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Evaluation of personalized treatment goals on engagement of SMI patients with an mHealth app

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ABSTRACT

***Abstract*—Mobile health (mHealth) tools are regularly used in a wide range of mental health domains to assess and monitor patients, potentially increasing patient engagement. Recent studies demonstrated that tailored approaches provide better results than generic approaches. However, the effectiveness of tailoring has not yet been investigated empirically for patients with severe mental illnesses (SMIs). It also remains unclear how personalized goals, which are critical from a treatment point of view, impact engagement. Therefore, we designed a novel mHealth tool to increase SMI patient engagement with their personal goals which we evaluated empirically. We designed a two-period, two-arm within-subject crossover study in which 4 participants were exposed to personalized and non-personalized behavioral goals. Contrary to expectations, personalized behavioral goals did not have a significant impact on engagement levels. When considering our participant feedback and also in the context of flow theory, we rationalized that our goal personalization strategy was too static for SMI patients. Therefore, in our future work, we will investigate dynamic strategies that adapt goal difficulty over time.**

***Index Terms*—mHealth, personalization, goal setting, engagement, severe mental illness, FACT.**

I. INTRODUCTION

One in four people will suffer from a mental health problem in their lifetime [1]. Individuals who experience mental disorders for an extended period (i.e., several years) and who have serious limitations in social and societal functioning, are considered to suffer from an SMI [2]. Mental health services in several countries prescribe Flexible Assertive Community Treatment (FACT) to treat and support SMI patients in their own environment in order to decrease admissions and to prevent dropping out of care [3]. During FACT, patients are regularly visited by their case manager (i.e., a healthcare professional), who continuously evaluates the risk of relapse [4]. These case managers are responsible for co-designing the treatment outcome goals together with the patients, which are documented in a patient's personal treatment plan [2].

Because the majority of SMI patients are living independently, it is difficult for case managers to monitor these patients and provide coordinated care. The mental health sector faces a shortage of staff and a limited budget, making it impossible to continuously approach and treat these patients individually at increasing scale [2]. Currently used digital tools, such as remote calling or e-mail, were not experienced by many patients as a viable alternative to standard home visits [5]. As a result, patients may not receive the care and treatment they need as case managers cannot monitor patients remotely [5]. There are currently no effective digital tools to help case managers monitor their patients individually, nor is there a tool to help patients work independently on the outcome goals found in their treatment plans.

Previous research has shown promising results in employing mHealth interventions among SMI patients to positively influence desired behavior change to help them adhere to treatment [6]. There is an emerging evidence base to support the use of mHealth tools in the assessment, monitoring and intervention of daily functioning of SMI patients [7]. A behavior change strategy is even more effective when an mHealth tool is personalized toward particular user needs or characteristics [8]. The absence of empirical results in the SMI setting provides an opportunity to personalize mHealth tools to improve patient adherence to treatment. Since SMI patients have treatment plans with personal goals, it is natural to tailor goal-oriented mHealth support accordingly.

This study aims to investigate the impact of personalized treatment goals on engagement levels of SMI patients with an mHealth tool. We explored the impact of both personalized and non-personalized tasks within an mHealth tool on engagement levels. These tasks are comparable to behavioral treatment goals, which, together with treatment outcome goals, were set and documented in a personal treatment plan. The treatment-related tasks were hand-tailored for each patient by their case manager. Tailored approaches are more effective and provide better results than generic approaches [9]. Therefore, we hypothesized that the impact of receiving personalized treatment goals in an mHealth tool would be larger than the impact of receiving non-personalized treatment goals on engagement levels of SMI patients.

II. THEORETICAL BACKGROUND

Personalization is a system or person offering tailored content or services to a user based on their needs and preferences [10]. There are three main components that are recommended to be tailored in an mHealth tool: activities, game elements (gamification), and persuasive strategies [8]. Gamification is the application of game elements in non-game

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environments to promote and affect behavior with gameful experiences [11].

