A Mixed-Methods Approach to Exploring Engagement in MoodTech: An Online CBT Intervention for Older Adults with Depression

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Abstract

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In recent years, online cognitive behavioral therapy (CBT) interventions have played an increasing role in treating late-life depression. Previous studies have reported that online CBT interventions can be effective in treating depression and promoting behavioral changes among older participants. However, inadequate engagement could potentially weaken their effectiveness, and the motivations and barriers to participation among older participants in these interventions are less well known. This study aimed to obtain deeper understandings of older participants' engagement patterns and subjective experiences of MoodTech, an online CBT intervention tailored for older adults with depression. I employed three different methods to analyze diverse forms of data produced during the intervention. There were three aims. First, I characterized the engagement of participants through visual analysis of log data. I visualized the frequencies of their online activities and skills practices, then identified patterns in each measure of engagement. A meta-pattern graph was created to facilitate identification of groups of individuals who shared similar patterns across engagement measures. Second, I conducted a network analysis of the participants who had access to the peer interaction features and compared engagement behaviors in three kinds of peer interaction networks (comments, likes and nudges). Third, I performed a qualitative analysis of the textual data, including messages, posts, comments and thought records of the participants. Using a qualitative analytic method based on Grounded Theory, I examined the application of CBT and how participants responded to CBT and engaged with the intervention. I also explored potential explanations for the observed behaviors in individual and network engagement patterns. With regard to the results, for the first aim, I observed great diversity, but also similarities, in patterns of engagement among participants. For the second aim, I found that the networks of nudges were less dense than the comments and likes networks and there were fewer people involved, which may show that older people attached importance to the actual contents of interactions. Last, I found evidence from the qualitative analysis that many participants learned CBT strategies and practiced them to understand why they were having sustained feelings of depression and low productivity. Some even successfully broke harmful cognitive or behavioral patterns. But other older adults encountered obstacles due to shortcomings in the website design or were reluctant to practice the CBT strategies because of previous unsuccessful experiences with CBT. Overall, engagement behaviors of older adults in online CBT interventions are hard to predict, but can potentially be influenced by technology use habits, contents of social interactions, and previous psychotherapy experiences. Future intervention design may take these findings into consideration and adjust lesson contents for different subgroups of participants, as well as improve the usability of the

intervention to meet the needs of older adults. The methodology of this study also shows that combining multiple methods is feasible and provides a richer characterization of engagement from different perspectives.

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Section 1 Introduction

It has increasingly become part of public awareness that depression in late life diminishes older people's life quality (Kok & Reynolds, 2017). Meanwhile, Internet-delivered cognitive behavioral therapy (CBT) could be an effective alternative for older adults who are reluctant to receive traditional psychological therapies (Dear et al., 2013). However, like most online programs, inadequate engagement will weaken the effectiveness of the CBT intervention (Donkin et al., 2011); thus, various strategies have been adapted to better engage the participants. In this study, I perform secondary analysis of data from MoodTech, an online CBT intervention designed for older adults with depression, in which both professional support and peer support were implemented to assist participants, and positive outcomes were achieved with either form of support (Tomasino et al., 2017). The pilot study provided rich data capturing users' online behaviors and cognitive processes, and these data could help characterize multiple forms of engagement among the participants and clarify reasons for varying engagement across participants.

This introduction section provides background information related to the current study. First, I will introduce the potential advantages of online depression interventions for older adults and the CBT principles that are widely used in those interventions. Then, I will review previous literature that examined engagement in online CBT interventions, and the different methods that were used in these studies. Based on this knowledge I identified the gap in the knowledge of older adults' subjective experiences using these interventions, which inspired my research interests. Last, I will describe the pilot study of MoodTech that provided the original data for this current study and propose my specific research questions.

1.1 Depression in Older Adults and Corresponding Online Interventions

Depression in later life (traditionally defined as age over 65 years) has become an increasingly prevalent health and social problem in many countries around the world (Kok & Reynolds, 2017; Laborde-Lahoz et al., 2015; Lu et al., 2016; Rodda, Walker, & Carter, 2011). Depression is usually associated with increased risk of suicide, functional impairment and disability, and poor quality of daily life (Rowser, 2010). Compared to a younger population, older people with depression are more likely to commit suicide, and the chance of survival and prognosis are also worse (Manthorpe & Iliffe, 2010). Moreover, common health problems like chronic diseases, dementia, stroke and Parkinson's disease can also complicate the acknowledgment and diagnosis of depression (Colasanti, Marianetti, Micacchi, Amabile, & Mina, 2010). People will easily mistake poor concentration or low energy as natural parts of the aging process, leaving depression undiagnosed and untreated (CDC, 2017). Although there is evidence showing that psychological therapy and drug treatment are as effective in older as in younger adults with depression (Cuijpers, Straten, Smit, & Andersson, 2009; Rodda et al., 2011), older adults are more likely to avoid or prematurely stop treatment, due to various reasons such as limited knowledge, negative beliefs about mental illness, and fear of stigma from society's prejudices (McKinnon, Conner, Roker, Ward, & Brown, 2017; Sirey et al., 2001).

Cognitive behavior therapy (CBT), as one of the most effective therapy choices to treat depression and anxiety, has been successfully translated into the Internet world (Andrews, Cuijpers, Craske, McEvoy, & Titov, 2010; Earley, Joyce, McElvaney, Richards, & Timulak, 2017; Richards & Richardson, 2012). For older adults, receiving treatment through the Internet can reduce access barriers such as transportation difficulties, a shortage of local providers, financial burdens, privacy concerns and stigma associated with revealing mental illness publicly

(Brenes, Danhauer, Lyles, Hogan, & Miller, 2015; Crabb et al., 2012). With the increasing rate of computer and smartphone use among the older population, online CBT interventions are gradually becoming an effective and acceptable alternative in late-life depression management and treatment (Choi, Kong, & Jung, 2012; Dear et al., 2013; Mewton, Sachdev, & Andrews, 2013).

1.2 Principles of Cognitive Behavioral Therapy (CBT)

One of the central ideas of CBT is that thoughts, feelings and behaviors are all linked; therefore changing one impacts the others (Greenberger & Padesky, 1995). When people feel depressed, they experience changes in what they do (behaviors) and how they think (cognitions). Often, depressive feelings lead to a lack of motivation and negative thinking patterns. On the other hand, behaviors can also impact one's thoughts and feelings: accomplishing tasks or engaging in pleasant events can boost mood and encourage positive thinking. Similarly, cognitive processes are closely related to emotions and behaviors, thus negative thoughts will aggravate depressed feelings and interfere with ordinary work and interpersonal communication. Based on these principles, CBT interventions teach individuals to practice various strategies including behavioral activation and cognitive restructuring, to improve depressive symptoms (Hawley et al., 2017).

Behavioral activation (BA) helps participants to recognize internal or external triggers that result in negative emotional responses, promotes awareness that avoidance behaviors are ineffective coping responses, and guides people to plan and do activities that could lead to mood improvement. Depressed individuals are often trapped in a Trigger-Response-Avoidance-Pattern (TRAP) that happens repeatedly, which in the short-term helps to escape from the uncomfortable feelings but in the long run leads to increased symptoms (Carlbring et al., 2013; Hopko, Lejuez, Ruggiero, & Eifert, 2003). BA aims to break this harmful cycle by reengaging the participants with active coping strategies and healthy behaviors. Participants are taught to assess their own behavior and identify the TRAP, then consider whether they will continue escaping or instead plan activities that solve the real problem and improve their mood. To facilitate the positive actions, additional treatment options include rating the pleasure of activities and planning activities that increase mastery and pleasure, mindfulness training or relaxation exercises, self-reinforcement and so on (Martell, Addis, & Jacobson, 2001).

Learning cognitive restructuring (CR) strategies involves evaluating and challenging harmful thoughts. Participants are encouraged to use thought records to examine the evidence for or against their negative thoughts and generate more balanced ways of thinking (Hawley et al., 2017). There are various patterns that can distort thinking, such as thinking in extremes, seeing only the things that confirm the negative view or jumping to negative conclusions. By identifying these patterns and challenging them with alternative thoughts that are objective and encouraging, CR is helpful to change emotions and stimulate positive behaviors.

In the setting of online CBT interventions, BA and CR are widely incorporated into different tools, and the overall outcome of the interventions has been proven to be effective (Andersson et al., 2005; Hawley et al., 2017; Richards & Richardson, 2012). However, interventions often involve many different features and contents, and the clinical trials evaluating these CBT interventions have generally used numeric scales to assess symptom changes or engagement behaviors (Carlbring et al., 2013; Hawley, Rector, & Laposa, 2016; Richards & Richardson, 2012). Additionally, as little qualitative data has been collected or presented in prior trials of online CBT interventions, it has been difficult to determine which features or lessons have contributed to positive outcomes or examine changes in participants' cognition or behavior.

1.3 Investigation of Engagement and User Experience in Online Interventions

A significant shortcoming of online interventions is high attrition and low engagement, especially in self-help applications (Eysenbach, 2005). Participants may fail to begin the intervention after registration, quit the intervention prematurely against recommendations, or spend an inadequate amount of time accessing the online materials. It is commonly believed that sufficient participation in the program contributes significantly to the positive outcomes, yet low adherence to the therapy can be a major concern associated with reduced efficacy (Coon & Thompson, 2003; Donkin et al., 2011; Hilvert-Bruce, Rossouw, Wong, Sunderland, & Andrews, 2012). Most online CBT interventions require a certain extent of exposure to the intervention content, such as reading assignments, diary or homework tasks, to achieve the anticipated effectiveness (Hawley et al., 2017). However, it is hard to keep participants motivated throughout the intervention, especially when they only pay minimal or no cost to the service, and when the program fails to meet the special needs of the users (Christensen, Griffiths, & Farrer, 2009).

Older adults, who have relatively inadequate health literacy and computer skills compared to younger population, as well as possible visual impairment, may be more likely to encounter frustration and difficulties when using online CBT to treat depression by themselves (Crabb et al., 2012). Support from external resources could be beneficial to keep the participants engaged with the program. The most common solution to addressing low engagement has been to deliver online interventions with therapist support (also referred as coaching), but the amount of time spent per participant, frequency of contact, and media used for communication between therapist and participant vary considerably (Alfonsson, Olsson, Linderman, Winnerhed, & Hursti, 2016). Three major formats of guidance can be used to promote engagement in online interventions, including administrative guidance (providing technical support and push notifications), adherence-focused guidance (reminding participants to use the program by emails or telephone) and content-focused guidance (sending personalized written feedback) (Zarski et al., 2016). Other studies have also shown that compared to self-guided online programs, interventions that involve high quality and frequent contact with professionals are more likely to attain higher engagement and better outcomes (Alfonsson, 2016; Carlbring et al., 2007; Hilvert-Bruce et al., 2012).

Nevertheless, the inclusion of therapist guidance and personalized feedback requires resources and may consequently limit the generalizability and availability of treatment (Gershkovich, Herbert, Forman, Schumacher, & Fischer, 2017). In consideration of this, researchers are searching for alternative ways to maintain engagement. Evidence has shown that adding collaborative peer support can produce clinical benefits and potentially reduce the input required from therapists (Lattie et al., 2017; Nelson, Abraham, Walters, Pfeiffer, & Valenstein, 2014; Pfeiffer, Heisler, Piette, Rogers, & Valenstein, 2011). Additionally, collaborative peer support could enhance feelings of connectedness with others, which could have a positive effect on individuals with depressive symptoms (Cruwys et al., 2014). Seeing the popularity of online social network and support communities, interventions that feature peer support as a supplement to a modest amount of therapist support may be able to maintain engagement and potentially contribute to better outcomes.

Still, even with external supports, the participants may encounter other barriers that keep them from fully utilizing the online program. From a human-computer interaction (HCI) perspective, engagement can be defined as “a quality of user experience with technology” (O’Brien & Toms, 2008). In other words, engagement is an important aspect of user experience and should be examined from the perspective of the participants. Intervention contents and external supports can influence engagement by raising interest and stimulating interactions of the participants. Moreover, the usability variables that are commonly studied in user experience research, such as aesthetics, novelty, functionality, appropriate challenge and feedback, are also factors that can attract users' attention and motivate user engagement (O'Brien, 2010).

From reviewing the literature, I noticed that previous studies of engagement in online interventions, engagement was often studied in a cohort of users as a collective measurement. For example, a group of researchers regarded engagement as the opposite of attrition and depicted engagement by the number of users who completed a given number of sessions (Doherty, Coyle, & Sharry, 2012). As for the measurement of engagement, according to a methodology review, engagement is usually viewed as a combination of participant exposure and skill practice (Danaher & Seeley, 2009). Visit frequencies, webpage views and online durations are common measurements of participant exposure, while skill practice can be assessed by the completion of tasks or record of diaries. But in practice, researchers usually employ one of the two types. Many studies have used participant exposure to represent engagement, using the frequencies and durations of visits or numbers of page accesses during the intervention (Brouwer et al., 2011; Danaher, Boles, Akers, Gordon, & Severson, 2006; Glasgow et al., 2011; Strecher et al., 2008). Other studies have defined engagement as the completion of homework tasks or practicing of skills (Alfonsson et al., 2016; Coon & Thompson, 2003).

I have found limited precedent that considered the different forms of engagement in the context of intervention features, especially investigating engagement in peer interactions. Rather, many studies have tried to identify predictors of engagement including demographics (gender, age, education level, immigration background), symptom-related factors (stress, depression, emotional exhaustion), intervention design and usability factors (delivery mode, interface design, guidance and support), and variables concerning beliefs and attitudes of the participant, but the results are either conflicting or not significant (Kaltenthaler et al., 2008; Stein-Shvachman, Karpas, & Werner, 2013; Zarski et al., 2016). Most of these studies used scaled questionnaires and performed statistical analyses, but the subtle reasons that were hidden in users' specific experiences remained untouched. Particularly, for those participants who dropped out early and did not complete questionnaires, reasons for dropout were not formally examined (Christensen et al., 2009). There have been a few systematic reviews of several qualitative studies pertaining to user experience, acceptability, accessibility and adverse effects in computerized CBT interventions for depression, yet there has been little examination of the experiences of special patient groups such as older people, black and minority ethnic groups, and also insufficient understanding of their special needs (Knowles et al., 2014; Waller & Gilbody, 2009).

To conclude, online CBT programs incorporate multiple features to maintain a certain level of user engagement and the data from their usage affords a great opportunity to study user experiences from different kinds of data. Previous studies have mainly conducted statistical analysis using quantitative data; yet I believe it is important to incorporate qualitative analysis and other methodologies to better understand individual engagement and examine reasons for participants' behaviors. Particularly for groups of older users who have not been traditionally well represented in studies of online CBT interventions (Crabb et al., 2012), it is worthwhile to examine their subjective experiences, which served as a major motivation behind the current study.

1.4 Introduction of MoodTech

The data used in the current study came from a pilot study of an online CBT intervention MoodTech, which was designed to treat depression in adults who are 65 years and older (Tomasino et al., 2017). It was built on the ThinkFeelDo platform and could be accessed via computers, tablets, and mobile phones (Schueller & Mohr, 2015). The study investigated the clinical outcomes and acceptability of two forms of delivery: an individual internet intervention (III) and an internet intervention with peer support (II+PS). All the participants were exposed to the same basic therapy lessons and tools that focus on strategies of BA and CR, while the participants in II+PS form also had access to the peer support and associated features (activity feeds, status posts, comments, likes, and nudges). Participants in both forms had access to a coach (who could be one of two clinicians who supported the intervention), but while participants in the III form were contacted weekly by their coach, individuals in the II+PS form were only contacted upon request or when login reminders were needed.

The results showed positive changes in self-reported depression and anxiety scales in both III and II+PS delivery forms when compared to the wait list control (WLC), and significantly less coach time was required for those who received extra peer support (Tomasino et al., 2017). The results suggested that it was feasible to use peer support as a mechanism to reduce the input of the coach and produce comparable outcomes in online CBT depression interventions. This pilot study was innovative in terms of the integration of peer support in an Internet-delivered CBT intervention aimed specifically at older adults. There have not been many precedents that involved peer support in this target population, and the association between the social interaction features and the intervention effect has not been adequately studied (Elaheebocus, Weal, Morrison, & Yardley, 2018). The comparison between the two delivery forms showed that features that involve social interactions may be appealing options to increase the cost-effectiveness of interventions targeting depression.

Tomasino et al.'s study mainly used quantitative data including self-reported scales for depression, anxiety, social isolation, social support and usability. The comparison of input and outcomes was conducted between groups, and the conclusions were drawn for whole groups of participants. Similar to many previous clinical trials, evidence relating to individual experiences was not reported, but data that could provide additional insight into participant experiences was collected. For example, the log data of the website captured details of the participants’ use behaviors, and the textual data generated by participants mirrored their cognitional and emotional changes. I believed that I could analyze this data to better understand participants’ engagement patterns, social interactions, complaints and praises towards the intervention, and their practice of the CBT strategies. More specifically, observing user experiences from log data and textual data can provide a different view from the self-reported questionnaire or scales collected after the intervention period. As stated before, previous studies have reported that older adults with mental and physical co-morbidities are traditionally underrepresented in online CBT interventions, and the user experiences of diverse subgroups has not been qualitatively studied (Crabb et al., 2012; Knowles et al., 2014). Therefore, exploring individual engagement behaviors with data collected in MoodTech can help me understand the unique experiences of older adults, identify potential subgroups among participants, and learn lessons for future design of online CBT interventions tailored for older populations with depression.

