinical supervision, verifying that patients perceived the app as easy to use in BA was particularly important.

Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new system. Statements in this category include "*My therapist thinks that I should use MUBS*" and "*My family (e.g., spouse) think that I should use MUBS*". We found that patients are almost evenly split or neutral on these statements; a small majority disagree that important others influence their use. This again reflects the design goal of MUBS as a tool for BA, which can be used independently of the clinic.

Facilitating conditions are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system. We see that most patients agreed that sufficient organizational and technical support for MUBS would be available.

Behavioral intention is defined as the degree to which an individual intends to use MUBS after the study period. We see that patients are somewhat split on these statements; some disagree, and some agree that they would use MUBS after the study.

In summary, based on the 8-week trial period, patients expected that MUBS would help them attain gains in health, found MUBS easy to use independently, and that sufficient organizational and technical support would be available. Yet, patients were rather split as to whether they intended to use the system in the future. As shown in Table 2, the group of patients was very heterogeneous, with very different occupational status and experiencing anything from minimal to severe depression. The following section details more qualitative results to further investigate how MUBS was used as part of the patients' everyday life.

Qualitative Feedback

In general, patients found MUBS useful and easy to use – as put by P1: "*It has been really easy to use the app, it is pleasant to use, very user-friendly, not at all advanced* ". The thematic analysis of the interviews revealed five different ways in which MUBS supported patients to; (i) engage in activity planning leading to BA, (ii) find simple and yet useful inspiration and recommendations for activities, (iii) personalize rewards and stay engaged, and (iv) build awareness.

Activity Planning for Behavioral Activation

Patients, in general, found the app useful in activity planning, and the workflow of adding activities was described as motivating – as P11 explained: "*It was easy to find the relevant activities and add them. If there was an exception, I just*

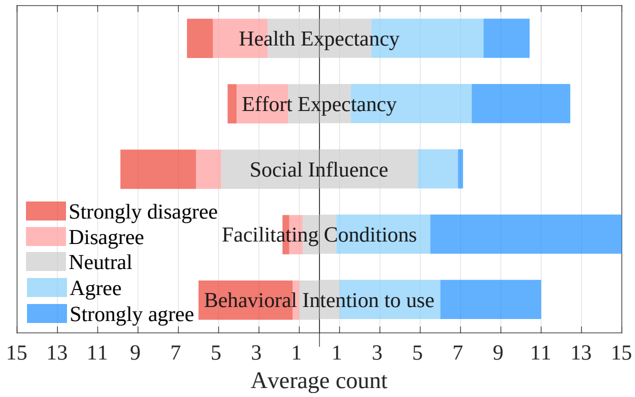

Figure 3. The distribution of answers from the Unified Theory of Acceptance and Use of Technology (UTAUT) questionnaire on a 5-point Likert scale.

created one myself. Moreover, I like the 'morning-afternoon-evening' split – this made it easy to schedule [activities]". As for the routine schedule, some – although not all – patients used this feature. For example, P8 explained how she could quickly add an activity to the weekly routine: "*When completing one of those planned activities, it is really easy to make it a routine, just press [the button]*".

The patients noted the benefits of activity planning leading to BA – the core ingredient of BA therapy. For instance, as pointed out by P7: "*It is more likely that you get activated if you have planned activities. When you wake up and you have nothing to do, it can make you feel bad. But when you wake up and you already have a plan, it is really nice*". Similarly, P11 noted:

> "*It worked best when I wrote down [activities] either in the evening or the following morning – what I had to do that day. I experience a more efficient day when I make the plan in advance. It provides satisfaction during the day that you have executed them [activities]: Now you are done with this, now that. In this way, I have a more structured day, more efficient because there is less time for drifting off.*"

The word 'structure' was often used by patients to explain how MUBS helped them activate themselves. As expressed by P13: "*It helped me plan in advance when to go for a run, so it was not just any time, but something I did, e.g., in the morning. I think that it helped me to have this structure*".

Inspiration and Recommendations

Patients reported that MUBS became a source of inspiration for them and often would recommend relevant and sometimes surprising activities. One line of inspiration and recommendation was to look for more enjoyable activities in their everyday life, for example, during busy, stressful, or negative periods. As P14 explained: "*If I have a stressful period e.g., due to work, I am often thinking like; what should I do, to have some fun today? And then I just look through all the fun things that you guys have made [the catalog] – and then I often think; aha this is also exciting, I can try to do this*".