First, studies could benefit from the relationship between the patient and their caregiver, by having the caregiver define the tailored content within the health intervention [12]. In the context of remote SMI management, case managers can take over this task due to their close relationship with their patients and their ability to identify possible risks.

Second, the use of gamification in mHealth research has received considerable interest for its potential to increase engagement and target behavior change [10]. Tailoring game elements can potentially achieve better results, although this has not yet been supported by empirical evidence [13]. The number of applied gamification elements is growing. The most used elements in mHealth tools for SMI patients are: levels, narrative or theme, points, rewards and avatars [10].

Lastly, several studies applied a tailored persuasive strategy, which are strategies to communicate with a user [8], [12].

III. Methods

Desk Research

During preliminary desk research, patient treatment plans from January 2010 until February 2022 were retrieved from the Dutch Institute of Mental Health and Addiction Care. This data was analyzed to evaluate the current state of the goals found within treatment plans and to identify if there were any differences in goal setting with patients within FACT teams. This was done to contact FACT teams with experience creating measurable goals with their patients. Text mining and Natural Language Processing (NLP) techniques were used to prepare, model and evaluate the data. Tokenization was applied. These tokens were normalized, and non-informational text was filtered out (e.g., punctuation, stop words and verbs). It was assumed that words and sequences of words that occur frequently indicate important content. N-Gram models were used to predict the occurrence of a sequence of N words. Frequent important words could be split into two groups, resulting in two *bag-of-words* for data modeling.

Intervention Trial

A. Recruitment

1) Case managers: were essential to recruit before patients, for the design process of the intervention trial. It was also important to recruit from a FACT team that had experience with creating behavioral goals with their patients.

2) Participants: were recruited among SMI patients who receive treatment from the chosen FACT team in the Netherlands, in April and May 2022. Case managers approached SMI patients they deemed fit and who were willing to participate in the intervention. Thereafter, explicit consent of all participants was collected upon registration for the mHealth program by the researchers. All procedures including data preservation and privacy security were approved by the ethical committee of Eindhoven University of Technology (experiment ID: RB2022IEIS8) and were not subjected to the Medical Research Involving Human Subjects Act (WMO), as reviewed by METC Isala Zwolle (experiment ID: 220401 SGP).

B. Intervention context

To evaluate personalized behavioral treatment goals the GameBus gamification engine was used for this study (see www.gamebus.eu). Our customized configuration of GameBus was a multi-platform web application that runs on any web browser and was designed to promote engagement of SMI patients by rewarding performed tasks with points. Proof of a conducted task was based on a given description by the participant. Data management of the application is in accordance with the guidelines set by the Technical University of Eindhoven and the Dutch Institute of Mental Health and Addiction Care.

The designed application was titled *"Samen Gezond met Joe"* (i.e., *"Healthy together with Joe"*). The overall goal of the intervention from the perspective of the patients was to obtain as many points as possible by performing treatment-related tasks. To stimulate participants to be actively involved during the intervention, a certificate of participation was awarded to participants that obtained at least 150 points, by the end of the campaign. Participants could only track their own performance and compare themselves against the average performance across all participants on a leaderboard.

C. Study design

This study had a duration of 2 weeks and was designed as a two-period, two-arm (2x2) crossover design where each participant was randomized to a sequence of treatments administered sequentially during treatment periods. An advantage is that crossover designs require fewer participants than a parallel design because participants serve as their own control group [14]. This was especially useful with the limited number of available participants.

In the first week, participants were randomly assigned to either personalized or non-personalized tasks. In the second week, participants were assigned to the other treatment group. The tasks for each week were set in collaboration with the case managers and researchers, in a workshop session [15].

1) Personalized treatment: For each individual patient, a number of personalized behavioral goals were defined by the case manager. These goals were tailored based on task complexity, which implies tailoring the frequency (i.e., how many times performed in a given timeframe) and/or intensity (e.g., for how long, for how far, etc.) [16]. These personalized behavioral goals were used as personalized tasks within the GameBus mHealth tool, each patient was given 3 to 6 personalized tasks. Each task was rated between 1 and 5 to classify importance (i.e., 5 being the most important).