Based on the available data and my research interests, I identified multiple methods to obtain new insights from the intervention and viewed engagement in complementary angles. The details of methodology will be introduced in the Methods section, and the aims of the study were to:

1. Characterize participants' online behaviors using visual analysis of log data and identify patterns of engagement that were shared among participants.
2. Conduct a network analysis of the social interactions of participants who received peer support to explore the differences of engagement in group environments.
3. Perform a qualitative analysis of textual data to examine the application of CBT principles and to explore how participants responded to the CBT and engaged with the intervention.

Section 2 Methods

In this study, I employed three different methods (visual analysis, social network analysis and qualitative analysis) to understand engagement in MoodTech. In this section I will introduce the dataset, review previous literature on each method, and describe the procedures that I used for each aim.

2.1 Dataset and Variables

2.1.1 Background

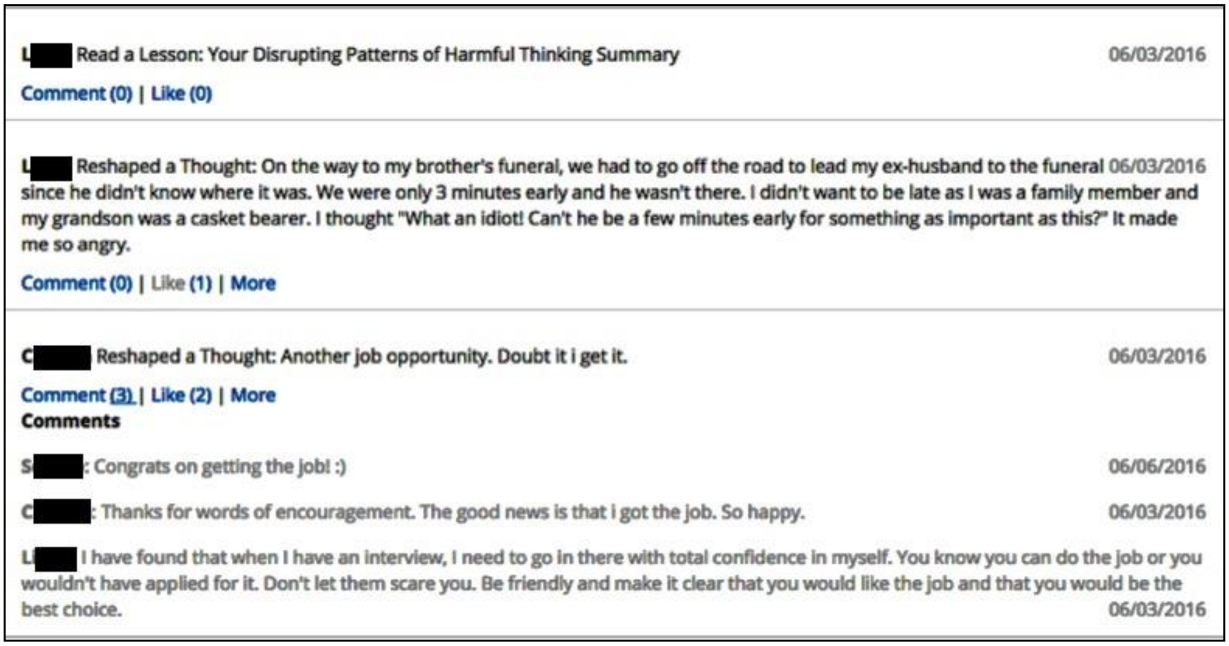
The data was collected during a pilot study of an online CBT intervention targeting depression in adults 65 years and older (Tomasino et al., 2017). Participants were recruited from clinical research registries, online and community advertisements, and clinic referral, and were screened to meet the criteria for depression level and the ability to use technology. Those who were receiving or planning to receive psychotherapy were excluded, as well as others with psychotic disorder or cognitive impairment. As a result, 47 participants were enrolled and were assigned to 3 different groups: an individual internet intervention group (III, n=12), an internet intervention with peer support group (II+PS, n=23) and a waitlist control group (WLC, n=12). The II+PS group included two cohorts in order to “provide additional experience with this novel intervention component” (Tomasino et al., 2017, p. 4). One cohort (n=11) began the intervention in February of 2016, and the other cohort (n=12) began in April. The two cohorts did not overlap in their usage of the program. After the 8-week waiting period, the WLC group also received the same individually delivered intervention as the III group. One participant in the III group and another one in the WLC group did not use the online intervention; therefore, the dataset includes 45 participants. Self-reported assessments were completed before the intervention and during the last week via REDCap, an electronic data capture tool (Harris et al., 2009).

The intervention lasted 8 weeks and 2 lessons were provided each week, including didactic content and tasks to practice. The lessons focused on introducing the concepts and coping strategies from behavioral activation (BA) and cognitive restructuring (CR). Tools are provided to facilitate the consolidation of the theory and the practice of the core skills: 1) cognitive restructuring; 2) mood and emotion monitoring; 3) behavioral activation; 4) relaxation and mindfulness; and 5) goal setting. Peer support features, which only the II+PS group had access to, included personal profiles, an "activity feed" that showed other people's activity and posts, "comment" and "like" on the activity feed, and a "nudge" feature which sent an automated notification to the recipient (Figure 1). The two coaches used a dashboard to view the progress of each participant and provide individual coaching via phone calls or private messages. Additionally, for II+PS, coaches interacted with the participants using the social features and monitored the activity feeds.

Clinical outcomes were assessed, and usability feedback collected, using self-report questionnaires. Coaches tracked all time spent on phone and message communications. The results reported showed that III and II+PS delivery had equivalent effects in reducing depressive symptoms, but the group that received II+PS required less coach time (Tomasino et al., 2017).

I now proceed to describe the data variables that I have extracted from the original dataset. There were two types of data: log data and textual data. All the data was de-identified before the study started, and the variables were extracted, cleaned up and summarized for analyses. The names and explanations of the variables will be described here, while descriptive statistics for the dataset will be presented in the Result section.

Figure 1 - Snapshot of the "Activity Feed"



2.1.2 Log Data

Log data captured participants' online actions and served as a major quantitative information source to indicate engagement. Below I list the variables that I extracted and categorized from the original dataset and provide brief explanations. The last two variables marked with asterisks only existed for the II+PS group.

- *Login*: logins during the intervention
- *Online event*: actions taken by participants, categorized into three types: "click weblinks", "render contents" (activities like writing messages, practicing skills that requires textual input or sharing status posts) or "watch videos"
- *Task completion*: record of what task was completed at what date, such as planning activities, positive coping for anger and irritability or identifying harmful thoughts.

- *Tool access*: log of visits to different tools, categorized into “navigation and help”, “behavioral activation”, “cognitive restructuring”, “emotion tracking”, “relaxation exercise” and “summary”
- *Visit duration*: duration of visit (minutes)
- *Like**: likes sent out by the participants or coaches
- *Nudge**: nudges sent out by the participants or coaches

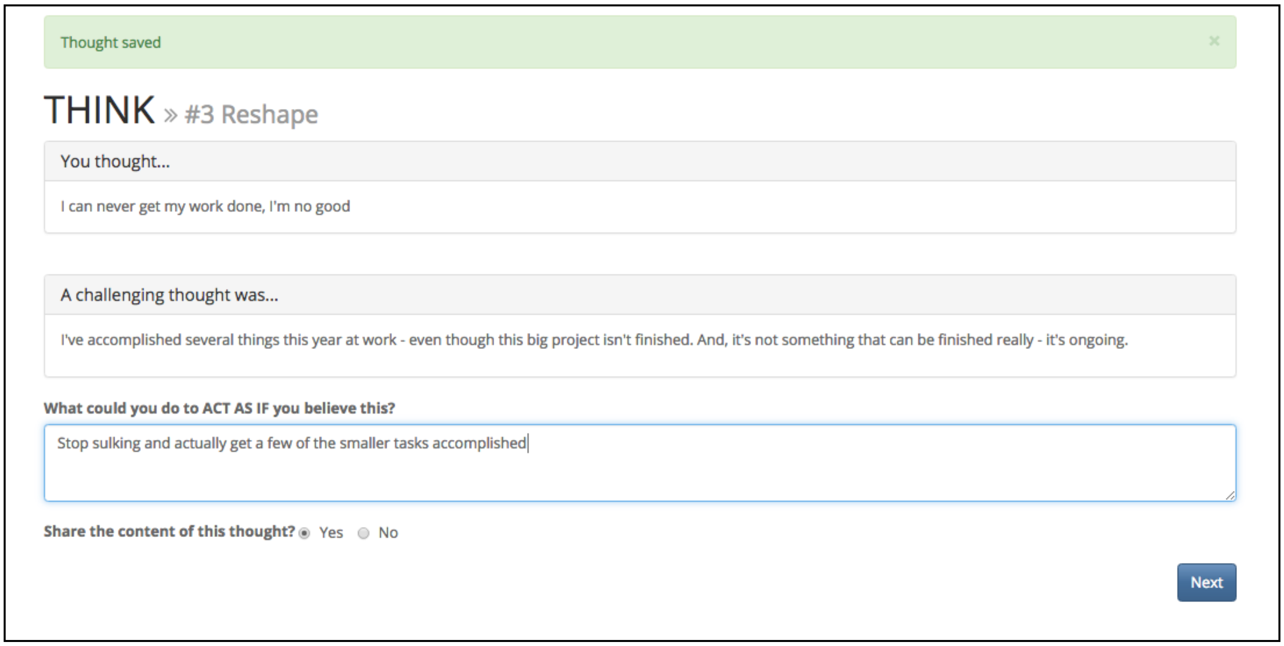
2.1.3 Textual Data

The dataset also included textual content authored by participants during practicing the skills or interacting with peers. There were four different sources of textual data that was comprised of sentences or paragraphs and was used in my analysis. Short phrases from planning activities or setting goals were not included. The last two marked with asterisks only existed in the II+PS group.

- *Messages*: Private messages sent by the participant to the coach. The coaches’ replies were not included in the analyses because I was focusing on the experiences of the participants.
- *Thought records*: Records of the user practicing cognitive restructuring using online tools. There were three steps in the practice: identify harmful a thought, come up with a challenging thought, and think about what action could be taken if the challenging thought were believed. Figure 2 shows a snapshot of the cognitive restructuring practice. The three steps are considered a complete process of cognitive restructuring, but some participants might not have completed all three steps, especially if they had difficulties coming up with a challenging thought or positive action.

- *Status posts**: These are the contents the participants and coaches in the II+PS group shared in the "activity feed" (Figure 1). System messages such as lesson progress or profile updates were not included in the analysis.
- *Comments**: Comments sent by the participants and coaches to others' status posts. Figure 1 shows several status posts with comments and likes. The system treated all comments as responses to the original posts even though the participants were having a conversation.

Figure 2 - Snapshot of "Cognitive Restructuring"



2.2 Visual Analysis of Log Data

The first aim of the study was to use log data to characterize individual online behaviors and identify engagement patterns that participants shared. As described previously, there were multiple variables in the log data and each variable could be considered a different type of engagement. It was important to choose a method that could be used with these multiple measures of engagement to form a comprehensive understanding. In this current study, I used a visual analysis approach to compare and cluster participants' online usage patterns. In the following subsection, I will review methods that have been used to characterize engagement in previous research and explain why I chose visual analysis. Then, I will describe the analysis procedure used in this study.

2.2.1 Literature Review

Engagement is a complex concept and includes many aspects of user behavior in the context of online interventions. The measures used to depict engagement have varied in previous studies, as well as the methods used to investigate them. I reviewed the literature on characterizing engagement in online behavioral interventions and compared the methods.

As introduced previously, there have been different definitions and measurements of engagement in online interventions. Moreover, researchers have also employed different approaches to characterize and investigate engagement. I found three general approaches. The first and most commonly used approach involves using statistical methods such as correlational or regression analyses to establish associations between engagement and various predictors. Those predictors, as mentioned in the Introduction section (subsection 1.3), include demographic, personality, disease symptom or intervention design factors (Christensen et al., 2009). The second approach involves qualitative analysis of data collected from post-study questionnaires and examines participants' perceptions of the intervention. The results were often focused on acceptability, barriers and adverse effects (Earley et al., 2017; Waller & Gilbody, 2009).

The third approach employs visualizations to examine engagement and use patterns. For instance, Castro and colleagues created an engagement trajectory using black and grey colors to represent whether the participants answer the question or not, as shown in Figure 20 in the Appendix (Castro, Haug, Filler, Kowatsch, & Schaub, 2017). Morrison and Doherty developed a Navigation Graph to depict an individual's temporal process of interaction with the program (Figure 21 in the Appendix), and then used the visualization to compare patterns of use (Morrison & Doherty, 2014). The vertical axis in the figure is the sequence of modules, while the horizontal axis represents a time sequence. They found four patterns of use trajectories through this Navigation graph (Figure 22 in the Appendix). If frequency of actions is plotted on the vertical axis and time sequence on the horizontal axis, it can be used to compare the density of activities over a period of time, as in the example in Figure 23 (Lehmann, Lalmas, Yom-Tov, & Dupret, 2012).

2.2.2 Rationale for Conducting Visual Analysis

The three different approaches previously described are appropriate in their respective study contexts, and each has its own limitations. Similarly, I should choose methods that are most suitable for the analysis of log data in MoodTech.

The rich data from MoodTech offers us an opportunity to gain rich understanding of the user experience, but the possibility of information overload could eventually lead to improper interpretation of the data (Caban & Gotz, 2015). It is hardly possible to synthesize multiple variables into a single measurement as "engagement", but it is also hard to examine or compare multiple variables using statistical methods. Also, the sample size of this intervention limits the possibility to make accurate statistical inferences from correlational or regression analyses.

I chose to use visual analysis to characterize individuals' engagement patterns for several reasons. First, it is possible employ visualizations to capture the temporal change of engagement and explore the relationship between engagement and course design of the intervention

(Morrison & Doherty, 2014). Second, visual analysis is especially useful in searching for patterns in complicated human experiences (Gotz, Wang, & Perer, 2014; Leeuwen & Jewitt, 2001). Third, there were multiple variables in the log data, and each reflected a different aspect of participants' engagement. Visualizations can combine multiple variables of multiple participants and present them in an brief and readable way, allowing me to directly interact with the data and draw conclusions (Bernatavičienė, Dzemyda, Kurasova, Marcinkevičius, & Medvedev, 2007).

2.2.3 Study Procedures

Based on the discussion above, I decided to examine multiple aspects of engagement using visual analysis. There were two categories of measures of individual engagement: participant exposure and skill practice (Table 1). These were further subdivided into five measures of engagement. I employed different visualizations for the different measures.

Table 1 – Variables and Measures of Engagement

Category	**Variable**	**Measure**	**Description**	**Visualization**
Participant Exposure	Login	Login	Counts of logins per day	Histogram
	Online event	Clicking	Counts of online actions per day, categorized into three types: clicking a weblink, rendering contents and watching videos	
		Rendering contents		
		Watching videos		
Skill practice	Tool access	Tool access	Numbers of accesses to the different tool pages, categorized into "navigation and help", "behavioral activation", "cognitive restructuring", "emotion tracking", "relaxation exercises" and "summary"	Scatter plot

I used R statistical software to render visualizations and sort them into patterns, with the help of the ggplot2 package. For participant exposure, I employed histograms to demonstrate the frequencies of activities and used the number of days since the participant started the intervention on the x-axis. The histograms were colored to separate the activities in every week and later were used to compare the trends of usage. For histograms, I only plotted the activities that happened during the 8-week intervention, therefore the activities before the intervention started or after the intervention ended were not included in the analysis.

For skill practice, which was represented by access to online tools, the scatter plots were used to analyze the usage sequence of different tools comparing to the lesson content sequence. The x-axis represented the date when the access happened. The vertical order of the categories was in alphabetical order. If participants did not have an action in one of the categories, that category would not appear in their graph.

I examined the visualizations to identify a set of common engagement patterns. A meta-pattern graph, modeled based on heatmaps, was created to compare the patterns of engagement that all the individuals demonstrated. Heatmaps are tools that includes multiple dimensions, which can be used to display data matrices and search for patterns (Kelleher & Wagener, 2011). Examples of the uses of heatmaps include the presentation of the spatial distribution of user behaviors on geographical maps, or visualization of software application usage using eye tracking data (Chae et al., 2014; Matejka, Grossman, & Fitzmaurice, 2013). In biological studies, heatmaps are commonly used to present gene expression data, and can be used to search for patches of color that may indicate functional relationships (Wilkinson & Friendly, 2009). An example of a heatmap is shown in Figure 24 in the Appendix.

In this study, I employed a heatmap-inspired meta-pattern graph to present the engagement patterns of all the participants and identify meta-patterns. I represented a single participant using a sequence of cells in a row, with each cell depicting an engagement pattern exhibited by that participant. The colors represented different patterns for the measures and I manually sorted the rows to group those who have similar color distributions and search for general meta-patterns.

