User Experience Design to Enhance the Effectiveness of Mobile Technologies for the Treatment of Mental Health

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Abstract - **In America, half of the population experiences mental health issues in their lifetime. Less than one third, however, will receive treatment. The National Institute of Mental Health calls for research on new, scalable methods for treating mental illness. Cognitive Bias Modification (CBM) is used to alter responses to situations that make participants feel anxious or upset. In this paper, we analyze data from an online, session-based, CBM training program for anxiety in order to make recommendations to improve the user experience increasing engagement and adherence to the program. Our objectives include maximizing user value, decreasing attrition, and minimizing user burden. To meet our objectives, we are analyzing data related to attrition and user engagement and implementing principles of user experience design such as improved visuals and typography and elements of gamification. Preliminary analyses indicate that the highest number of dropouts were less educated participants leaving the program early. Additionally, a redesigned interface will be deployed and future data will be collected to determine its effect on attrition.Both insights can contribute to an improved online treatment program.**

Index Terms - User experience design, Cognitive bias modification, Attrition analysis

INTRODUCTION

The National Institute of Mental Health estimates that 31.1% of adults in the United States will experience an anxiety disorder at some point in their lives, yet less than one third will receive treatment [1]. One-on-one sessions with a healthcare professional are the most common form of treatment, but it is not always feasible for a participant to receive such care. General anxiety disorders are characterized by restlessness, exhaustion, difficulty concentrating, irritability, tension, and reclusiveness. These symptoms can interfere with everyday life by causing issues in work, school, and relationships. Anxiety disorders are additionally often coupled with depression, increasing the strain on a participant's life [2].

Cognitive Bias Modification (CBM), one common method utilized in the treatment of anxiety disorders, allows participants to gain practice in thinking about stressful situations in new ways so they become less habitually negative and threatening. An example of a negative belief is an individual believing an audience is glaring at them during a speech, when they actually have neutral expressions. The effectiveness of CBM treatments has been demonstrated for both generalized social phobia and generalized anxiety disorder [3]. CBM for interpretation bias (CBM-I) has shown to be particularly effective when administered in laboratory settings through computers [4].

In this work, we evaluate MindTrails [5], an online anxiety treatment program currently being used to test the effectiveness of CBM-I delivered via computer and mobile phone. While over 1,000 people have signed up for the program, nearly 73% of participants leave the treatment program before completion, creating a challenge for the MindTrails team and overall effectiveness of the study.

Prior studies have been conducted to determine how to reduce attrition in online learning programs. Angelino L. M. et. al. looked at engagement strategies to reduce online student attrition rates [6]. Tyler-Smith, K. examined different sociological, psychological and cognitive factors that may indicate a user will drop out early on in an eLearning program [7]. However, there is very limited work done on specifically CBM-I online treatment programs. A meta-synthesis of online anxiety and depression treatments highlighted several points from past research, leading us to believe that an improved interface would help keep participants in the program. Users reported wanting a more personalized experience and did not feel like current programs were sensitive enough to their feelings.

Additionally, many reported that the programs felt like work and added stress instead of mitigating it [8].

Thus, our goal is to reduce attrition by identifying significant predictors and making design changes to the website that will help to reduce dropout.

DESIGN OBJECTIVES

The first objective in reducing attrition was to determine which participants were most likely to leave the study and when the dropout would occur. Metrics involved in these goals included the drop-out rate per session and the demographic trends associated with people leaving the program. We hypothesized that most users would leave the program in the beginning, based on conclusions of prior behavioral research programs, in which early stages of intervention experienced higher attrition rates[9]. Additionally, we predicted that users with lower educational levels or lower incomes would be more likely to quit because of limitations with literacy and experience using online programs, as shown in prior online content research [10].

The second objective was to analyze the level of engagement of individuals over the course of the program to determine where design improvements could be made. We anticipated based on previous research that users who were less engaged with the website would be more likely to leave the program [8]. From this hypothesis, we developed several design recommendations based on user experience design principles as outlined by Jakob Nielsen [11]. These proposals will be presented and potentially implemented in order to continue toimprove the program and reduce user dropout.

METHODOLOGY

To reduce attrition, we first identified factors that could cause a participant to leave the program. To determine these factors, we utilized participant data gathered by the study such as demographic information, method and duration of interaction with the training modules, overall performance, and feedback from users about their experience with the program. This data was then evaluated to identify a potential relationship between these variables and a participant's likelihood of drop out. The data was cleaned by removing outliers and missing fields, and preliminary visual analyses were conducted to inform the variable choice in our statistical models. These statistical models were then used to test our hypotheses about the significant factors affecting the rate of attrition. Lastly, recommendations for changes to the study were made to correct the identified factors proven to significantly impact attrition.