MUBS also facilitated awareness that even small and negligible activities also played a role in BA. For example, simple things like taking a bath, treating oneself with ice cream, or put on moisturizing cream and perfume, are all small but significant personal activities which are important first stepping stones in BA therapy. As put by P9: "*Every morning I take a shower, put on perfume, and put cream on my face – and that is never something I think about. But it is actually a small luxurious thing that I do for myself. I have learned to appreciate this*". This awareness could also happen in the evening when the patients were assessing their overall day. As P13 clarifies: "*When I had a bad day, I scrolled down [the catalog], and then I realized that I had done good things – such as applied lotion on my hands, used lavender-oil or something like that. It contributed to the awareness that also such things are part of everyday life and add to it all*". Hence, the catalog of activities and the recommendations both served as inspiration when planning activities, but certainly also when patients were reflecting on a day, e.g., in the evening when they would realize that they actually had activated a positive behavior that day, which made them feel good.

Personalize Rewards and Engagement

Most of the patients mentioned the 'difficulty point' system as useful, and a large group of these argued that the point system was strongly engaging. P2 argued that the point system proved a valuable source of motivation, enabling him to carry out more activities: "*At four points, I could feel that it provided a positive effect. A boost in self-esteem: Yes! I have accomplished something*". The ability to adjust the difficulty points of an activity according to e.g., the depressive state of the patient, turned out to be used and appreciated by patients. This also proved a motivation for P8: "*I like that I can choose the difficulty. On those bad days, I still managed to take those three weights [difficulty points] activities – it makes it a bit more of a success*". P13 provided a related example and explained how the points were used as a personalized reward; "*I think I registered it [Taking her grandmother to the doctor] as; 'Doing a favor for someone'. And then I gave it a thumbs down because my grandmother is a pain in the butt. But then I set it to three [difficulty points] – I did something that was really difficult and then it was okay that I did not do anything else that day*".

Awareness of Behavioral Activation

As patients used MUBS over the study period, they gradually built awareness of how they could plan and carry out activities of different types and difficulty levels. The visual feedback of the pyramid and the bar-charts (Figure 1E) helped patients to see progress in terms of gradually activating increasingly difficult tasks (the pyramid) as well as engaging in different types of activities (the bar-chart), which all were used to balance activation. For example, P7 explained her use of the bar-chart:

> "*I really like how the activities are divided into categories – you can quickly see the types of activities that you have done – the distribution. That made me aware if I did too much of a certain activity [type]. For example, if I see a lot of blue – meaning that I have done a lot of social stuff – I would consider doing other categories*".

We found that not all patients found the pyramid useful, but for some patients, the pyramid helped them build awareness of how they were progressing in undertaking increasingly difficult activities. P14 explained how she used the pyramid to motivate the planning of activities:

> " *It [the app] has made me do different things. Especially because it feels like playing a computer game. I'm trying to get all these [pyramid steps] to even up. So if one of the categories is low, I go [into the catalog] and look for inspiration for what to do. Once I got almost all [the pyramid steps], I took a screenshot and send it to my sister. To me, it is really motivating. I'm super proud of this.*"

DISCUSSION

This paper has focused on individuals who experience depressive episodes and would benefit from an intervention to get back on track with their daily life. The mHealth application MUBS was designed through careful consultation of both the specific characteristics of this user group and existing evidence from psychological theories. BA was chosen as the therapeutic approach due to its straightforward methods and wealth of clinical evidence. Currently, this approach relies on paper-based material, while MUBS translates its principles into a digital form. The final design incorporates support for the core aspects of BA, including a unique content-based recommender algorithm.

To understand how this kind of mHealth technology for mental health can benefit and help depressed patients, we ran a feasibility study to provide detailed quantitative and qualitative insight into the usage of MUBS.

Usage Patterns

As expressed in the interviews and summarized in statements concerning 'Effort Expectancy' (Figure 3), patients found MUBS easy to use with little effort. They understood that it was a stand-alone system to be used as a personal assistive tool without involvement or endorsement from the clinic or significant others ('Social Influence'), and found that they had access to the necessary resources to use MUBS ('Facilitating Conditions'). Overall, MUBS covers the fundamental needs of a personal tool to facilitate daily planning and registrations of activity.