2.3 Social Network Analysis in II+PS Cohorts

The second aim of the study used social network analysis to examine the social interactions in the II+PS delivery group. While the visual analysis for aim 1 focused on individual engagement behaviors, social network analysis focused on interaction patterns of participants who were in the same cohort of the intervention. There were two cohorts in the II+PS delivery group, and the social interactions within each cohort formed a small networking environment and potentially influenced the ways that people engaged with the CBT intervention. There have been studies showing that peer networking could improve adherence in online behavioral interventions among adolescents (Ho et al., 2016), but the question of whether it has a similar effect in older adults' engagement or not remains unclear. In this subsection, I will review basic concepts in social network analysis and describe the analysis process in the current study.

Social network analysis is commonly used for investigating online communities in social science (Borgatti, Mehra, Brass, & Labianca, 2009; Pfeil & Zaphiris, 2009). It can be used to study relationships between members of the network and how these relationships affect the people who are part of the network (Laat, Lally, Lipponen, & Simons, 2007). Density and centrality are common properties used in social network analysis. Density provides a measure of the overall connections (edges) between the nodes and is defined as the number of actual edges divided by the maximum number of possible edges (Scott & Carrington, 2011). Centrality is related to the behavior and importance of a member in the network, and has different types such as degree centrality, closeness centrality and betweenness centrality (Hanneman & Riddle, 2005). Degree centrality represents how many connections an actor has: in-degree and out-degree are differed in the direction of connections. Closeness centrality emphasizes the distance of an actor to all others, and betweenness centrality "captures the property of frequently lying along the shortest paths between pairs of nodes" (Freeman, 1977). Nodes with high betweenness centrality are likely to be more important and influential in the network because they are the bridges connecting nodes that could have no other ways to interact.

In health-related online communities, social network analysis is often used to study the categories of support, communication content, or the structures of the network (Chang, 2009; Goggins, Galyen, & Laffey, 2010; Pfeil & Zaphiris, 2009; Zhang & Yang, 2015), but few have considered user experiences or engagement as the research object. Also, there were only a few previous studies using network analysis on subject of older adults with depression. As an example, a group of researchers studied the communication of depressed older adults in online communities and found that empathic communication connected members better than factual communication in a social network (Pfeil & Zaphiris, 2009). In MoodTech, older adults interacted with peers and coaches, and I regarded social interactions as another form of engagement apart from participant exposure and skill practice. Thus, I believe the characteristics of the networks and the different behaviors of older adults among networks are worth investigation and can be used to improve intervention design.

I used social network analysis to study the three types of social interactions: commenting, liking and nudging. Networks were rendered separately for each of the two cohorts in the II+PS arm. The visualization of the networks can illustrate the extent to which participants were involved in each type of interaction, who the active participants were, as well as who participated only peripherally. The differences between the networks were also examined by calculating the density and degree centrality. I used the *Gephi* software (version 0.9.2) to render the visualizations and calculate the statistics (Bastian, Heymann, & Jacomy, 2009). The nodes were defined as the participants and coaches, and the size of the nodes was based on the number of social actions a participant took of the given type (out-degree centrality). The directions of the edges followed the direction of the actions, and the edge weight was determined by the number of times an interaction happened. For example, one comment action produces an edge that started from the sender to the receiver of the comment, and four comments from the same person to the same receiver would create an edge with a weight of four. I chose the Force-Atlas layout, in which linked nodes are attracted to each other and non-linked nodes repel each other (Bastian et al., 2009; Valdez et al., 2012). I then adjusted the repulsion strength and attraction strength to have a clear distribution of the nodes. Different color themes were used for three social interaction types.

2.4 Qualitative Analysis of Textual Data

The last aim of this study was to investigate the qualitative evidence to contextualize the experiences of participants in MoodTech. I examined the application of CBT principles in the program and the success or failure of those principles based on qualitative evidence. As mentioned in the Introduction section, older adults are relatively underrepresented in studies of online CBT interventions, and they may experience various difficulties during these interventions due to age-related health problems and other barriers. Given the small sample size of the participants and the rich qualitative data types in MoodTech, I used a qualitative approach based on grounded theory and developed a coding structure relating to CBT principles in order to examine the application of them. In this subsection, I will review previous literature on qualitative research and grounded theory methods, and introduce the specific methods used in this study.

Qualitative researchers focus on the unique “lived experience” of individuals (Charmaz & McMullen, 2011), and qualitative methods can be used to understand how people make sense of things that happen to them and how they view the world. As such, qualitative methods can be useful to understand the experience of users in the field of mental health interventions. In the context of CBT, what matters most is what participants think and feel, because thoughts and emotions will impact what actions they take and in turn affect their emotion. Extraction and interpretation of what participants have written and expressed are important and useful processes for examining the user experience. For example, it helps to understand the in-depth motivations or barriers related to their engagement, reflections or attitude towards the intervention, and the effect of practicing the CBT coping strategies. Successful mastery of CBT strategies could not only produce positive clinical outcomes, but also affect participants’ cognitive and behavioral processes, which are related to engagement as well. Therefore, one of the objectives of this qualitative analysis was to examine the application of CBT principles in MoodTech. In addition, I also used qualitative evidence to contextualize the patterns and characteristics observed in the previous aims.

The Grounded Theory Method is a widely used qualitative research method in a wide range of disciplines. It requires systematic and inductive inquiry into the data and constantly involves the researchers themselves in the process through theoretical sampling, coding, memo writing, and constant comparison, which can eventually lead to the formation of a theory that accounts for the observed behaviors (Bryant & Charmaz, 2007). The fragmental materials in the current study were highly heterogeneous in length, topics and styles; yet all could potentially reflect the individual's psychological status and behavioral patterns. I believed it was suitable to conduct an approach that was based on the Grounded Theory Method to explore participants' experiences of CBT, examine whether the CBT was helping them or not, and what motivated or discouraged their engagement in the program.

ThinkFeelDo, the website platform used for the MoodTech intervention, contained lessons that taught the basic principles from CBT. Participants practiced the skills and wrote about their achievements or confusions in website pages, messages or posts. These were the sources of textual data I used in the qualitative analysis, including messages, thoughts, posts, and comments that were composed by the participant. I also used coaches' notes and messages as additional references if clarification was needed. Except for the messages, most of the textual data tended to be several sentences long, while messages were similar to emails in that they could be over a hundred or several hundreds of words but could also be very short and brief. To analyze the textual data, I created one document for each individual, comprised of all the data produced by the individual during the intervention, and imported it into ATLAS.ti, a qualitative data analysis software (Hwang, 2008). For participants who received the III intervention, the texts only included messages and notes; for the II+PS group, all four types of textual materials were included.

I applied employed qualitative methods to identify themes in the data. One of the important principles of Grounded Theory Method is making use of the Constant Comparative

Method, which requires that each new finding and interpretation should be compared with existing ones (Bryant & Charmaz, 2007; Corbin & Strauss, 1990). In the coding process, I started by coding the text line-by-line, creating codes on quotations that refer to the thoughts, feelings or behaviors of the participants during the intervention, since according to the CBT principles, they were closely related and interacting with one another. New codes in a single document for one individual were compared with the existing ones in other documents for other individuals. Eventually, codes that pertain to the same aspects were grouped into categories. Although each participant's experience was unique in the context, the codes and categories were unified under a single standard through constant comparison. After iteratively reviewing all the documents, all the documents were conceptualized under a consistent system of codes and categories. I kept a log trial and wrote memos to ensure consistency and rigor during the coding process. In this process, I noticed several themes from the final categories and also discovered evidence to contextualize the engagement patterns and explore user experiences under the CBT framework.

Section 3 Results

3.1 Descriptive Statistics

3.1.1 Log Data

I calculated the means and deviations of the variables of interest in the three delivery groups. Table 2 shows the summary of log data in three groups. The last two variables in the table only existed to the II+PS group and they are marked with asterisks. Since the coaches also contributed performed social interactions, the actions rendered by the coach and by the participants are separated in the table. The number of active participants who actually have produced that kind of data is also counted because some participants never used certain features. I calculated the mean and standard deviation (SD) of the activities in each group to display the variability among the participants. There were two coaches, and each was responsible for one cohort in the II+PS group; thus, the mean and SD was not calculated for coaches' contribution. From Table 2, it is noticeable that the WLC group had the fewest online actions when compared to the other two groups, even though the WLC group received the same form of intervention as the III group.

Table 2 - Summary of Log Data in Three Groups

Data	III (n=12)			II+PS (n=23)				WLC (n=12)		
	Active Participants			Active Participants			Coaches	Active Participants		
	n	Mean (SD)	Total	n	Mean (SD)	Total	Total	n	Mean (SD)	Total
Online event	11	2,345.7 (1,359.5)	25,803	23	2,694.5 (2,182.9)	61,974		11	1,744.1 (971.0)	19,185
Login	11	55.3 (35.9)	608	23	50.8 (34.5)	1,169		11	42.4 (24.2)	466
Task completion	11	20.6 (12.1)	227	21	18.8 (13.6)	394		11	15.7 (10.5)	173

Tool access	11	366.9 (249.9)	4,036	23	380.9 (341.8)	8,760		11	255.1 (170.3)	2,806
Visit duration (min.)	11	45.0 (191.0)	23,156.2	23	210.5 (1,166.1)	243,958.5		11	23.3 (146.1)	8,827
Like*				19	25.7 (52.0)	488	140			
Nudge*				9	5.7 (8.2)	51	11			

3.1.2 Textual Data

Similar to the log data, I also summarized the number of total records in textual data (Table 3). The three steps in cognitive restructuring were counted as one unit of thought record, and those who lack one or two steps were also counted as one unit. The last two variables were marked with asterisks, which means they only existed in the II+PS group. Similarly, the actions rendered by the coach and by the participants are also separated. Means and SDs were calculated for the active participants only.

Table 3 - Summary of Textual Data in Three Groups

Data	**III (n=12)**			**II+PS (n=23)**				**WLC (n=12)**		
	Active Participants			**Active Participants**			**Coaches**	**Active Participants**		
	n	**Mean (SD)**	**Total**	**n**	**Mean (SD)**	**Total**	**Total**	**n**	**Mean (SD)**	**Total**
Messages	11	11.7 (5.7)	129	22	9.1 (7.2)	200		11	10.5 (6.2)	115
Thought records	11	10.2 (7.5)	112	20	11.8 (10.8)	236		9	11.9 (6.9)	107
Status posts*				10	19.7 (16.6)	197	69			
Comments*				19	20.3 (23.6)	386	92			

3.2 Visualizations of Engagement Measures and Patterns Observed

The first aim was to characterize engagement by visualizing the log data. I first rendered visualizations for five measures of engagement, and then created a meta-pattern graph to identify overall patterns of engagement exhibited by participants.

3.2.1 Visualizing Measures of Engagement

I focused on five measures to depict different aspects of engagement. In the following subsections, I will present these patterns in order, first considering participant exposure and then skill practice.

3.2.1.1 Participant Exposure

From the histograms, I observed four types of patterns under the category of participant exposure. The names and explanations of the four patterns are presented in Table 4.

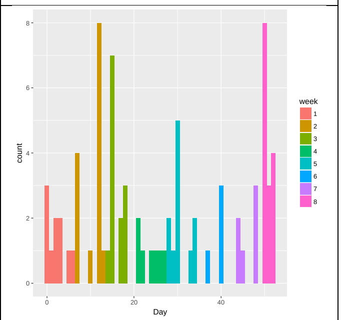
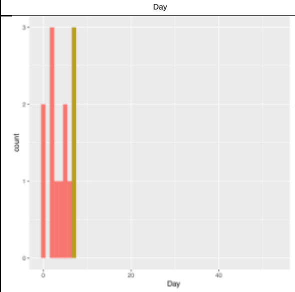
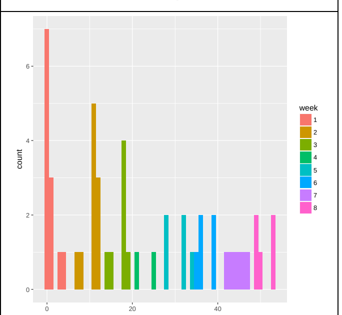
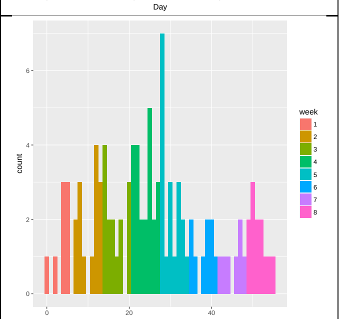
Table 4 - Patterns of Participant Exposure

	Pattern	**Explanation**
1	**Swinging**	The graph shows periodic swinging between a highest value and a lowest value, the bar height fluctuates within a relatively consistent range. There is no single notably high peak during the intervention, and the high peaks appear more than once. Participants completed the 8-week intervention.
2	**Drop-out**	This type of graph ends before the complete 8-week scale, which means that the participant dropped out during the intervention.
3	**Gradually decreasing**	There is one prominent peak in the graph and the highest value appears at the beginning. Later the usage declines gradually and never reaches to that height again. Participants still completed the 8-week intervention.
4	**Single peak**	There is one prominent peak in the graph and it appears in the middle or later stage of the intervention. Participants also completed the intervention.

I will present the patterns for each measure, first through a summary table and then through detailed tables including all of the graphs of individuals demonstrating specific patterns, by intervention delivery conditions.

3.2.1.1.1 Login

Table 5 – Summary of Login Patterns in Each Delivery Group

	Login Pattern	Group	n	Example Graph
1	Swinging (n=15)	III	4	
		II+PS cohort 1	2	
		II+PS cohort 2	4	
		WLC	5	
2	Drop-out (n=8)	III	2	
		II+PS cohort 1	1	
		II+PS cohort 2	2	
		WLC	3	
3	Gradually decreasing (n=13)	III	3	
		II+PS cohort 1	4	
		II+PS cohort 2	5	
		WLC	1	
4	Single peak (n=9)	III	2	
		II+PS cohort 1	4	
		II+PS cohort 2	1	
		WLC	2	

The login histograms depict the frequencies of logins on a daily basis. Tables 6-9 show the actual graphs for each pattern. In the swinging pattern (Table 6), most of the participants had relatively stable amount of daily actions, and on several days, they would have higher activity, but the peaks were not alone. For some participants, the trends looked like a letter "U" with relatively low activity in the middle and gradually increased till the end. In single peak pattern (Table 9), the highest peak usually happened in the middle of the intervention, with some appearing earlier or later.