After completing participant data analysis, we focused on analyzing and improving the user experience and design of the online program. These design changes are intended to be tested later to determine their effectiveness of reducing attrition. Each member of the team completed several training modules to give feedback on the participant experience. Additionally, we analyzed survey responses from participantsabout their reasons for leaving the program. After compiling design suggestions based on the team's feedback along with user experience (UX) principles and literature, we presented our recommendations to the larger MindTrails team and worked with developers to improve the website.

RESULTS

Data Analysis:

Based on user interaction data, we generated several statistical models to understand the occurrence of attrition from the program. Our models addresswhen participants will leave the program, which participants will leave the program, and the level of participant engagement.

The first model was created to determine when participants were most likely to drop out of the program. Based on the model, we concluded that most user attrition occurs between sessions rather than within a single session. Figure 1 shows the number of participants remaining at each page during each session, and the Figure 2 represents the attrition rate for each interval between sessions and specific program pages. In both figures, the x-axis represents different tasks in different sessions; y-axis in Figure 1 represents the percentage of remaining participants among total participants, and y-axis in Figure 2 represents the attrition rate corresponding to each specific task. Equation (1) was used to calculate attrition rate (A) when x is the number of people who participate in the next task and y is the number of people who finish the current task.

$$A = \frac{1-x}{y} \quad 100\% \qquad (1)$$

Although 49% of participants dropped directly after finishing the 4th session, the post follow-up survey is not part of the intervention program and thus will not be considered. As we can observe, the greatest attrition happens at the interval between the 1st and 2nd sessions, in which 39% of participants choose to drop out. A possible design suggestion to combat this issue is to send participants additional reminders after finishing the 1st session to encourage and remind them to stay in the study. Further research is needed to determine the most effective way of reducing dropouts between sessions.

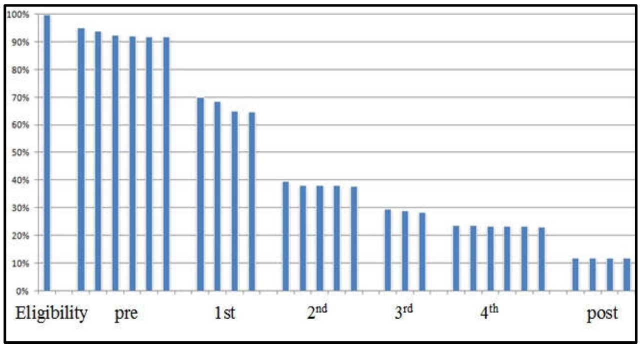

FIGURE1
PERCENTAGE OF PARTICIPANTS REMAINING AT EACH PAGE

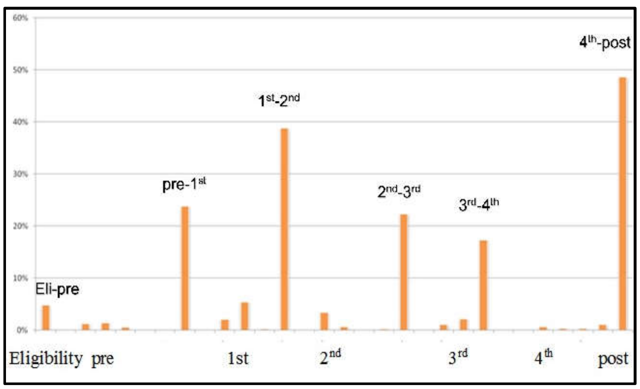

FIGURE2
ATTRITION RATE AT EACH PAGE

The second objective addressed attempted to determine which participants were most likely to drop out. Based on the demographic parameters from the data, several models were generated to determine trends in attrition. Predictors included level of completed education, employment status, time on page, income, race, ethnicity, gender, and marital status. These were implemented in a binomial regression model using the binary response variable of each session completed (1) or not completed (0). After running a stepwise regression of each complete model, education, income, and time on page were determined to be the only significant predictors. Based on the p-values shown in Table 1, participants with a Master's or Ph.D. had a much greater odds of completing session 2, and participants with higher education had a much greater odds of completing session 3.