2) Non-personalized treatment: Each case manager defined non-personalized behavioral goals, which they thought were relevant for every patient. Those goals were either lifestyle or socially related. The top 5 most relevant non-personalized behavioral goals for the participants were selected and approved by the case managers. These tasks were assigned to all participants. As opposed to the personalized tasks, these non-personalized tasks were equally important and not tailored to frequency or intensity.

For both personalized and non-personalized tasks, participants were able to perform up to 35 tasks and accumulate a maximum of 105 points [15].

D. Study procedures

Throughout the intervention period, several emails have been sent and meetings have been scheduled with the participants and case managers. At the start of the campaign, a kick-off workshop was scheduled to inform every participant on how to get started with the application [15]. Since the accounts were pre-configured, every participant received an email with personal credentials for the application and was requested to complete the pre-test survey. At the end of each week, another email was sent with the request to complete the intermediate test and post-test survey, respectively. Finally, after the two-week campaign, interviews were scheduled with several participants to evaluate the mHealth application.

E. Measurements

Engagement in mHealth behavior change interventions is important for intervention effectiveness [6]. The following measures were used to measure engagement: system usage data from the mHealth application, pre-test, intermediate-test, and post-test surveys, and interviews.

1) Objective system data: To objectively measure participant engagement, system data was recorded. In this study, engagement was captured through two variables: 1) the number of days a participant had been online (passive engagement) and 2) the number of virtual points a participant had scored, which is considered as a relative scale of task attainment in a particular week (active engagement). This variable was introduced to compare individual patients in terms of active engagement, since each participant was assigned to a different number of tasks.

2) Subjective survey data: Three surveys were used to collect subjective data of participants. A pre-test survey was used to gather: 1) demographic data (i.e., gender and age) 2) data related to intrinsic motivation, and 3) data related to personality traits. Intrinsic motivation related to the mHealth application was measured using 4 sub-scales from the Intrinsic Motivation Inventory [17]: 1) enjoyment, 2) perceived choice, 3) perceived competence, and 4) tension. This multidimensional scale assesses participants' subjective experience related to a target behavior through self-reporting. The enjoyment scale measures intrinsic motivation, the perceived choice and perceived competence scales are positive predictors of intrinsic motivation. The tension scale is a negative predictor of intrinsic motivation [17]. All items were measured on 5-point Likert scales.

The intermediate- and post-test were used to measure intrinsic motivation, after a participant had received personalized or non-personalized treatment during one week. Both measured on 5-point Likert scales. An overview of the pretest, intermediate-test and post-test survey questions can be retrieved from Figshare [15].

3) Subjective interview data: At the end of the intervention, semi-structured interviews were conducted to further analyze why the participant was involved in the intervention or not. All participants were invited to an individual 30-minute interview, on location.

F. Data analysis

To evaluate the impact of personalized treatment goals on engagement levels of participants, four different analyses were performed. Statistical tests were two-tailed and a *p*-value of 0.05 was considered statistically significant. First, an exploration of user statistics was conducted, including descriptive statistics of demographics. Additionally, details about the number of participants enrolled in different study phases were provided. Second, statistical analyses were performed to evaluate the impact of personalized treatment goals on engagement levels of participants. These analyses focused on evaluating: 1) passive engagement levels and 2) active engagement levels. Mean plots and paired sampled t-tests were performed to examine potential differences between treatment groups and study arms. Third, statistical analyses were performed to evaluate the impact of personalized goals on levels of intrinsic motivation, including 1) enjoyment, 2) perceived choice, 3) perceived competence, and 4) tension. Again, analyses were performed using mean plots and repeated measures ANOVA tests, including A Tukey multiple pairwise-comparison, to examine potential differences between treatment groups, including a pre-test condition (i.e., control group). Finally, quotes that indicate 1) a like or dislike of the mHealth app, 2) preference for (non-) personalized tasks, and 3) motivation, were selected during interviews. If there were no clear preferences within an interview regarding these three elements, patients were asked if they agreed with quotes from prior interviewees. Interviewees were not notified that these quotes were from other interviewees. Digital recordings of the interviews were transcribed and organized per question.