Table 6 - Login Pattern "Swinging"

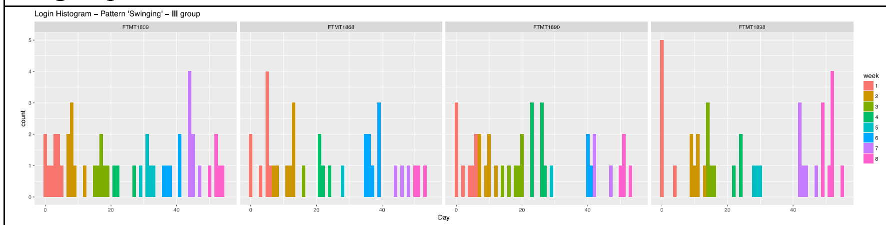
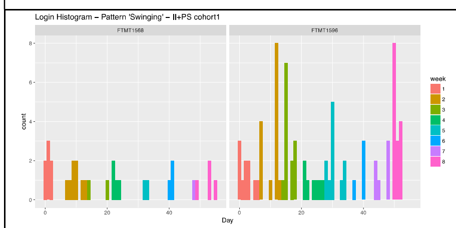
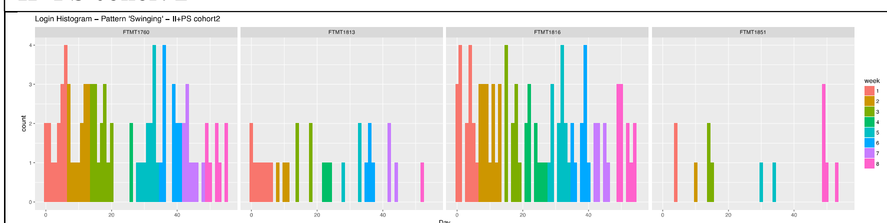
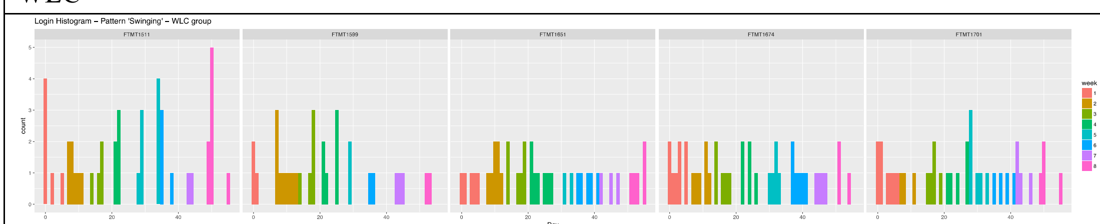
Pattern 1: Swinging
III group

II+PS cohort 1

II+PS cohort 2

WLC


Table 7 - Login Pattern "Drop-out"

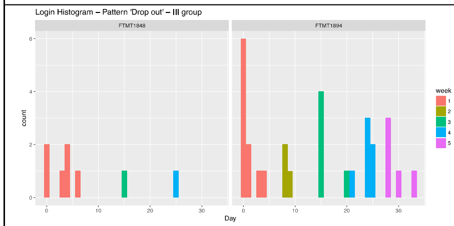
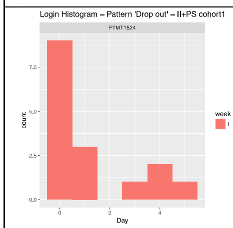
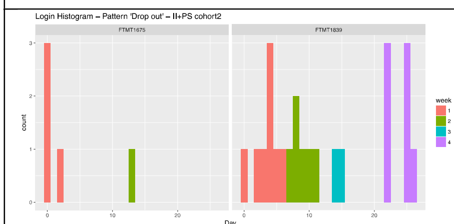
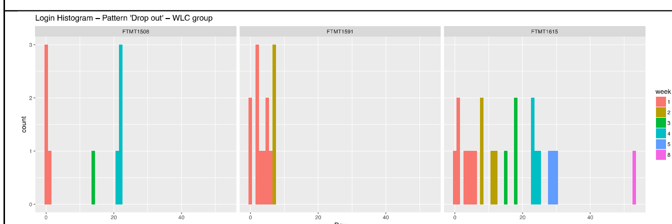
Pattern 2: Drop out
III group

II+PS cohort 1

II+PS cohort 2

WLC


Table 8 - Login Pattern "Gradually Decreasing"

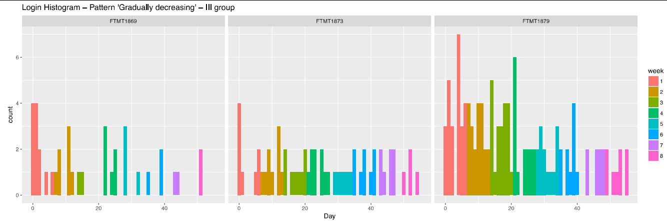
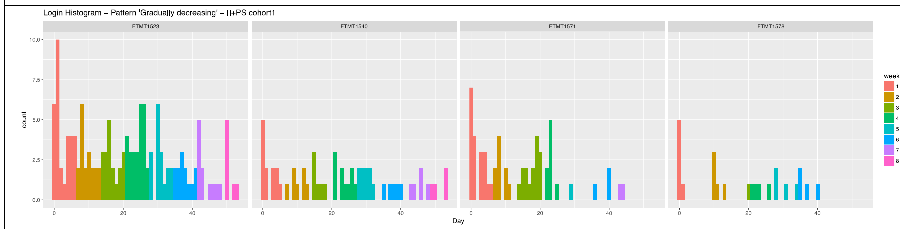
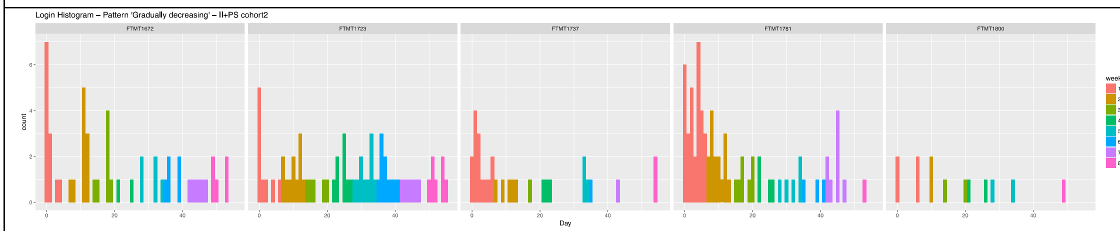
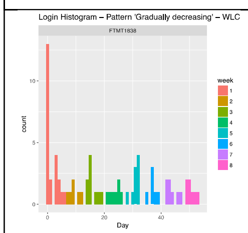
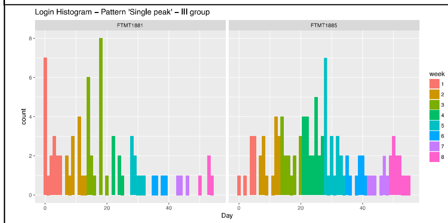
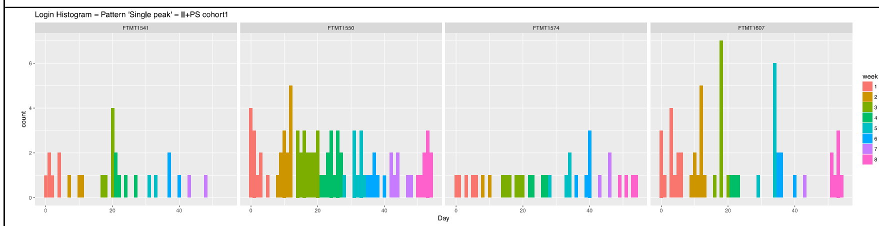
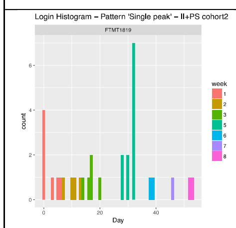
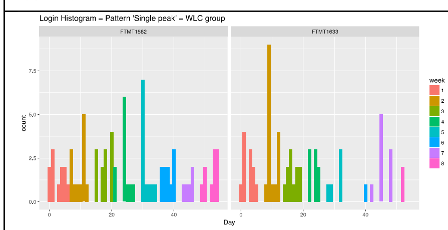
Pattern 3: Gradually decreasing
III group

II+PS cohort 1

II+PS cohort 2

WLC


Table 9 - Login Pattern "Single Peak"

Pattern 4: Single peak
III group

II+PS cohort 1

II+PS cohort 2

WLC


3.2.1.1.2 Clicking

Like login, the swinging pattern was also the most common pattern in clicking actions, but more participants exhibiting single peak patterns in clicking activities compared to the previous measure (Table 10). Tables 11-14 show the details for each pattern. Among the swinging pattern users, some had relatively fewer active days, like FTMT1851, FTMT1737 and

FTMT1607, but it was interesting to see that the frequencies were gradually increasing over time, even though the highest value was not distinguishably regarded as a peak (Table 11).

Table 10 - Summary of Clicking Patterns in Each Delivery Group

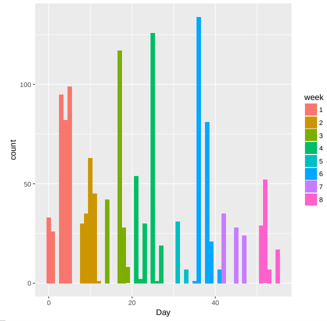
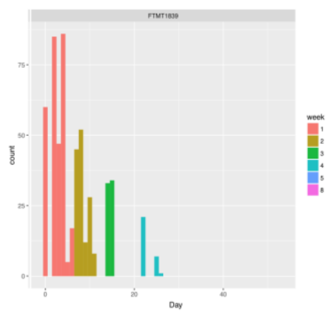
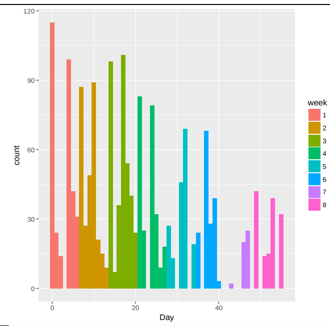
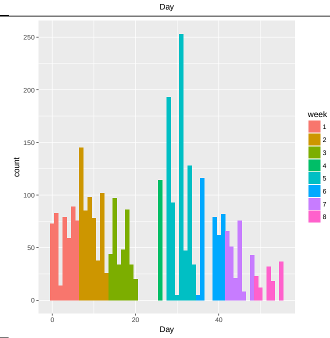
<table>
<tr><th></th><th>Clicking Pattern</th><th>Group</th><th>n</th><th>Example Graph</th></tr>
<tr><td rowspan="4">1</td><td rowspan="4">Swinging
(n=15)</td><td>III</td><td>2</td><td rowspan="4"></td></tr>
<tr><td>II+PS cohort 1</td><td>4</td></tr>
<tr><td>II+PS cohort 2</td><td>5</td></tr>
<tr><td>WLC</td><td>4</td></tr>
<tr><td rowspan="4">2</td><td rowspan="4">Drop-out
(n=8)</td><td>III</td><td>2</td><td rowspan="4"></td></tr>
<tr><td>II+PS cohort 1</td><td>1</td></tr>
<tr><td>II+PS cohort 2</td><td>2</td></tr>
<tr><td>WLC</td><td>3</td></tr>
<tr><td rowspan="4">3</td><td rowspan="4">Gradually decreasing
(n=10)</td><td>III</td><td>4</td><td rowspan="4"></td></tr>
<tr><td>II+PS cohort 1</td><td>2</td></tr>
<tr><td>II+PS cohort 2</td><td>3</td></tr>
<tr><td>WLC</td><td>1</td></tr>
<tr><td rowspan="4">4</td><td rowspan="4">Single peak
(n=12)</td><td>III</td><td>3</td><td rowspan="4"></td></tr>
<tr><td>II+PS cohort 1</td><td>4</td></tr>
<tr><td>II+PS cohort 2</td><td>2</td></tr>
<tr><td>WLC</td><td>3</td></tr>
</table>

Table 11 - Clicking Pattern "Swinging"

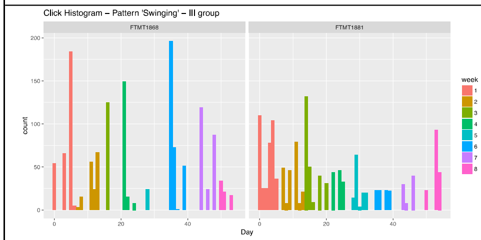
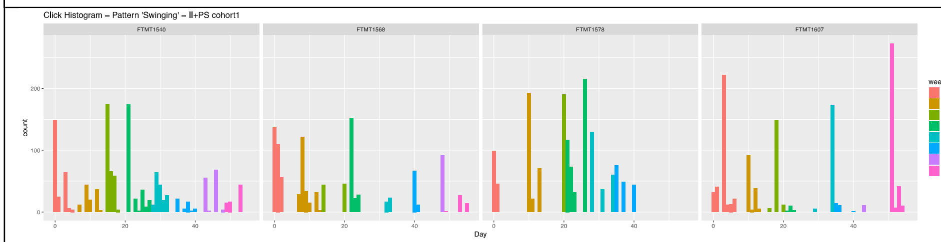
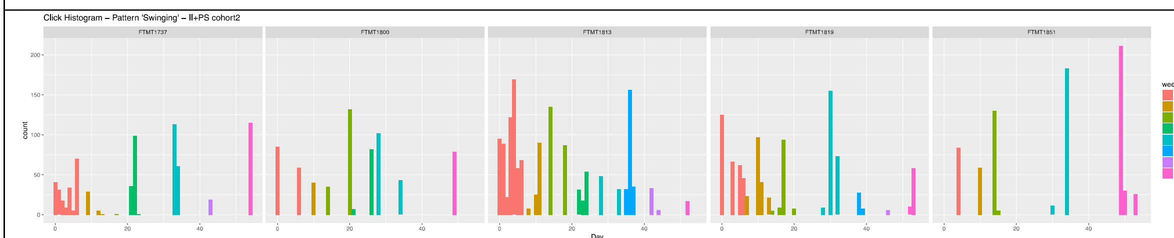
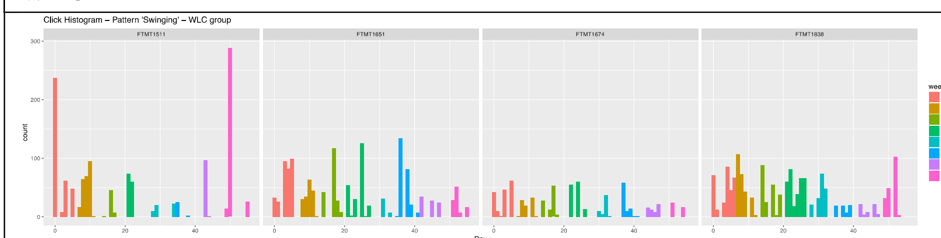
Pattern 1: Swinging
III group

II+PS cohort 1

II+PS cohort 2

WLC


__Table 12 - Clicking Pattern "Drop-out"__

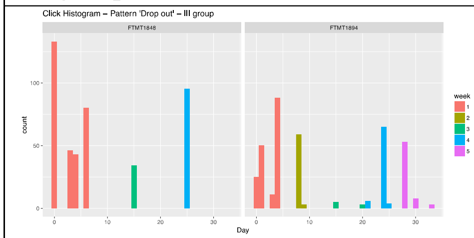
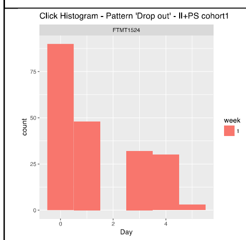
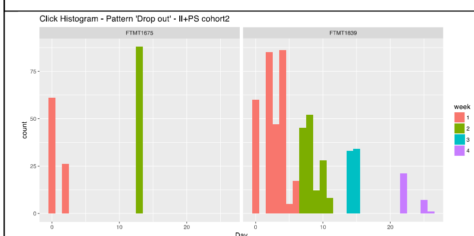
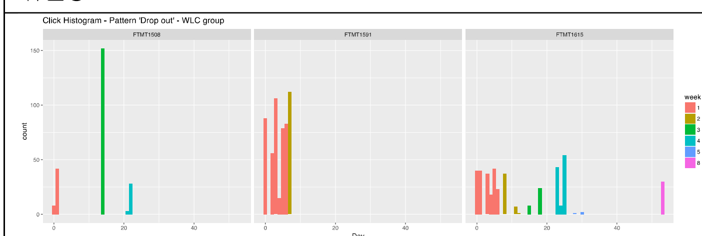
Pattern 2: Drop-out
III group

II+PS cohort 1

II+PS cohort 2

WLC


Table 13 - Clicking Pattern "Gradually Decreasing"

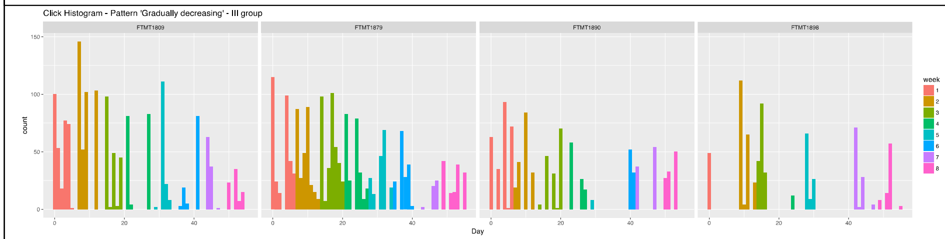
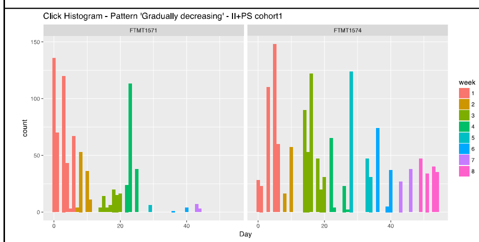
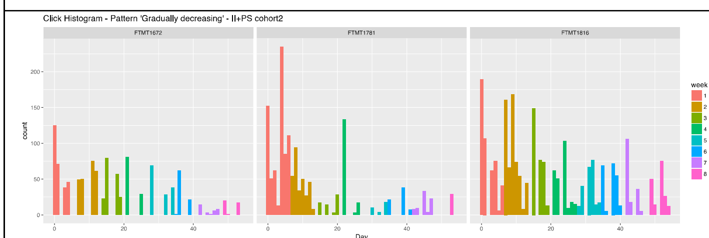
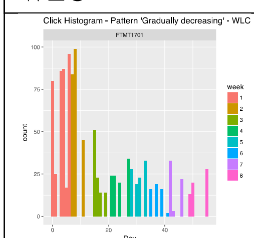
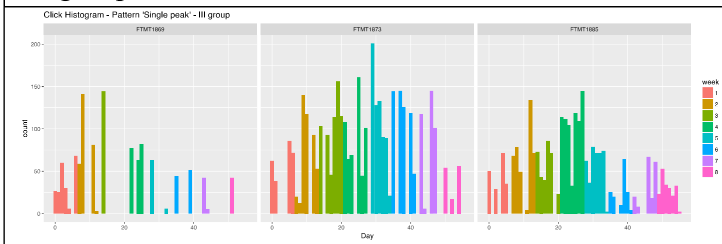
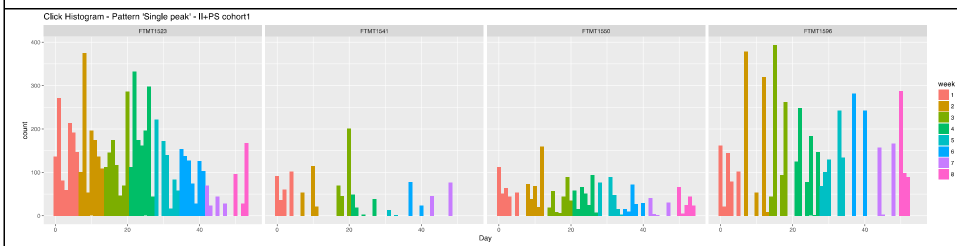
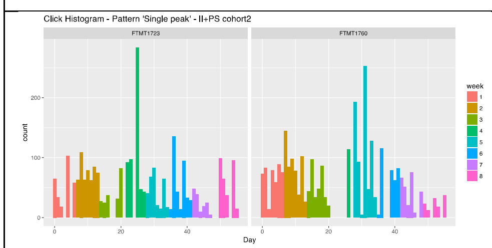
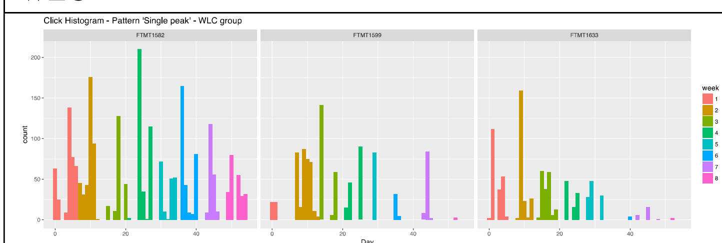
Pattern 3: Gradually decreasing
III group

II+PS cohort 1

II+PS cohort 2

WLC


Table 14 - Clicking Pattern "Single Peak"

Pattern 4: Single peak
III group

II+PS cohort 1

II+PS cohort 2

WLC


3.2.1.1.3 Rendering Contents

Table 15 shows the summary of patterns in the measure of rendering contents. Unlike the previous two measures, the pattern that included most participants was the single peak pattern. Tables 16-19 are the details for each pattern. In the WLC group swinging pattern (Table 16), it was noticeable that the overall frequencies were lower than the other groups, and this phenomenon did not appear in the other patterns. In both the swinging pattern and single peak pattern (Table 19), there were several participants who reached the peak of frequency near the end of the intervention (like FTMT1511, FTMT1607, FTMT1737, FTMT1838 and FTMT1851). They demonstrated gradually increasing trends in their patterns, but I still categorized them according to the number and position of peaks. For example, two of them, FTMT1607 and FTMT1851, were categorized into the single peak pattern because their highest peaks were so distinct.