TABLE 1
SIGNIFICANCE OF EDUCATION RELATED TO ATTRITION

Session:		High School	Bachelor's Degree	Master's Degree	PhD	Other Adv. Degree
	Coef.	-0.43	-0.46	1.03	1.32	0.02
1	OR	0.65	0.63	2.81	3.75	1.02
	P-value	0.47	0.13	0.33	0.08	0.94
	Coef.	0.61	0.52	0.92	1.22	0.65
2	OR	1.84	1.68	2.52	3.38	1.92
	P-value	0.47	0.40	0.06	**0.04**	0.27
	Coef.	1.47	2.22	2.44	2.98	2.80
3	OR	4.35	9.25	11.5	19.7	16.44
	P-value	0.25	**0.03**	0.38	0.06	**0.05**
	Coef.	0.00	0.00	0.04	0.00	0.00
4	OR	1.00	1.00	1.04	1.00	1.00
	P-value	1.00	0.99	0.99	0.99	1.00

Note: p-values in bold are significant predictors within a 95% confidence interval, OR = odds ratio

The third objective sought to identify the users' level of engagement on the site. To accomplish this, data regarding participant interaction with the site during each training session was evaluated. The metric considered for this objective was participants' response time to trials completed during the intervention. Each training session is composed of 127 trials which can be one of four types: filling in a missing letter, revealing the next sentence in a training story, answering the post-scenario yes/no question, or navigating to the next screen. An example a training scenario is presented in Figure 3 below.

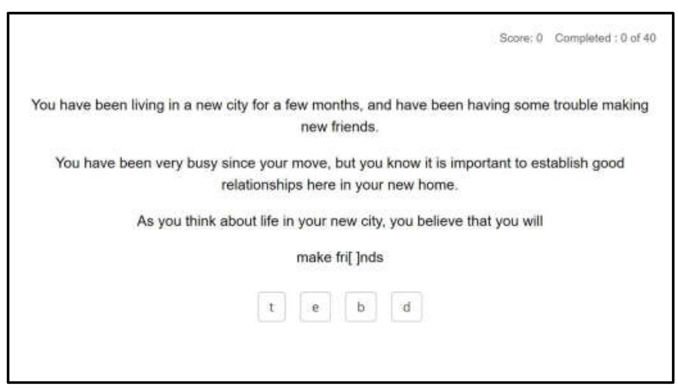

FIGURE 3
EXAMPLE TRAINING SCENARIO

The fourth trial type was not considered in the analysis as it was assumed that time spent navigating to the next screen is not reflective of user engagement. Extreme response times representing 6% of the data set (outside of the 95th percentile) were removed prior to analysis. It was hypothesized that user engagement, as measured by trial response time, would decrease significantly as the number of completed trials increased. To evaluate this hypothesis, we analyzed the average response times for each of the three relevant trial types plotted against trial index. Figure 4 shows shows average response times verses trial for the task of revealing the next sentence in a training story.

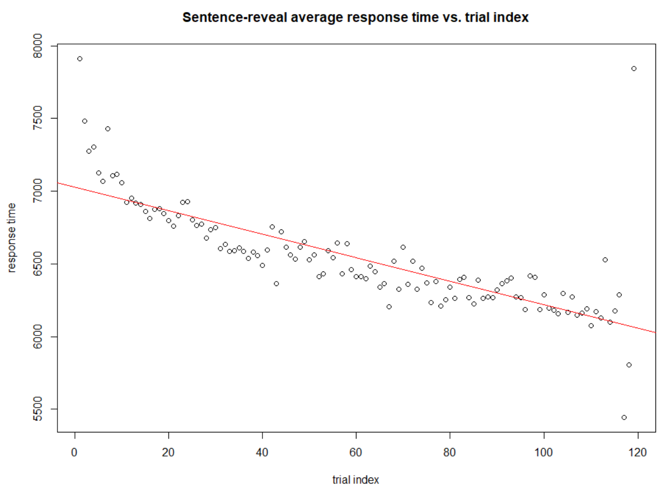

FIGURE 4
RESPONSE TIMES FOR INTERACTING WITH THE SYSTEM

To confirm our hypothesis, a linear model was built with response time as the outcome variable and trial index as the explanatory variable. Running a model utility test produced a p-value of < 2.2e-16, indicating that trial index is a significant predictor of response time. The model also produced a coefficient of -8.10 indicating that response time decreases by 8.10 ms as trial index increases by 1.

Design Recommendations:

Improvement on the design of the website based on UX design principles was suggested in hopes of improving user engagement and reducing the number of participants leaving the program. The initial design issue of the online program was the burden on the users, as it was very reading intensive. Participants had to read stories about everyday activities that could trigger anxiety. The program consists of several training modules, each typically containing 40 short passages for participants to read and surveys to track any changes in their mental health. The site itself had very little visual stimulation in which to engage the users. Based on these initial issues with the program, we developed several design recommendations to improve the participant online experiences in an effort to improve user adherence to the program.