IV. RESULTS

DESK RESEARCH

We found that 3,392 unique patients were treated by 15 different FACT teams, each with a treatment plan containing on average 4.17 treatment goals. Each goal contained a description. The treatment plans mostly consisted of immeasurable goals which could not directly be used as measurable behavioral goals within an mHealth application. However, it was observed that words forming the first-person narrative (e.g., *"I will"*) and the words *"action(s)"* and *"goal"* were often transcribed in the treatment plan, resulting in the first and second bag-of-words respectively. Additionally, it was observed that several special characters were used as abbreviation for different important words (e.g., *"a/"* or *"*"* stands for *"action"*). The modeled bi-grams and tri-grams validated the importance of the first-person narratives [15].

Results showed that the frequency of the first bag-of-words was different for each FACT team. On average, 22.5% of the descriptions contained at least one token of that set of words, and only 4 FACT teams were performing better than average. This may indicate that the treatment plans often contained unclear structures and did not contain specific behavioral goals (e.g., *"goal: I am going for a walk"*), and therefore, are not directly suitable as input for the intervention design. The frequency of the second bag-of-words was more equally distributed among the FACT teams. On average, 56.4% of the descriptions contained at least one of the first-person narratives from that set of sequences. However, it was unclear whether all these first-person narratives were related to a behavioral treatment goal or not. It was also observed that a first-person narrative might also be related to a treatment outcome goal (e.g., *"I would like treatment for my addiction"*). Overall, these results suggest that most case managers did not document specific behavioral goals in a patient's treatment plan. Ultimately, a FACT team that scored higher than average based on the frequencies of the first bag-of words was approached to participate in the intervention trial.

Intervention Trial

A. User statistics

In total, 5 participants were enrolled in this study of which one participant did not give informed consent for data collection. The remaining participants were randomly assigned to either personalized tasks or non-personalized tasks, in the first week. These 4 participants completed the pre-test survey, performed at least one task during the first week, and completed the intermediate-test survey. During the second week, 1 participant who was assigned to non-personalized tasks, was not actively nor passively engaged. At the end of that week, both participants with non-personalized tasks completed the post-test survey, while both participants with personalized tasks did not. At the end of the campaign, 3 participants completed the post-interview. One participant who did not take part in the interviews, provided qualitative feedback by email.

B. Analysis of objective measures of engagement

There were no significant differences in passive engagement levels between both study arms. A paired samples t-test revealed that treatment groups were indeed not statistically different from each other in terms of passive engagement levels. Figure 1 displays active engagement levels, per week, per study arm. No statistical differences were found between both study arms regarding active engagement levels. Active engagement seems to decrease over time in general. The same decreasing effect over time as with passive engagement was observed for the number of points obtained, per study arm, although not significant. Regarding the number of tasks performed it was observed that this decreased faster over time when a participant changed from non-personalized tasks to personalized tasks. Statistical results and figures can be retrieved from Figshare [15].

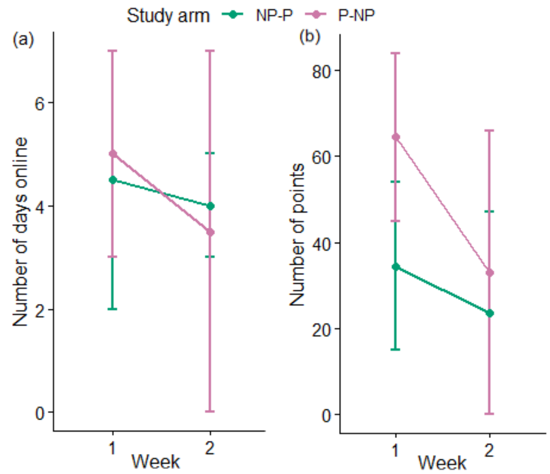

Fig. 1. Mean plots of: (a) the number of days online and (b) the number of earned points

C. Analysis of subjective measures of engagement

1) Evaluation of survey data: Before the intervention, responses of the pre-test survey were collected and served as a control baseline. Visual inspection suggests that participants enjoyed the application less and experienced more tension after they received personalized treatment. One-way repeated measures ANOVA tests revealed that treatment groups were significantly different from each other in terms of tension ($p = 0.022$). A Tukey multiple pairwise-comparison revealed that personalized treatment was found to have a significant higher level of tension compared to non-personalized treatment (i.e., 0.70 higher at $p = 0.023$) and the control group (i.e., 0.65 higher at $p = 0.032$).