Table 15 - Summary of Rendering Patterns in Each Delivery Group

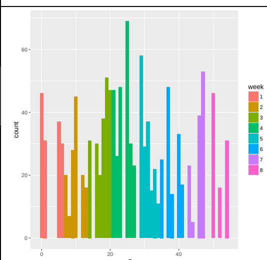
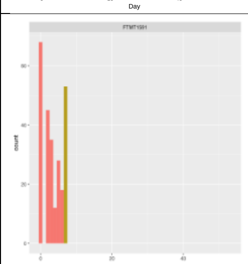
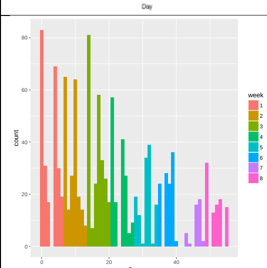
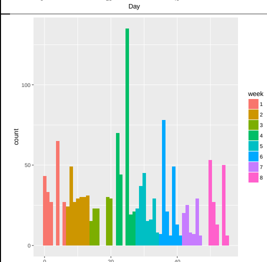
	Rendering Pattern	Group	n	Example Graph
1	Swinging (n=12)	III	3	
		II+PS cohort 1	1	
		II+PS cohort 2	3	
		WLC	5	
2	Drop-out (n=8)	III	2	
		II+PS cohort 1	1	
		II+PS cohort 2	2	
		WLC	3	
3	Gradually decreasing (n=9)	III	2	
		II+PS cohort 1	4	
		II+PS cohort 2	2	
		WLC	1	
4	Single peak (n=16)	III	4	
		II+PS cohort 1	5	
		II+PS cohort 2	5	
		WLC	2	

__Table 16 - Rendering Pattern "Swinging"__

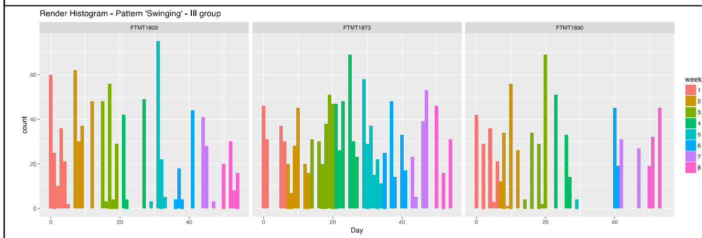
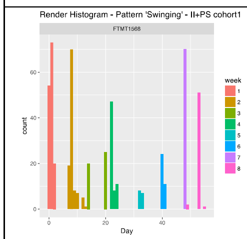
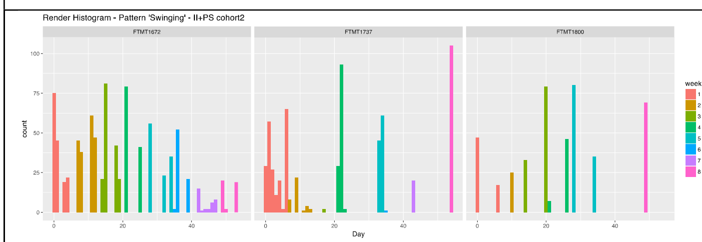
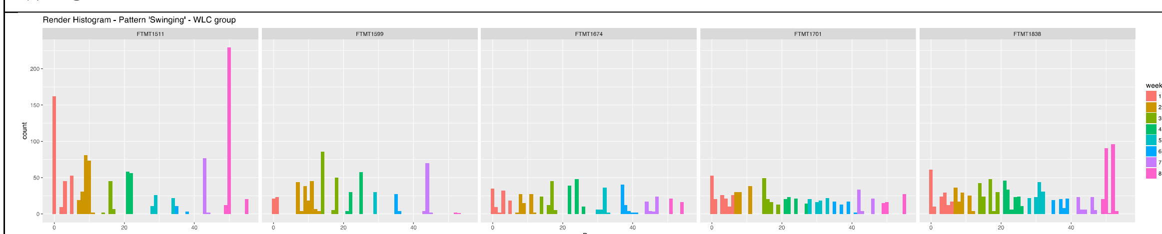
Pattern 1: Swinging
III group

II+PS cohort 1

II+PS cohort 2

WLC


Table 17 - Rendering Pattern "Drop-out"

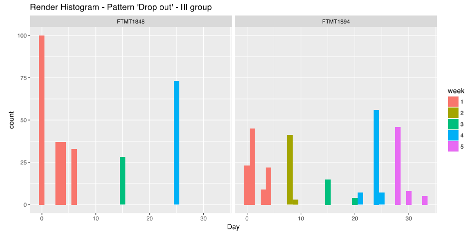
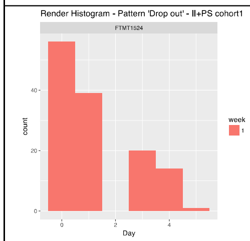
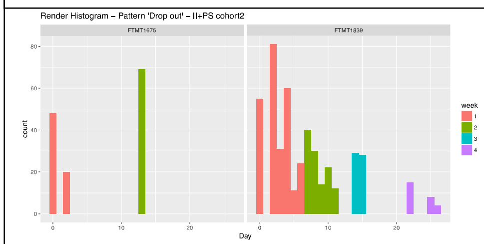
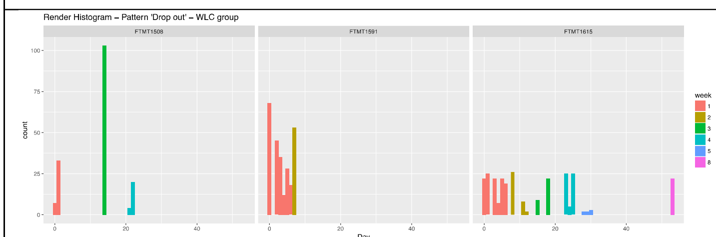
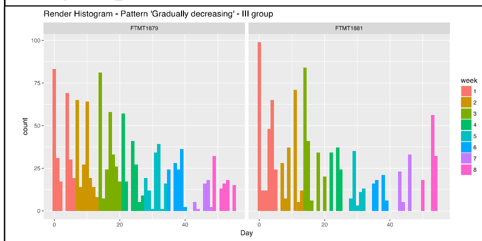
Pattern 2: Drop-out
III group

II+PS cohort 1

II+PS cohort 2

WLC


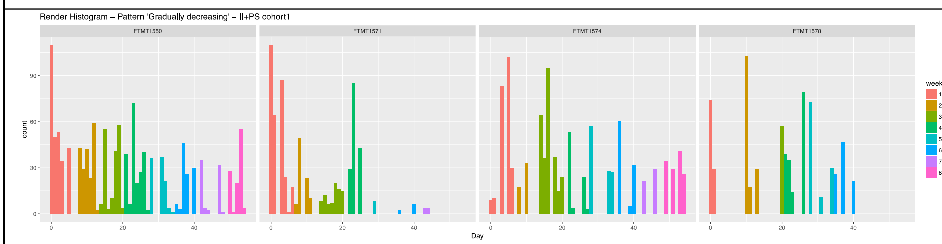
Table 18 - Rendering Pattern "Gradually Decreasing"

Pattern 3: Gradually decreasing

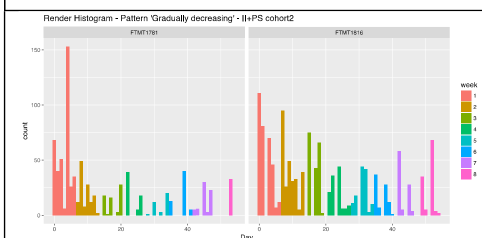
III group



II+PS cohort 1



II+PS cohort 2



WLC

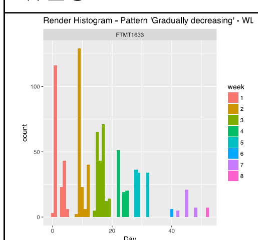
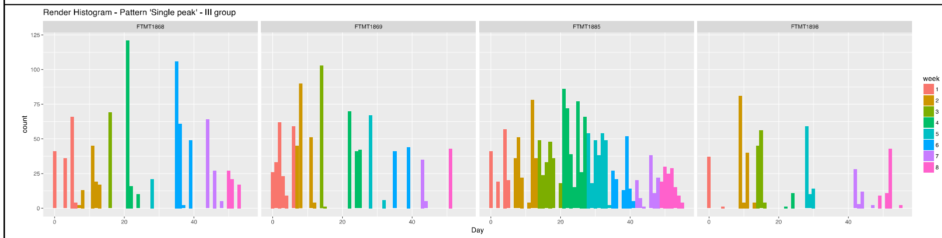
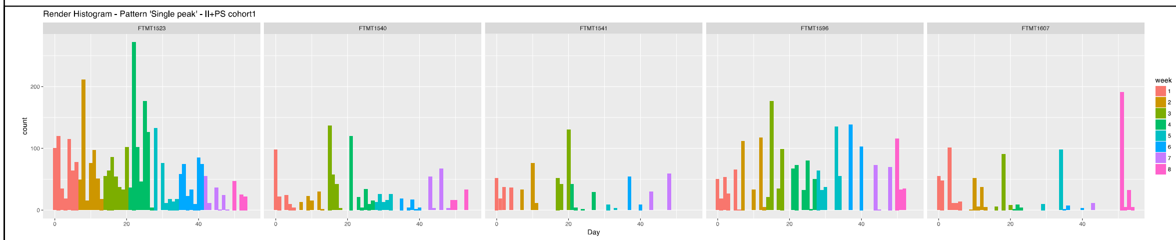
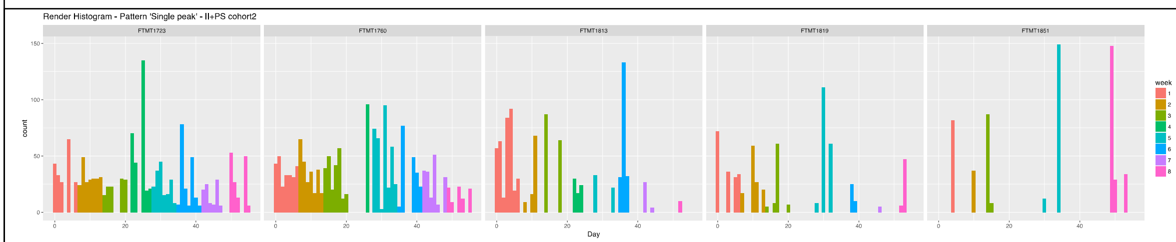
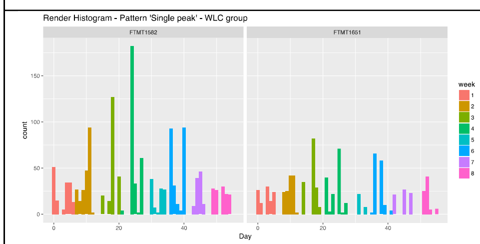


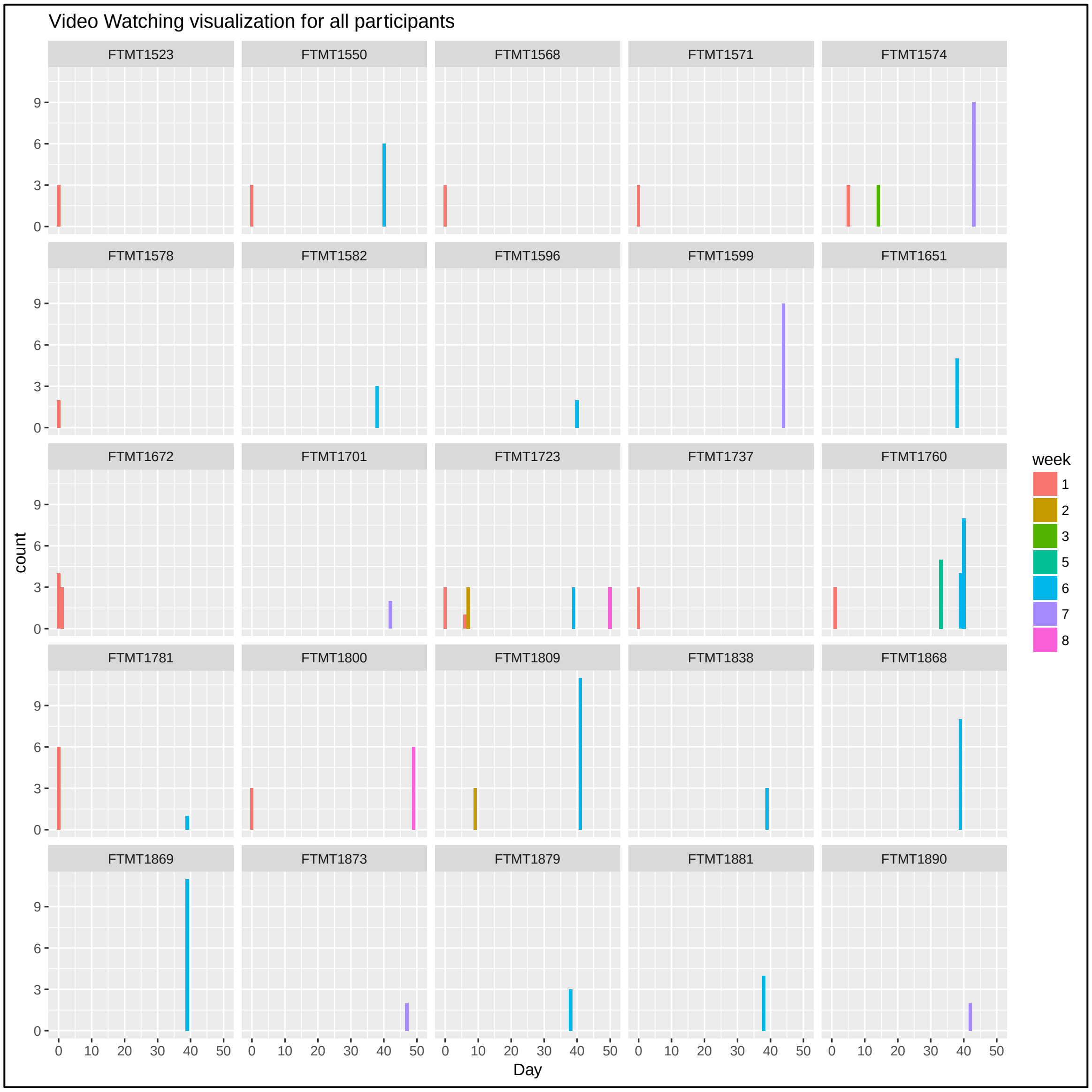
Table 19 - Rendering Pattern "Single Peak"

Pattern 4: Single peak
III group

II+PS cohort 1

II+PS cohort 2

WLC


3.2.1.1.4 Watching

Not until I had conducted the analysis did I realized that the amount of activity in “watching video” was very small compared to the total number of online actions (176/106,962), and only 25 participants ever engaged in this type of action. As shown in Figure 3, the overall frequency of this online action was so low that it is almost impossible to identify meaningful patterns. Therefore, for this action type I only divided the participants into two types: “used” and "not used". The participants in Figure 3 were included in the "used" type, while the others were the "not used" type. Later, I noticed that watching videos was related to the relaxation practice, therefore could be better depicted in the skill practice visualizations.