The first suggestion was to implement gamification, which is described as "the use of game-play mechanics for non-game applications", and which has been shown to improve online learning when integrated into lessons [12]. Several techniques from gamification were suggested to improve the anxiety training program. First, a points system could be implemented into the training stories. Users would receive a point after correctly responding to a question after a training story. Additionally, to increase feedback, we suggested a progress bar that would allow users to see how far they have progressed through the lessons. These suggestions were intended to make the program more fun and engaging so that more participants would be inclined to complete the training.

Another suggestion made for improving the site was to modify the overall website aesthetic. The original program had a basic design that was text-dense and neutral-colored. We believed improving the visual quality of the site could increase the user's desire to continue in the program, an assumption based on research conducted by Kent State University professors that found high website aesthetic treatment produced higher user engagement and credibility for the site itself [13]. Using established design and user experience principles, we created a wireframe proposal of a new web page design. The original and proposed designs for the landing page can be seen in Figure 5.

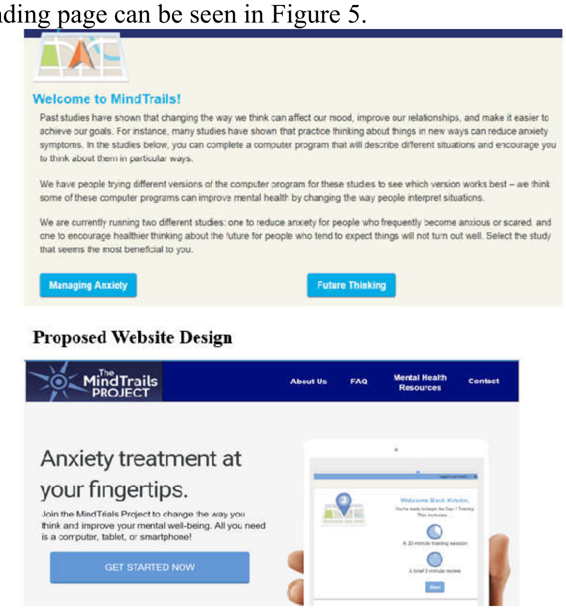

FIGURE 5
ORIGINAL AND PROPOSED WEBSITE DESIGNS FOR THE TREATMENT PROGRAM [5]

Finally, we recommended that images be integrated into each of the training stories. As part of the program, users are directed to visualize each situation presented in a training story vividly, in order to feel how they would in real life. We proposed introducing images that supported the story, which would allow users to have a visual example of the situation and help them more vividly imagine themselves in the situation.

Survey Analysis

To further analyze factors that may contribute to attrition, we looked at two surveys that were conducted: one that collected responses from participants who completed the program, and one that collected responses from participants who dropped out of the program. The first group of participants completed the survey to give feedback on the user experience of the program, whereas the second group completed the survey to indicate their reasons for leaving. Both groups of participants were relatively small, each around 30-40 people. A comparison of the survey responses found the biggest difference between the two groups of participants to be the time spent on each page. Participants who completed the program spent on average 160 seconds on each page while those who dropped out spent 120 seconds on average. Therefore, participants that did not complete the program generally spent less time on each page.

Additionally, users who completed the program also gave a higher score on average to understanding the assessments and treatments, whereas users who left the program were more likely to think the questions were not easy. These values are listed in Table 2, which shows average ratings for each training aspect on a scale of 0 to 5 as assigned by users who completed the survey.

TABLE 2
RESULTS FROM SURVEY DATA

Survey Field	Score	SD	Conclusion
Helpfulness of Treatment	1.38	1.31	Slightly to Somewhat
Easiness to Complete	3.71	0.69	Mostly to Very
Quality of Program	1.21	1.25	Slightly to Somewhat
Improvement of Mood	1.42	1.32	Slightly to Somewhat
Interest in the Program	2.70	0.82	Somewhat to Mostly
Aesthetics of the Website	2.83	1.00	Somewhat to Mostly
Understanding of Assessments	3.46	1.02	Mostly to Very
Understanding of Treatments	3.42	1.06	Mostly to Very
Fear of Privacy	0.58	1.14	Not at all to Slightly
Trustworthiness of Information	3.14	1.12	Mostly to Very
Tiredness from Program	0.88	0.80	Not at all to Slightly
Distraction during Program	1.59	1.22	Slightly to Somewhat
Tech Problems on the Site	0.67	1.31	Not at all to Slightly

Note: SD is standard deviation

The survey results indicate that most users found the program easy to use and understand. Overall, users also trusted the information taught in the lesson. The program showed room for improvement, however, in the user's perception of the quality of the program. Additionally, users did not believe the program greatly improved their mood.