Investigating the specific usage of MUBS, we observe a small reduction over the 8-week study period (Figure 2). This is a small reduction compared to 'normal' dropout curves in mHealth systems for mental health [26]. Despite this reduction, on average, there were 3 ($SD = 1.65$) activities registered every day, which is one per time period and equivalent to what is recommended in BA. A majority (62%) of the planned activities were picked directly from the catalog while fewer were custom created (34%), which indicates that the patients found the predefined activities useful.

Designing for Behavioral Activation

To support BA, there is a need for a therapeutic tool to engage its users in doing ('activating') pleasant activities. However, a certain level of design flexibility is required to account for various depressive stages, backgrounds, and engagement levels from focused to casual forms of use. Users should not feel forced to use specific features of an app. They should instead feel able to decide whether the app is appropriate for the current circumstances of their lives and then understand – and adjust – how they would prefer to use it to improve their specific condition. Therefore, the interaction with an mHealth system like MUBS is expected to vary from patient to patient, given that this is a vulnerable group of users [15, 44]. This section reflects on the goals of designing for BA and discusses the implications for design arising from the process of developing and studying MUBS.

Activity Tracking and Registration

Activity tracking and registration were adapted to the personal needs of each patient, a functionality that is known to improve retention rate and overcome patient barriers to system usage [34, 56]. Patients who experienced worsening of their condition typically demonstrated a higher level of granularity in their registrations, adding simple 'daily living' activities such as "*Making a pot of tea*" or "*Singing in the shower*". In better periods, the patient was aware of – and possibly carried out – such activities, but did not consider registering them in MUBS. Patients explained how they increased the difficulty points to motivate the initiation of specific activities. Once completed, the reward was experienced as an increase in self-esteem and relief. Ly et al. included a similar catalog of 54 activities [35], but in this study, the participants argued that the activities were too simple. Hence, using a catalog of inspiring activities with different difficulty levels seems to be relevant in the design for BA.

Activity Planning and Engagement

Scheduling and enacting activities are the central components of BA [13]. In therapy, patients are assisted by clinicians to 'discover' and plan such behavior. MUBS provided patients with a tool to enhance self-efficacy and the motivation to plan different types of activities independently. The qualitative results confirmed that patients found the system very beneficial for planning, and revealed increased awareness and commitment when planning activities – borrowing from P11's own words, creating a 'contract' with oneself. A similar result was also found in the EmotiCal study [22], which demonstrated the effect of planning activities. In the EmotiCal study, participants were explicitly informed that the act of planning activities would help change their mood. This was not the case in this study, and even so, the patients, by themselves, found MUBS useful in reducing their depressive symptoms.

BA recommends planning activities the evening before or in the early morning. However, day-to-day planning is not practiced in therapy, likely because sessions are spread weeks apart, and planning takes part together with the therapist. With the use of mHealth technologies like MUBS, much better support for daily planning and engagement is introduced. This included daily visual reminders, structuring activities, daily reward arising from challenging activities with greater difficulty, and personalization towards meaningful activities. Interestingly, these facilitating support methods are also mentioned as important factors to engage in everyday activities by patients with neuropsychiatric symptoms [16].

Additionally, we also found that day-to-day planning can be difficult for patients in a full-time job. This group found the routine feature useful since it enabled them to schedule reoccurring activities. For example, P14 and P16 both mentioned how they were inspired to introduce more enjoyable activities during otherwise monotonous periods. Often a therapist would be aware that patients who work full-time have limited opportunities for doing anything else, and would hence help to schedule enjoyable activities within these limits [31]. Our study suggests that MUBS and its activity catalog and recommendations enabled patients with full-time employment also to plan such activities.