Figure 3 - Video Watching Usage Visualization for Participants Who Used it (n=25)



3.1.1.2 Skill Practice

In my study, tool access data was considered as the depiction of participants practicing the CBT skills. There were many modules and tasks included in the CBT intervention, but they all directed participants to use the tools. Therefore, I summarized the destinations of access into six categories: behavioral activation, cognitive restructuring, emotion tracking, navigation and help, relaxation exercises and summary. I produced individual scatter plots for tool access, with each point representing a visit to the tool. If a participant visited a tool multiple times on a single day, the points would be stacked.

The comparisons of graphs were based on two aspects: the sequence of visits to the tools and the overall frequency of tool access. The lessons in MoodTech introduced all the tools in the beginning but gradually gave specific instructions as the intervention went on. Therefore, the sequence of starting the tool accesses according to the lesson recommendations would be "behavioral activation" and "emotion tracking" first, "cognitive restructuring" appear in the middle and "relaxation exercises" appear in the last. The plots can also be used to compare the overall amount of access to the tools.

The results showed that most of the participants (29 out of 45) only used the tool during a period of time when it was actively introduced or instructed in the lessons and stopped after the lesson contents finished. However, other participants (n=11) made more spontaneous visits to the tools and continued to do so even after the lessons ended. They were self-motivated to practice the skills according to the ideal recommendations of the program. There were also five other participants who had relatively low activity and hardly used "cognitive restructuring" and "relaxation exercises" because they often dropped out in the early or middle stage of the intervention, and therefore did not learn the instructions about those tools. Overall, considering the sequence of lessons affected the tool access largely, I categorized the participants into "following instruction users", "early drop-out users" and "self-motivated users". Table 20 is the summary of patterns in each delivery group, and Tables 21-23 show details for each pattern.

Table 20 - Summary of Tool Access Patterns in Each Delivery Group

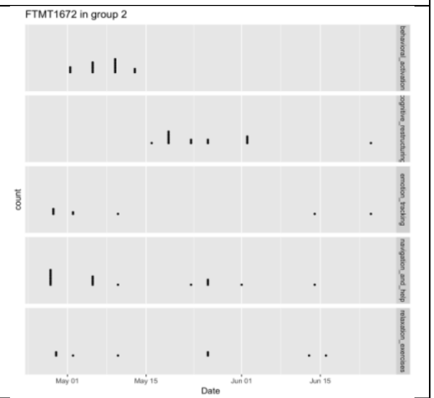
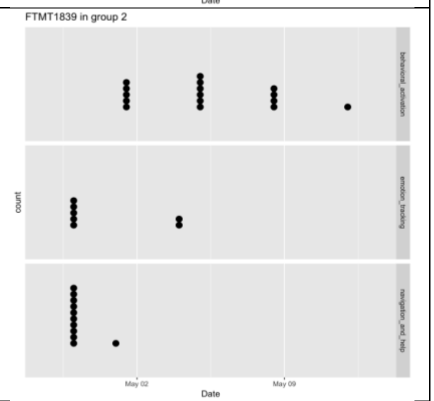
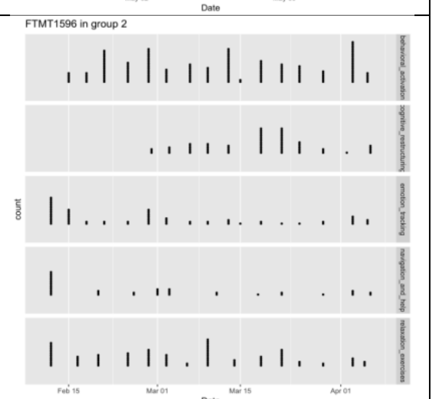
<table>
<tr><th></th><th>Pattern</th><th>Group</th><th>n</th><th>Example Graph</th></tr>
<tr><td rowspan="4">1</td><td rowspan="4">Following instruction
(n=29)</td><td>III</td><td>7</td><td rowspan="4">
</td></tr>
<tr><td>II+PS cohort 1</td><td>7</td></tr>
<tr><td>II+PS cohort 2</td><td>7</td></tr>
<tr><td>WLC</td><td>8</td></tr>
<tr><td rowspan="4">2</td><td rowspan="4">Early drop-out
(n=5)</td><td>III</td><td>1</td><td rowspan="4">
</td></tr>
<tr><td>II+PS cohort 1</td><td>1</td></tr>
<tr><td>II+PS cohort 2</td><td>2</td></tr>
<tr><td>WLC</td><td>1</td></tr>
<tr><td rowspan="4">3</td><td rowspan="4">Self-motivated
(n=11)</td><td>III</td><td>3</td><td rowspan="4">
</td></tr>
<tr><td>II+PS cohort 1</td><td>3</td></tr>
<tr><td>II+PS cohort 2</td><td>3</td></tr>
<tr><td>WLC</td><td>2</td></tr>
</table>

Table 21 - “Following Instruction Users" (n=29)

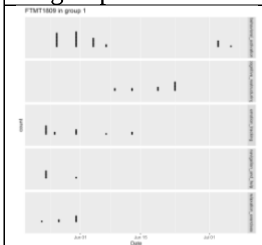
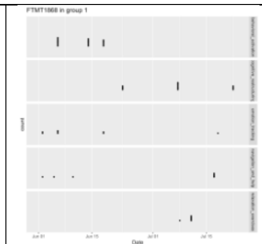
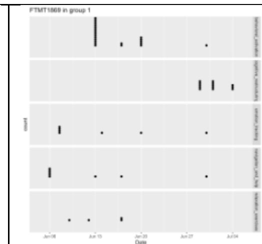
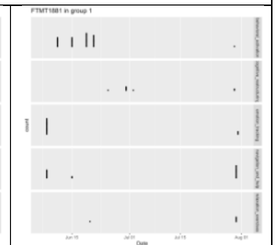
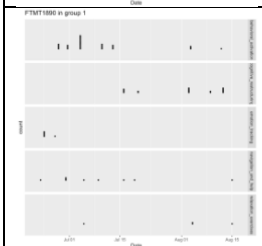
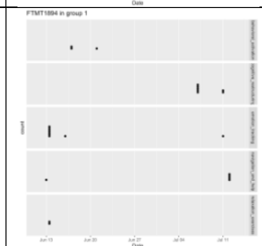
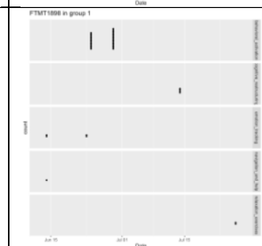
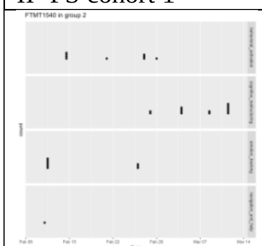
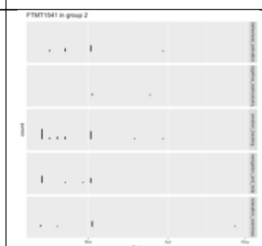
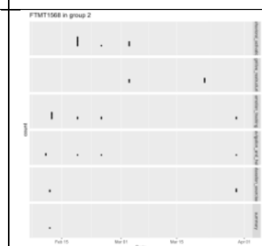
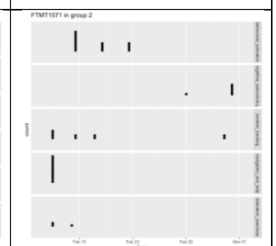
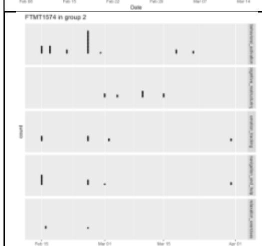
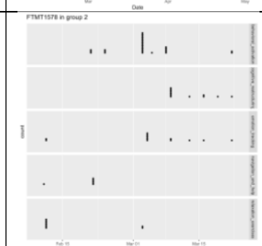
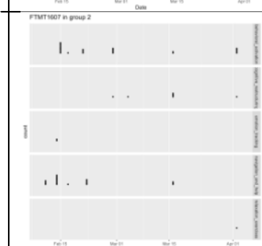
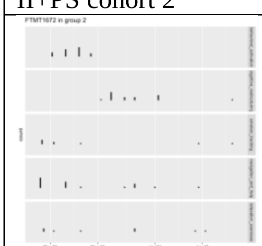
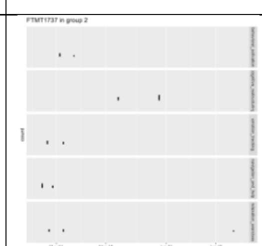
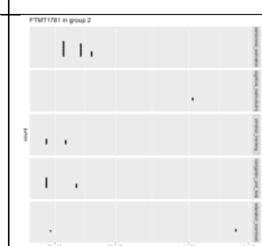
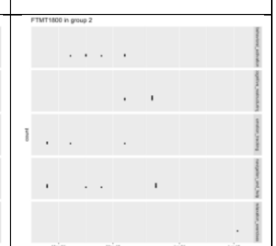
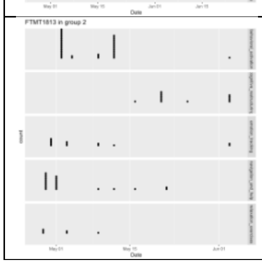
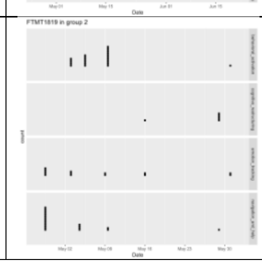
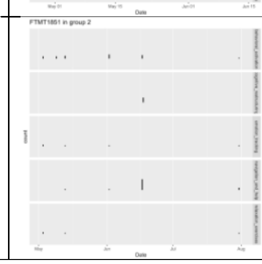
Pattern 1: Following instruction users			
III group			
			
			
II+PS cohort 1			
			
			
II+PS cohort 2			
			
			

Table 21 Continued

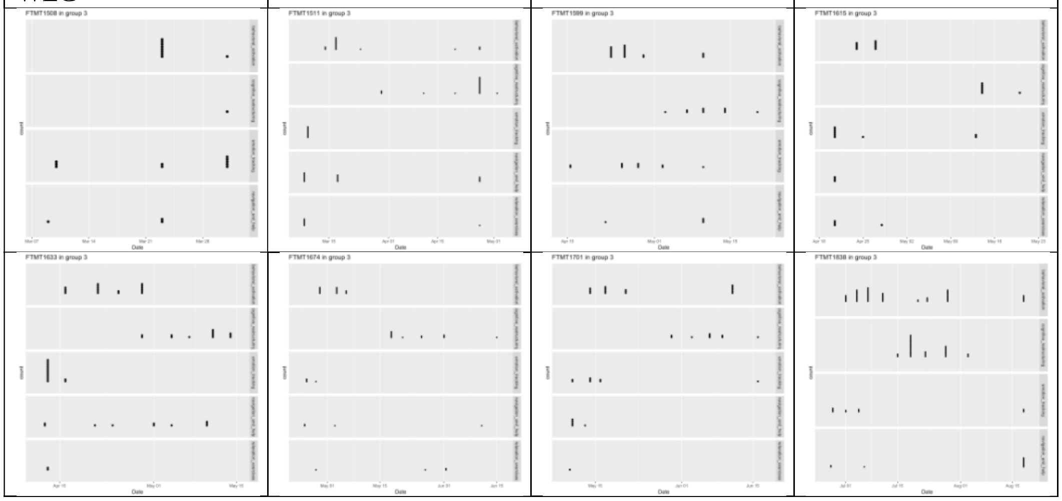
WLC			
			

Table 22 - “Early Drop-out Users” (n=5)

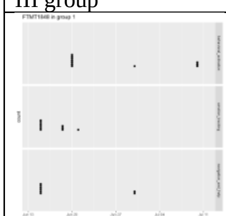
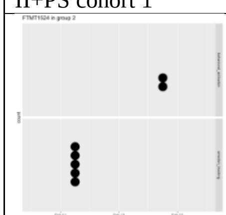
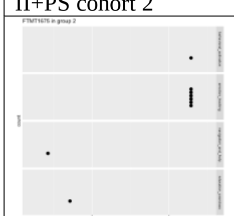
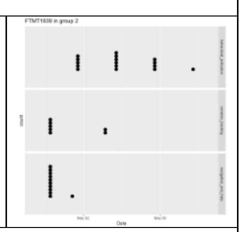
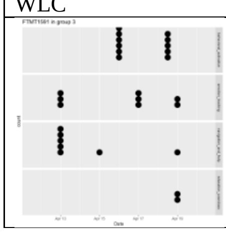
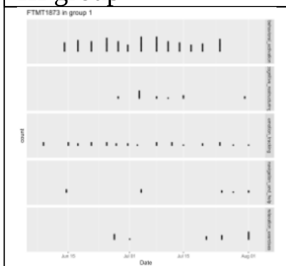
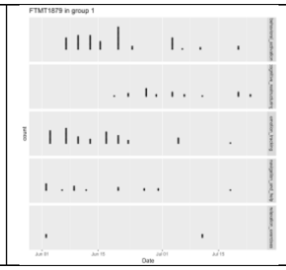
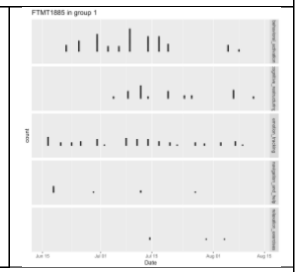
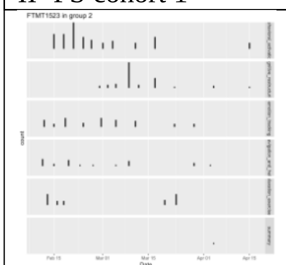
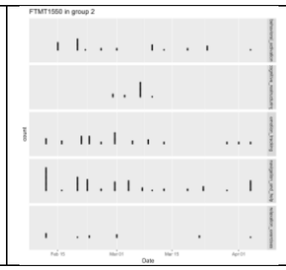
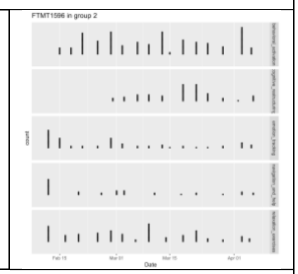
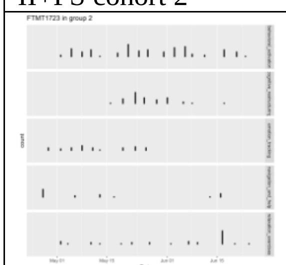
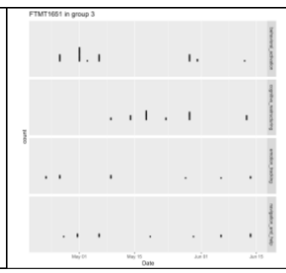
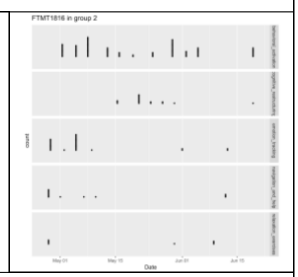
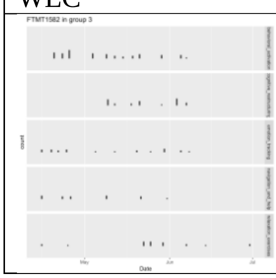
Pattern 2: Early drop-out users	
III group	
	
II+PS cohort 1	
	
II+PS cohort 2	
	
WLC	
	

Table 23 - "Self-motivated Users" (n=11)

Pattern 3: Self-motivated users		
III group		
		
II+PS cohort 1		
		
II+PS cohort 2		
		
WLC		
		

3.2.2 Meta-patterns of Engagement

I summarized the patterns of engagement that participants demonstrated in a heatmap and used color coding to indicate the meta-patterns (Figure 4). The rows were sorted to group those who had similar color distributions.

Figure 4 - Meta-patterns of Engagement

In this meta-pattern graph, I found that most individuals had similar patterns in two or three types of exposure engagement, and especially for those who dropped out early, their patterns were highly uniform. Additionally, self-motivated users in tool access also tended to have single-peak patterns in exposure measures. Figure 5 shows another version of the meta-pattern graph ordered by groups, and I cannot see clear associations between delivery groups and engagement patterns' distribution. The meta-pattern graph itself does not give clear reasons for these patterns, but it could be combined with the results from other aims to provide more insights, as I will discuss later.

Figure 5 - Meta-patterns in Groups

3.3 Social Network Analysis

The second aim examined the social interactions in the peer support arm. Two cohorts received the II+PS intervention, and each formed a small community which interacted in three types of features: comment, like, and nudge. All the networks included a coach because the coach was actively moderating the network and interacting with the participants. The cohort that started in February included Coach-1, and the cohort that started in April included Coach-2. I first compared the two cohorts under the same interaction type and then considered the differences among the different interaction types.