For the most part, correlations between survey fields were as we hypothesized; participants who rated the program positively in one category were more likely to rate it positively in other categories. There were however, some correlations that were not foreseen. For example, participants who both had concerns with privacy and complained of computer problems were more likely to think the treatment was helpful. This was surprising, because having computer problems and privacy concerns could logically be expected to make completion of the program more difficult, and therefore be unrelated to or negatively correlated with helpfulness. Furthermore, users who reported privacy concerns were also more likely to report computer issues, and vice versa. It is possible that experiencing computer issues may make someone more likely to have privacy concerns, and that having privacy concerns makes someone more likely to have computer issues. However, it is also possible that these users represent a subgroup that is more likely to answer survey questions in the affirmative. This is supported by the fact, as discussed previously, that the subgroup of users who reported both computer problems and privacy concerns also gave a greater level of helpfulness, at 2.25 to 1.38. These answers can be normalized in relation to other survey responses, but, with a larger number of responses, the influence of these "high-raters" should not be significant. However, it may indicate that if a user reports issues with one aspect of the program, then he or she is more likely to report issues with other unrelated aspects as well. Previous documentation also suggests that users are more likely to participate in a survey if they had an exceptionally good or bad experience, limiting responses of people with moderate feelings [14].

CONCLUSIONS

After evaluating when participants were most likely to leave the program, we determined that post-session reminders to continue the trainings could be late investigated to reduce attrition, as most people leave the study in the time between sessions. Additionally, more people leave the program between the first two sessions rather than later on, which supports the idea that engaging people early on in the program could help lower the attrition rate. Further research is required to determine if our hypothesis that early engagement and intervention will reduce attrition is accurate.

Based on the demographic analysis of the attrition data, education level has the greatest impact on the likelihood of a participant to stay in the program. In particular, various levels of college degrees appeared to be significant throughout the program. From this finding, we have determined that less educated participants will be more likely to dropout, therefore, several measures should be taken to increase their adherence. For example, measures can be taken to reduce the reading level of sessions and advertisements. Additionally, personalized coaching could be explored as a potential solution for maintaining presence in the program.

Evaluating participants' response times for the three relevant trial types over the duration of each session revealed a negative linear relationship between response time and trial index for all three trial types. The most significant negative relationship between these variables occurred when participants were revealing sentences in training stories, as shown in Figure 3. A linear model of this relationship confirmed the hypothesis that response time decreases as trial index increases, indicating that users are spending less time engaging with tasks as the session progresses. This informs the recommendation that the program adapt shorter sessions to ensure participants are remaining engaged. However, while the initial presumption was that decreasing response time reflects lesser engagement, it should be noted that these results may be indicative of the repetitive nature of the study. As participants repeat the same training process, they may be learning to better answer summary questions and select missing letters more quickly. One limitation of the study is that data is only gathered for participants who have completed an entire session, and not for those who dropout mid-session. In the future, the program will be able to track where a dropout occurs within a session, which will allow further analysis of the optimal number of trials per session to ensure user engagement.

A website redesign was proposed that contains less text and a greater number of images, which assists participants at lower education (and implied reading) levels, who are at a higher risk of dropping out. The aesthetics of the website landing page were also enhanced to create a more engaging invitation to users unsure of starting the program. Finally, gamification redesigns were proposed, such as the use of scoreboards and a point system to track the number of correct answers, as well as the use of a progress bar to track overall progression through the training modules. We predict that the addition of UX design features will reduce the number of participants leaving the program. Future analysis is required after the implementation of new design features to determine if our hypothesized relationship between user engagement and attrition is evident.

The survey results indicated that users who completed the program spent, on average, a longer time on each page than users who did not. Therefore, the team proposes a clock be added to each page to allow users to pace themselves accordingly. Alternatively, the website can prevent users from moving to the next page until a time limit is met. The survey results also indicated that users who completed the program were more likely to state that they understood the assessment and the training. Those who left were less likely to assess the program as easy. Because of this, clear explanations and justifications of training and assessment models should be provided. Finally, there is evidence that some users are more likely to rate categories in the affirmative, regardless of whether these categories are negative or positive. These users' scores could be normalized, but when regarding the data as a whole, are unlikely to be significant.

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