2) Evaluation of interview data: On average, the participants awarded the GameBus web application an 8 out of 10. Participants agreed that they *did enjoy the GameBus application"*. In general, the act of earning points was experienced as fun: *I really liked the points, it stimulated me to use GameBus every day"*. However, *I would like to level up after collecting several points, then the goals may also become more challenging as I progress"*. Participant 4 mentioned that *the point rating was just the same for each goal"*. Not all participants were able to use the application on a daily basis, due to health-related circumstances.

All participants had a clear preference for personalized tasks. Participant 1 *"liked the personalized tasks more, these are my own things after all"*. The participant added that *"it's all about finding ways that suit me and what works best for me. These tasks worked quite well, it could probably work out well in other areas of life"*. However, the participant was *"unable to complete all personalized tasks. I usually want to do everything right, which makes it difficult then"*. Participant 2 was generally satisfied: *"Although both sets of tasks were well put together, I prefer the personalized tasks because these were more applicable to me."*.

The non-personalized tasks were generally not challenging enough: Participant 2 mentioned: *"I did not find these tasks* *challenging enough. For example, you already brush your teeth and eat healthy meals and fruit every day"*. Participant 1 mentioned that *"these tasks were already quite present in my daily structure"*.

Overall, participants were satisfied with the use of the application. Participant 1 mentioned *"It has helped me a lot, also with regard to the progress of my treatment. With GameBus, it is easier to start with a goal and stick to it on a regular basis"*. Participant 2 mentioned that *"personalized, challenging tasks and points, in combination with levels and avatars, are likely to be motivating."*.

V. Discussion

A. Principal findings

In this pilot study, we evaluated the impact of personalized treatment goals on engagement levels of SMI patients with an mHealth tool. Interestingly, the personalized goals that were made together with the case managers did not significantly differ from participant to participant. From our statistical analyses, we also found that personalized tasks did not have a significant impact on both passive and active engagement levels, compared to non-personalized tasks. Engagement levels with the mHealth tool tended to decrease over time for both study arms. However, it was observed that both passive (i.e., number of days online) and active (i.e., the number of points obtained) engagement decreased faster over time when a participant changed from personalized tasks to non-personalized tasks. This implies that engagement of individuals tends to drop slower over time with the mHealth tool when receiving personalized tasks. This reflects in the findings of the post-interviews, where participants unanimously expressed a clear preference for the personalized tasks. Hence, our hypothesis that the impact of receiving personalized treatment goals in an mHealth tool would be larger than the impact of receiving non-personalized treatment goals was partially accepted.

Another interesting finding is that the difficulty level might be key when personalizing treatment goals within an mHealth tool. Surprisingly, we found that participants rated enjoyment lower and tension significantly higher after they received personalized treatment. This implies that patients were less intrinsically motivated to engage with the mHealth tool, since both dimensions are a self-report measure and negative predictor for intrinsic motivation, respectively [17]. Only significant differences in levels of tension were observed after a patient received personalized tasks, compared to receiving non-personalized tasks or the control condition. A potential explanation for this might be that a personalized task may be too challenging to complete, which one participant also mentioned during the post-interview. As a result, tension may rise due to the inability to complete tasks despite the desire to do so. This indicates that the behavioral goals set by case managers may have potentially been too difficult to complete, which may have harmed engagement. Conversely, participants indicated that the non-personalized tasks were generally not challenging enough. Since all tasks were static and not dynamic, the difficulty of a task did not increase or decrease. This implies that tasks were either too difficult or too easy to complete. According to Flow Theory [18], the trade-off between challenge and skills must be in balance for a person to be in flow. Participants even mentioned that tasks should become more challenging as they progress, possibly in the form of a level system. For participants to be more engaged with an mHealth tool, tasks should be updated continuously according to skills of that individual.