Inspirations and Recommendations

The quantitative and qualitative results of this study show that the 384 long activity catalog served several purposes. The patients mentioned it as a source of inspiration responsible for more than 60% activity registrations (Table 2). Particularly, inspirations were appreciated during episodes of more moderate depression, also – as stated by P3, P15, and P17 – when developing behavioral plans as part of treatment in the clinic. P3 provided an example of this: "*Think about something that you do not do anymore that you used to like to do - she [the psychologist] told me that, and I could not think of a single thing...*". This impairment in decision-making suggests that a mere tool for inspiration and examples of specific activities would be a valuable asset for this patient group. However, the availability of such tools is sparse, and for those that exist, the users reported them too short and simple [35]. With the contribution of the MUBS activity catalog, we hope to encourage more design in this domain.

The number of direct personalized recommendations selected by patients was, however, low (4%) although very spread ($SD = 6\%$), and the details in Table 2 indicate that some only used it. Looking at patients' demographics, the types of activities, and their difficulty level, there seems to be a pattern in how activities were selected. Figure 4 shows the distribution of activities divided by difficulty level depending on how an activity was created; recommended by the app, chosen from the catalog, or custom-made. The figure illustrates that patients used the recommender algorithm for less challenging activities that could easily be incorporated into the current context. As an example, P6 scheduled *'turning off electronic devices for an hour'* on a Monday afternoon. Furthermore, patients with a full-time job exhibited low uptake of recommended activities. At first glance, it seemed as though patients exposed to more sporadic behavior were more prone to accessing the recommender functionality. However, through the semi-structured interviews, we discovered that the behavior was a consequence of the design. When we asked the patients for the current context during recommendation selection, they were usually in a situation where they had not scheduled any activity and wanted inspiration on what to do in the current moment. The act of engaging in a here-and-now recommended activity is strenuous. Therefore, the natural consequence is the uptake of easily adaptable, short-term activities. As patients

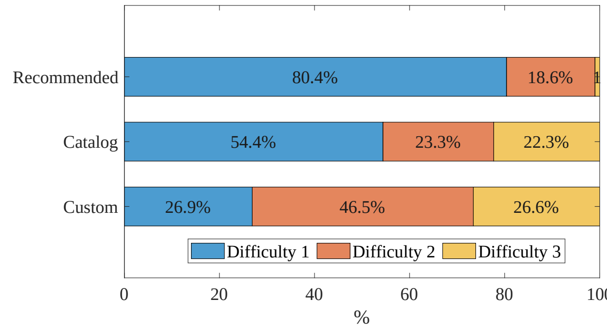

Figure 4. The difficulty of the activities that were selected from the three different sources; custom made, chosen from the catalog, or from the recommendations

in full-time job planned activities beforehand and extensively used MUBS to have re-occurring planned (routine) activities, it was no surprise that the uptake of the recommender part was small in this sub-group of patients. Recommendations are inherently a here-and-now action and were also perceived as such within MUBS. However, to support the utilization of personalized recommended activities, and to realize the benefits in a BA therapy context, we need to design recommendations as part of the planning phase. Planning activities facilitate action.

During the interview, P6 proposed the idea of planning recommended activities through notifications; "*When you are really bad, the app should know that and send you a notification of a really basic [activity] – such as 'wash your hair' or 'go for a walk'*". A study on text messaging interventions on users with depressive symptoms had a similar suggestion of approach [1], i.e., having messages suggesting concrete activities. MUBS was deliberately designed to present a list of recommended activities when the user requests recommendations (using the red plus button). This design was rooted in the design workshops based on a discussion of the problems that might occur if a phone starts telling a patient what to do. In light of these findings, however, there might be an option for revisiting the design decision to suggest recommending activities more actively.

Rewards and Incentives for Engagement

The results showed that the notions of 'thumbs-up' and 'difficulty points' were generally to serve as a positive design feature helping the patient become engaged in both easy and challenging activities while receiving rewards. We found that the thumbs-up / down reflection facilitated awareness of positive behaviors, which tends to be forgotten when encapsulated in negative thinking due to depressive symptoms. As a consequence, it improved patients' self-efficacy that enabled them to plan future positive activities, which aligns well with other findings in the literature [24]. Reflection on activities and its mood effect has an impact on overall well-being and promotes self-discovery [4, 51]. What we further discovered was that a majority of the registered activities were rated with thumbs-up. We discussed this with patients, and derived two main insights; (i) the act of engaging in an activity is almost always a positive behavior, and (ii) they might have, indirectly, chosen only to plan and register activities that are inherently positive. Prior research suggests that recording and reflecting on negative experiences reduces well-being [22]. Therefore, design for mainly positive activation may be necessary for these types of mHealth applications.