Statistics of each separate network are presented in Table 24. I calculated the density of each graph, and the mean and standard deviation (SD) of in-degree and out-degree centralities in each network. From the table, I noticed that the networks for the first cohort were denser than the second cohort in every type of interaction. The means of in-degree and out-degree were always the same because the total actions sent out and received in a network was balanced. But the out-degree had larger standard deviation than the in-degree in every network, which shows that participants have large differences in how many actions they initiated, but the number of connections they received were similar to each other.

Table 24 - Density and Degree Centrality for Each Network

	Cohort	**Graph Density**	**Average In-degree (SD)**	**Average Out-degree (SD)**
Comment	Cohort 1	0.47	5.17 (1.99)	5.17 (4.00)
	Cohort 2	0.37	4.46 (1.76)	4.46 (3.33)
Like	Cohort 1	0.45	4.92 (1.68)	4.92 (4.01)
	Cohort 2	0.34	4.08 (2.63)	4.08 (3.40)
Nudge	Cohort 1	0.22	2.18 (1.17)	2.18 (2.75)
	Cohort 2	0.19	1.14 (0.90)	1.14 (1.46)

3.3.1 Comment Networks

The two comment networks do not exhibit large differences (Figure 6 and Figure 7) in the shape of the network structure, especially in the size of the central nodes. The first cohort is denser than the second one and the central nodes are more closely connected, which reflected that there were more actions initiated in the first cohort. The coaches were not the only centers of the networks, and some participants were even more active than the coaches. The loops around some of the nodes represented that the person replied to themselves under his/her posts. It was not uncommon in either network, which is probably due to the design of the comment feature: you can only reply to the original post but cannot reply directly to the people you are having conversation with under that thread, or participants were replying to their own messages to extend the original post due to a length limit.

I also plotted the out-degree of the two networks and found that the distributions from the lowest to the highest were also similar (Figures 8 and 9). In Figure 8, there are five participants and one coach that have an out-degree higher than or equal to the average (mean=5.17, sd=4.00), and they are those who were located in the center of the network. I found these participants in the meta-pattern graph (red IDs in Figure 10), they included all three self-motivated users in that cohort, and the other two, even though were not self-motivated in using the tools, also had stable amounts of exposure, as demonstrated by the multiple “swinging” patterns in exposure measures.

Figure 6 - Cohort 1's Comment Network

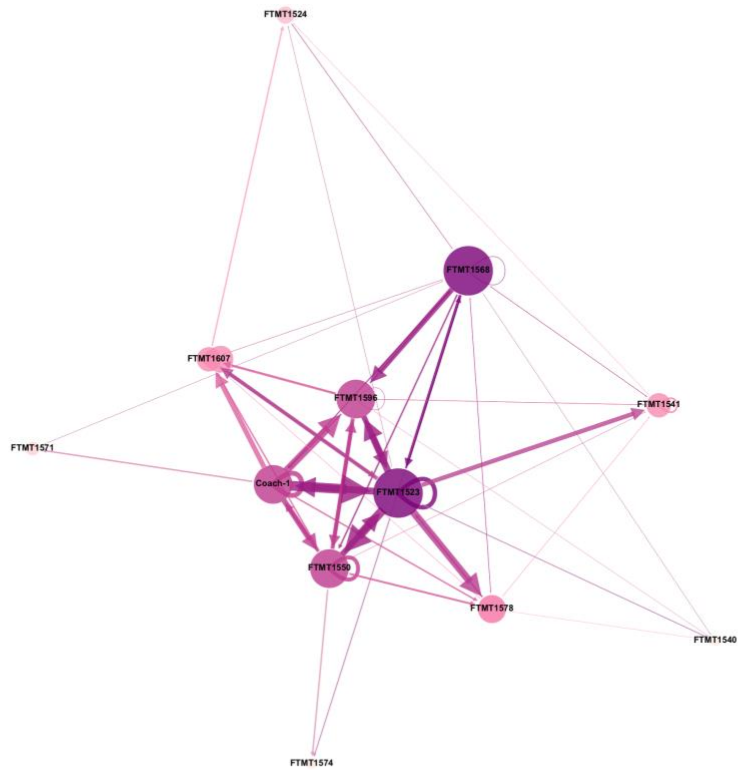


Figure 7 - Cohort 2's Comment Network

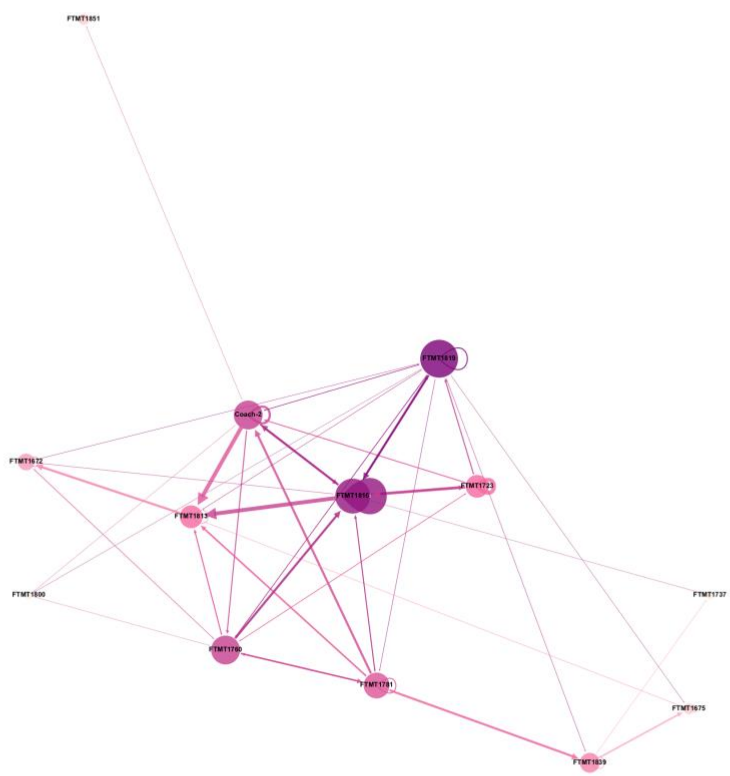


Figure 8 - Out-degree of Cohort 1's Comment Network

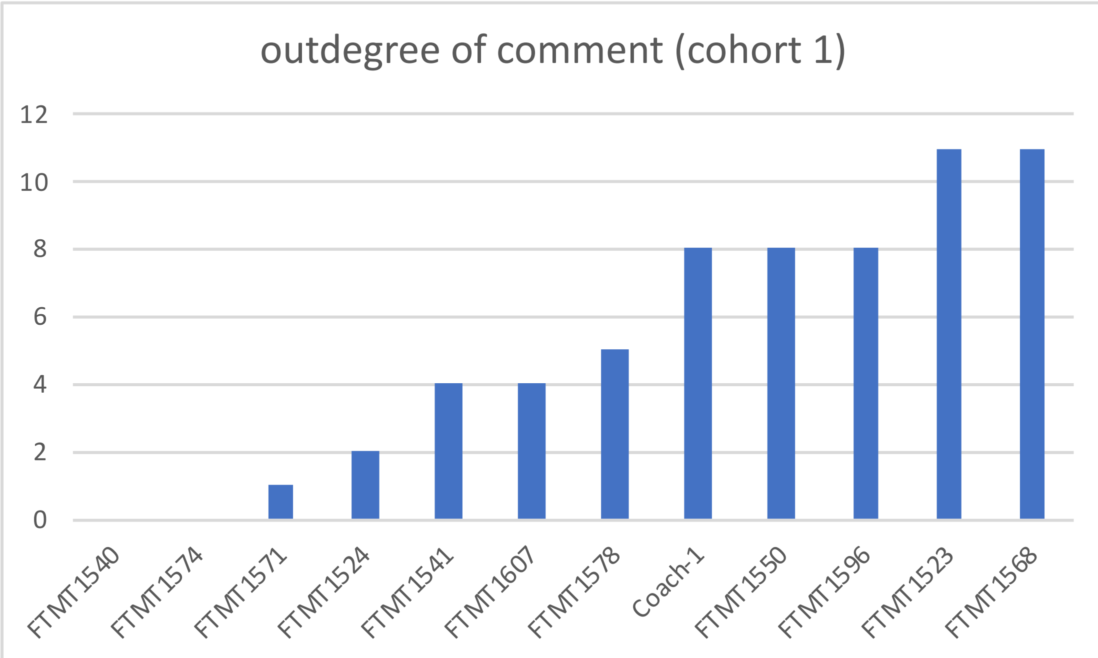


Figure 9 - Out-degree of Cohort 2's Comment Network

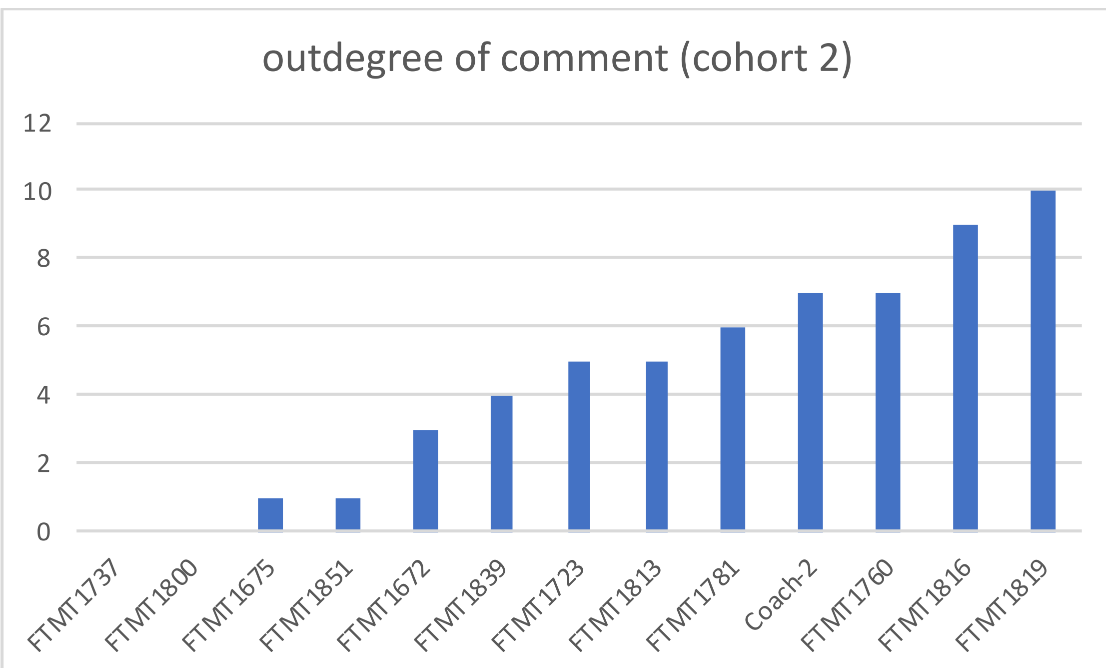


Figure 10 - Meta-patterns for Active Users in Cohort 1's Comment Network

ID	Group	Login	Clicking	Rendering	Video Watching	Tool Access
FTMT1524	II+PS _cohort1					
FTMT1571	II+PS _cohort1					
FTMT1574	II+PS _cohort1					
FTMT1541	II+PS _cohort1					
FTMT1550	II+PS _cohort1					
FTMT1523	II+PS _cohort1					
FTMT1596	II+PS _cohort1					
FTMT1578	II+PS _cohort1					
FTMT1540	II+PS _cohort1					
FTMT1607	II+PS _cohort1					
FTMT1568	II+PS _cohort1					

3.3.2 Like Networks

Figure 11 and Figure 12 are networks that depict the social interactions from liking actions. Comparing these two cohorts, the first network featuring Coach-1 has more closely related participants than the second network. As shown in Table 24, the density of the first network was larger than the second cohort, as well as the degree centralities. Compared to the comment networks, they are similar in terms of having multiple active users in the center, and there are also small loops encircling some nodes, indicating that the individuals liked content that they themselves had contributed. The out-degree of participants in these two networks are relatively similar, but the first one has a larger scale on vertical axis (Figure 13 and Figure 14).