Lastly, results from preliminary desk research suggest that the current goals in a treatment plan are often not behavior-oriented. Treatment plans contain long-term outcome goals often combined with unstructured description data. This indicates that case managers have no clear protocol for defining specific and challenging behavioral goals. Case managers define and document behavioral and/or outcome goals in the treatment plan based on their own routine or experience. This is in line with the results of this study, which confirm that the length of these descriptions varies by FACT team and descriptions are relatively simple instead of specific. This means that personalized tasks for an mHealth tool cannot be extracted directly from a treatment plan. Goals which are not behavior-oriented are difficult to measure, and therefore do not fit within an mHealth tool. Nevertheless, several FACT teams used specific words or sequences in the descriptions of the treatment plans. These teams clearly indicate an action or goal, often followed by the first-person narrative. This came closest to setting behavioral goals. The current strategy, including case manager recruitment, may not be the most optimal protocol to select behavioral goals for an mHealth tool. Therefore, a more structured way of defining and documenting goals in the treatment plan is desired.

B. Study limitations

This study was subjected to several limitations. First, this study has low power, as it used only a small sample of the FACT population. Not all participants completed the post-test survey and post-interview, further reducing the sample size for various analyses.

A potential reason for the low sample size is that the pilot study was performed at 1 FACT team, with 8 case managers who on average had 25 patients. Only half of the case managers were willing to participate in this study. In a presentation given to case managers presenting the results of the study, case managers agreed that a 2-week patient recruitment time was too short and suggested that the time be extended to 6-8 weeks. Case managers do not meet all their patients within 2-weeks, and meeting their patients does not guarantee that the patient is in an appropriate mental state to be recruited for a study. Case managers also only approached patients they believed would be interested in using a digital health tool, which potentially might have introduced a selection bias.

Unfortunately, due to the small sample size, we could not use advanced statistical analysis (i.e., linear mixed models) to analyze the effects of time on the crossover design.

Finally, this pilot study focused specifically on Dutch SMI patients who receive FACT. Therefore, the findings probably do not generalize to other groups of people or contexts.

C. Future work

Future work should focus on a more dynamic goal-setting strategy, in which tasks are continuously updated according to the skills and needs of a patient. A combination of points with level systems could be used to amplify this strategy. Then, the accumulated points are not only more meaningful [19], but it enhances the trade-off between challenge and skill [18]. It was mentioned by patients that the application may become more interesting if it included such avatars with their own storyline and backstory, which in turn is closely related to personalizing a persuasive strategy [8].

Unfortunately, case managers were unable to define personalized tasks with a balanced difficulty. Therefore, future work should focus on automated decision support, in which the difficulty of tasks is continuously updated by an automated system. Future research should focus on creating a framework or protocol that allows case managers to set treatment behavioral goals in a more structured way, which eventually can be used as a task in an mHealth tool.

Finally, goals in treatment plans are generally set for a longer period of time (e.g., one year). Therefore, the intervention period should be increased in order to evaluate the impact of an mHealth tool on long-term engagement levels. To effectively execute and evaluate this, future studies should focus on collecting more data, and include a more effective strategy to recruit patients.

VI. Conclusions

This pilot study aimed to evaluate the impact of personalized treatment goals on engagement levels of SMI patients with an mHealth tool. It was found that participants had a clear preference for personalized behavioral goals, however contrary to the hypothesis, it was found that these personalized behavioral goals did not have a significant impact on engagement levels compared to non-personalized behavior goals. It was found that patients experienced high tension when performing the personalized tasks, which implies that their motivation to complete tasks may have lowered. Future research should focus on dynamically challenging goals for patients over an extended period of time, balancing the right combination of goals and difficulty to get a patient into flow.

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