As discussed above, the use of difficulty points – and especially the option to personalize points – was found very useful in the study. However, while the patients found the circular point score on the homepage (Figure 1A) useful, we observed a split opinion on the usefulness of the pyramid visualization (Figure 1E). To some patients, it was proved difficult to interpret, and they did not know how to read it. The patients were less familiar with such a hierarchical visualization. Unlike a simple bar chart comparing the amount of given values, or evaluations in text (e.g., "*You have carried out less social-based activities last week even though it has a positive outcome on your mood*"), the patients were left with limited understanding to interpret (i) what the visualization is conveying, (ii) why the visualization is relevant, and (iii) how to act upon it. While these patients had no commonality within a socioeconomic or educational level, they were usually older. In particular, P5 stated that she was technology-illiterate and therefore, unable to understand the pyramid. Contrary, we found that younger patients liked the pyramid. This might be because the gamification element of 'filling up' the pyramid is engaging, which is known to be more easily adopted at a younger age [29]. To others, the pyramid visualization motivated the planning of activities within life areas, which were previously neglected (e.g., social activities). Hence, it was a reminder – or incentive – for patients to gradually expand or focus their behavior in other domains. In general, the study showed that this kind of progress visualization might be useful to only some patients and that personal relevance is core to their usefulness. To our knowledge, similar experiences were not commented on in mHealth systems that represented progress as a path from A to B [11, 18], which suggests that this design space needs further exploration [12].

Limitations

Limitations of the Design of MUBS

Mobile apps are proclaimed as a promising adjunctive and possibly stand-alone BA treatment option for patients with depressive symptoms [34]. Accordingly, MUBS is designed as a stand-alone BA treatment for patients with depressive symptoms and does not incorporate the support of a therapist, who can guide the patient during BA therapy. Although MUBS incorporates the core BA functionalities, there are still supportive aspects it does not consider. For example, the therapist could help the patient overcome barriers towards initiating activities by assisting him or her in splitting the activity into smaller, manageable sub-activities [31]. P2 explained how he used MUBS to split the activity of setting up a new wardrobe. He created activities such as "*Clear space for assembling the new wardrobe*", and "*Throw the old wardrobe out*". However, the current design of MUBS does not support such dividing or grouping of activities.

The recommender model did not include any post-filtering functionality on the recommended activities. Several patients mentioned that they received recommended activities such as "*Cuddle with your pet*", or "*Take a swim in the sea*" in cases where they did not have a pet or any beach nearby. Although they served as inspiration for similar activities – and patients mentioned it as a fun read – this could hurt the perceived usefulness of the recommender system. Adding more context-based information to the model, such as location, weather, and ambient noise, could be a future step to improve on the recommender algorithm.

Limitations of the Study

As shown in Table 2, the majority (n = 12) of patients were recruited online. As these were not treated by the clinicians involved in the study, and even though we carefully explained the inclusion criteria, we were not able to cross-check whether a participant had a clinical diagnosis. Patients were compensated a lump sum for their participation (which is a standard procedure in most HCI studies [22, 48, 49, 52]). The implication of this on recruitment is unknown, since this may attract patients with certain socioeconomic preferences. As an initial feasibility study, the study is also limited to a small sample size, and the statistics should be interpreted with caution. Finally, as a feasibility study, there is no long-term follow-up, and we have no knowledge of the sustainability of the usefulness and usability findings during the continued use of MUBS.

CONCLUSION

In a user-centered design process, we developed MUBS, an mHealth system, to support BA therapy for patients with depressive symptoms. Its features were designed to adhere to core BA principles. These include access to an inspiration catalog of 384 pleasant activities and personalized recommendations with specific activities to enact. We ran an 8-week feasibility study with 17 clinical patients. Through semi-structured interviews, patients reported that they *learned* to appreciate the smaller everyday activities. They became *aware* of positive daily inputs that were otherwise overlooked during depressive days. They managed to *plan* more enjoyable activities and felt *rewarded* when they followed their plan. We discussed how our system supported BA and the implications towards a future design in behavioral studies for patients experiencing depressive symptoms.

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