Figure 11 - Cohort 1's Like Network

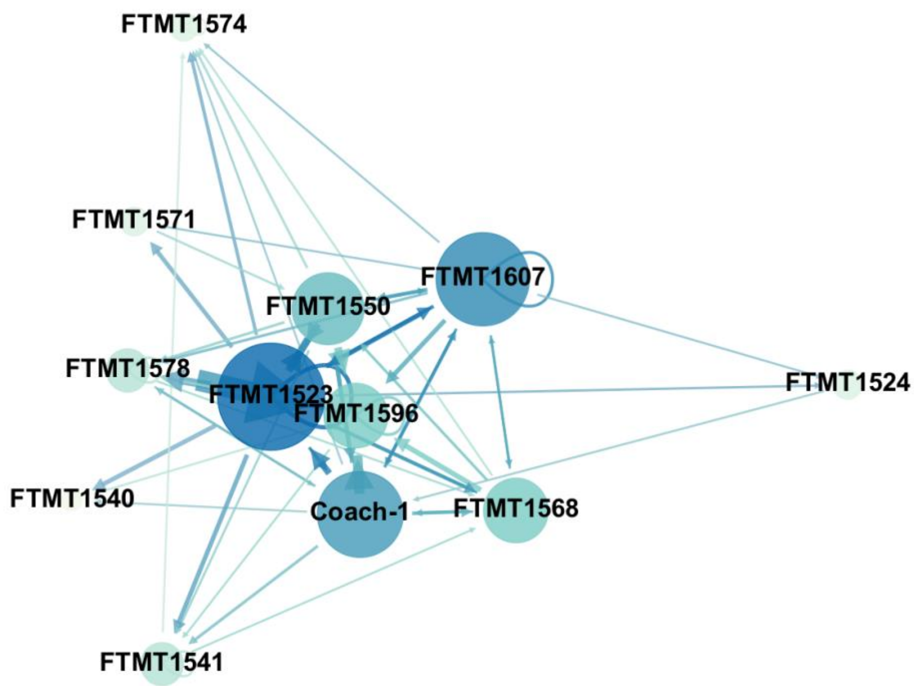


Figure 12 - Cohort 2's Like Network

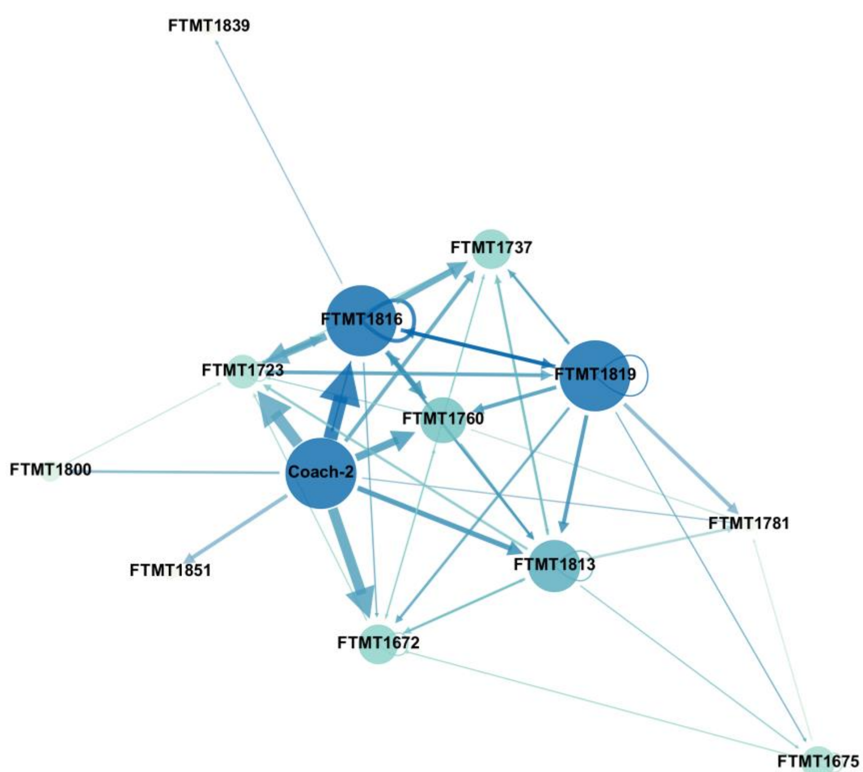


Figure 13 - Out-degree of Cohort 1's Like Network

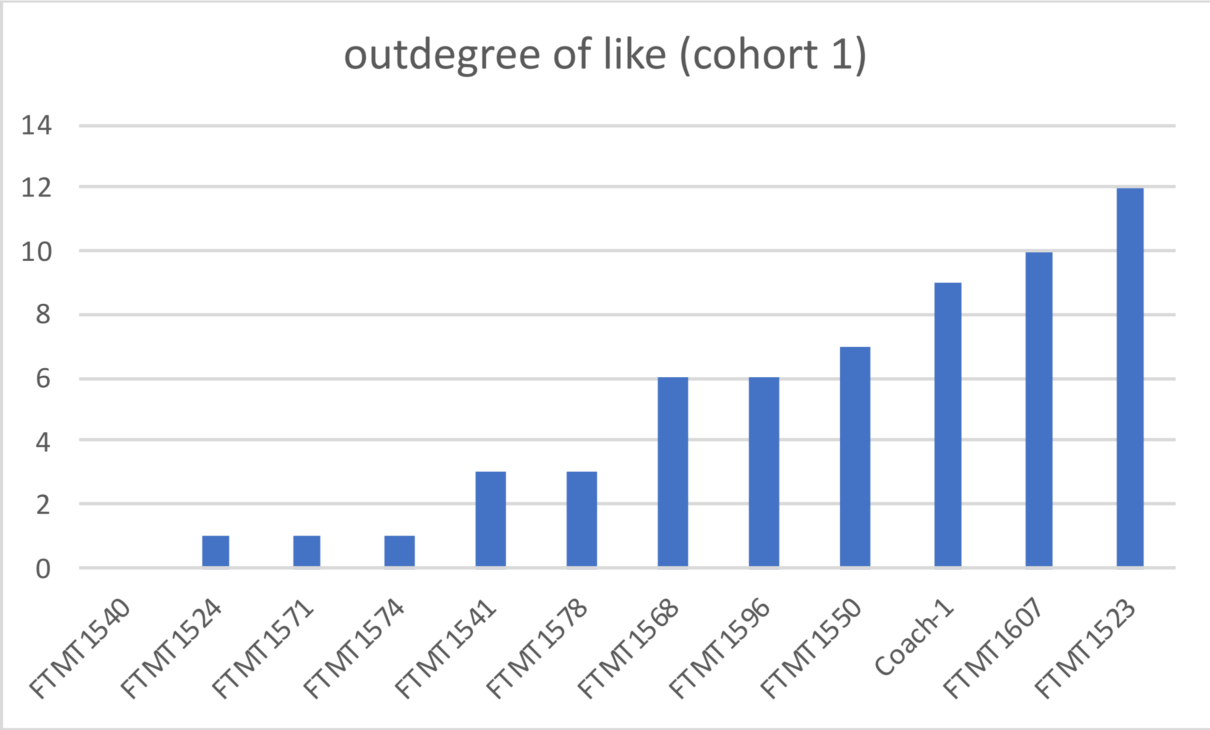
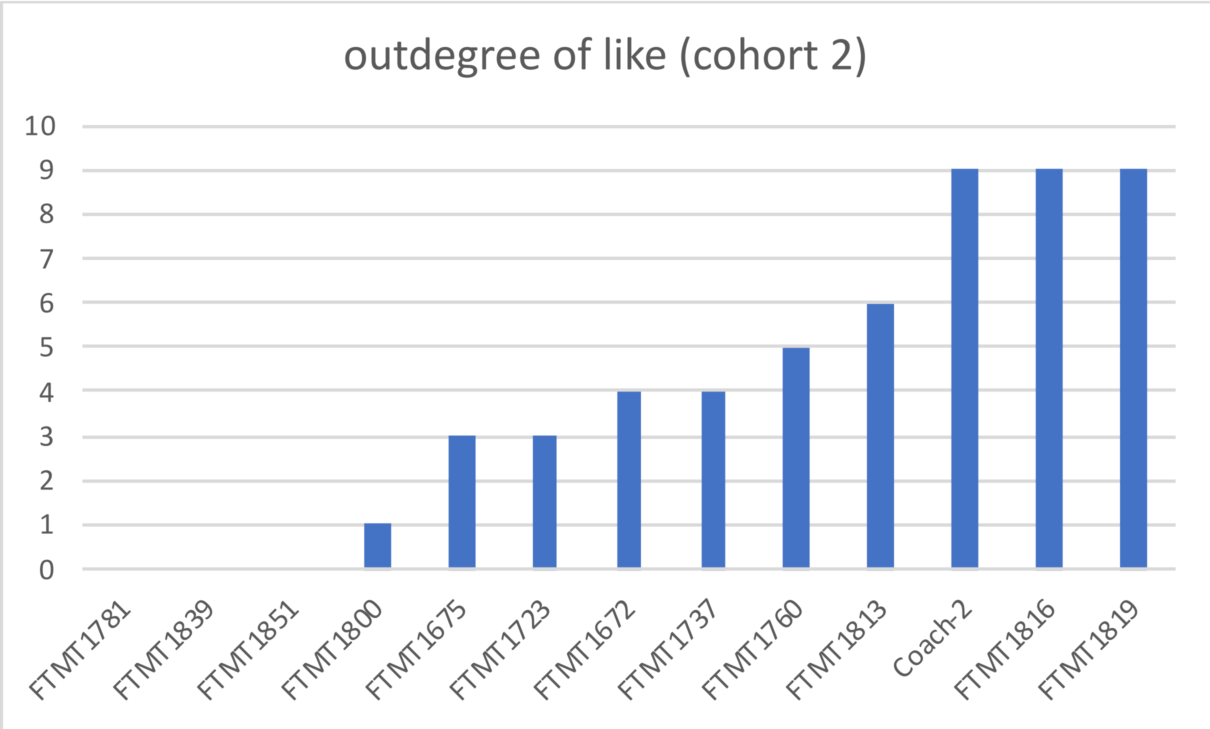


Figure 14 - Out-degree of Cohort 2's Like Network



3.3.3 Nudge Networks

The nudge networks are obviously different from the previous networks in shape (Figure 15 and Figure 16). There were fewer people who used the nudge feature than the comment or like features, and each network only had one member that was larger in size than all of the rest, and this member played most of the roles in the network. The previous networks all had two or more members who had the largest out-degree and connected to each other in a balanced polygon. The two cohorts also looked very different because the second network was extremely simple. From the out-degree charts it is clear that some of the participants did not perform any actions but were still involved in the network as the recipients of actions (Figure 17 and Figure 18).

Overall, the nudge networks confirmed the conclusion that only a small number of people used the feature, and most participants in the networks were only nudged by others. The fact that of the three types of networks, the nudge networks had the lowest average degree centralities also shows that the fewest participants used this feature. This was perhaps influenced by the features of popular social network websites, which often include features such as “comment” and “like,” but fewer have “nudge”. Additionally, since nudge actions did not include specific contents or were not object-oriented, the fact that this feature was used the least might show that older participants attach more importance to the contents of interactions.

In the previous aim we noticed that FTMT1737 and FTMT1851 had increased trends in both login and rendering frequencies. But in all three networks, they were not highly central and did not appear to actively interact with others. Therefore, their increased engagement level does not appear to carry over to social interactions.

Figure 15 - Cohort 1's Nudge Network

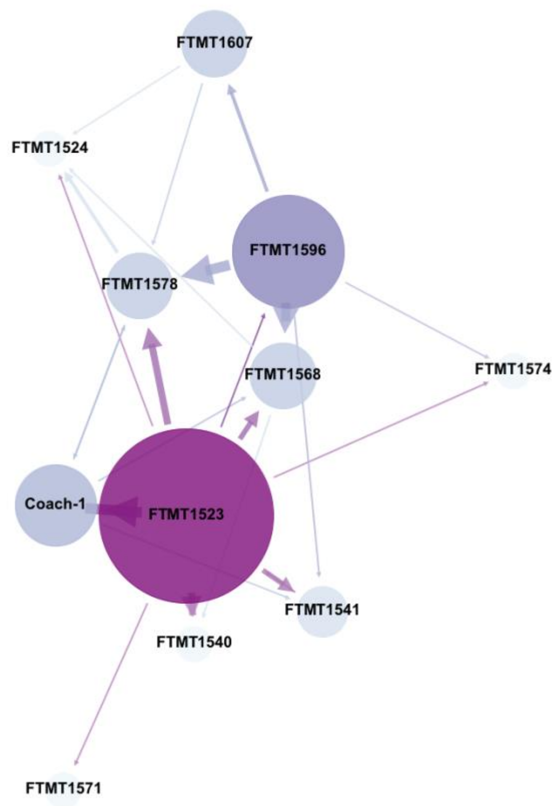


Figure 16 - Cohort 2's Nudge Network

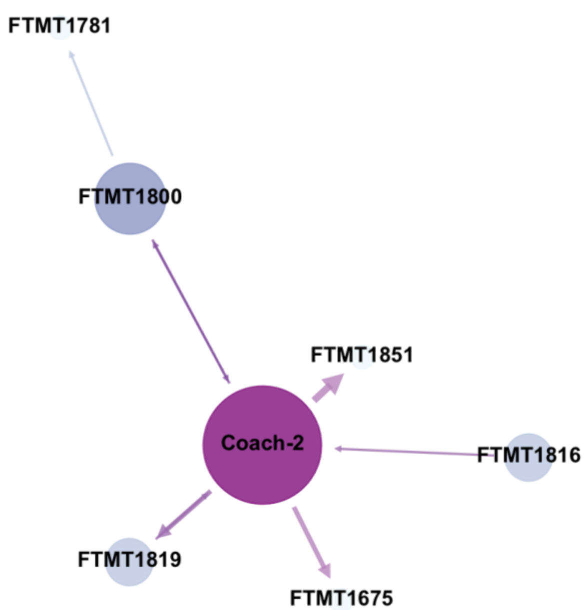


Figure 17 - Out-degree of Cohort 1's Nudge Network

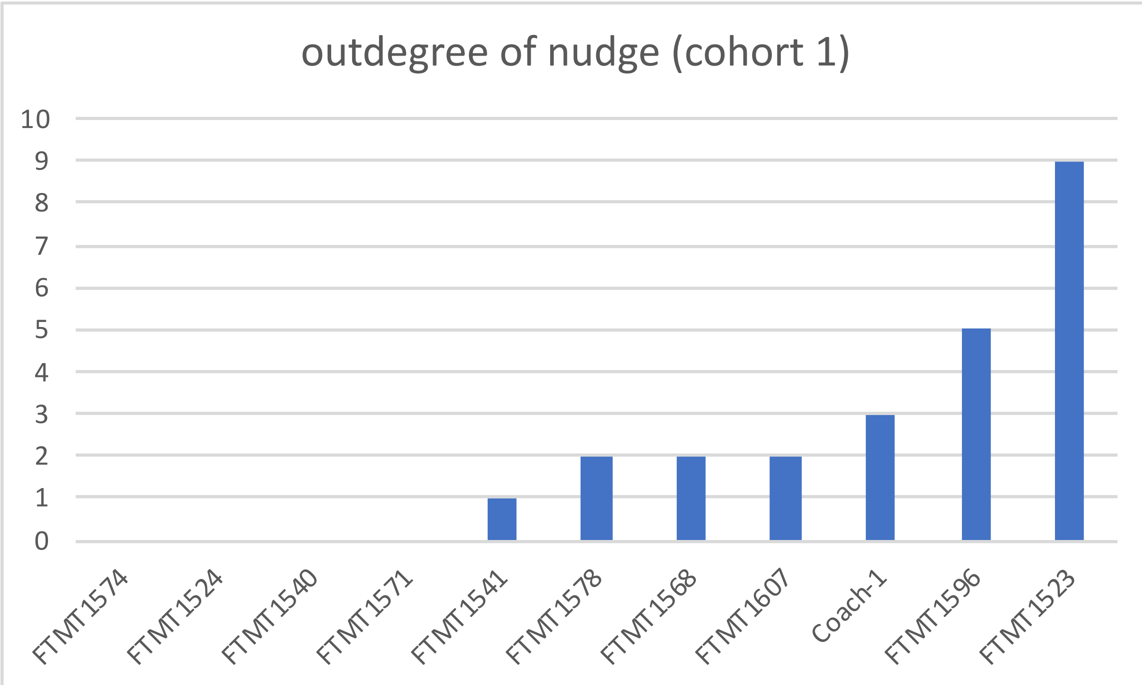
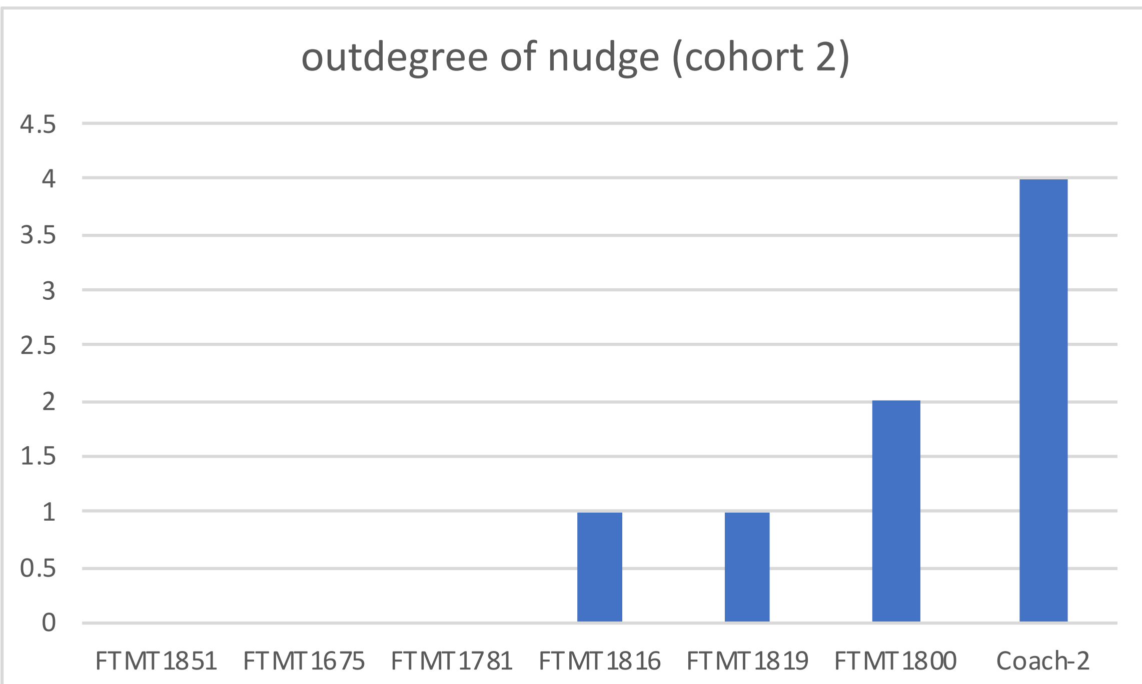


Figure 18 - Out-degree of Cohort 2's Nudge Network



3.4 Qualitative Analysis of Textual Data

After characterizing engagement at both individual and collective level, I started analyzing the textual data to examine the application of CBT principles and explore possible reasons for the different behaviors that participants demonstrated. The results from aim 1 suggested that the usage of tools was highly related with the lessons. I think successful application of the CBT principles should not only produce positive clinical outcomes, but also promise satisfactory engagement. Thus, I used qualitative methods to examine the application of CBT principles, which emphasize the three major parts: thoughts, feelings, and behaviors. The coding framework was developed according to these three categories, and also included the intervention and environmental factors that were not controlled by the participants themselves. After several rounds of coding, comparing and sorting of the codes as discussed in the Method section, I created a code book that divided the codes in to several subcategories under “think”, “feel”, “do”, “intervention” and “environmental” categories (Table 25).

Table 25 - Code Book in Qualitative Analysis

Category	**Subcategory**	**Code**	**Comment**
Behavior	Take actions	Get work done promptly	Including practicing the positive coping strategies in the CBT treatment, achieving goals in real life, or take actions that challenge bad situations
		Practicing mindfulness technique	
		Physical exercises	
		Health management	
	Planning actions	Planning and reviewing activities	Still in the planning stage in the behavioral activation treatment; review the pleasure or mastery of activities for future goal setting
	Avoidance	Avoidance/alternatives	Harmful coping strategies, escaping from the problem or choosing to do other things; procrastination; Low energy/tiredness
		Low efficiency and procrastination	
Thought	beneficial coping strategies	Self-adjustment	Recognizing the harmful patterns and challenging them by stop avoidance and planning positive actions. Strategies include self-encouragement and self-adjustment, thinking of positive and
		Practice TRAP method	
		Practice cognitive restructuring	
		Positive thinking	

			enjoyable things, seeking help from religious belief and other
	Psychosocial factors	Self-efficacy	The level of belief in oneself that one can accomplish something or not
	Unsuccessful coping strategies and “TRAP”	Harmful thoughts	"various patterns of harmful thoughts include absolutes thinking, guesses, labeling, magnifying or minimizing, overgeneralization, personalization, tunnel vision, self-blaming, self-denial
		Bothered by history factors	Still bothered by things in the past, vague memory
		Loss of interest and passion	Lack sense of accomplishment, cannot find enjoyable things, loss of concentration
Feeling	Positive feelings	Feeling well	Happy, relieved, sense of accomplishment, security, passion for work
	Negative feelings	Dwelling with depressed feelings	Angry, anxious, guilty, sad, frustrating, regretful, disappoint, worried, doubting, fear, panicked, feeling abandoned/not cared
Environmental	Social interactions	Enjoyable things	Travelling, companions of pet/friend/family, offering support to others
		Unpleasant social activities	issue with family members/friends, annoying people and tense relationships
	Personal conditions	Problems and tragedies	Family emergency, loss of loved ones
		Physical illness	Sleeping issues, Age-related conditions, chronic diseases,
		Concerns and stress	Financial concerns, stress from work, too busy, daily chores
Intervention	Negative feedback	Clumsy and confused situation	Technical problems which caused confusion, or the participants were clumsy in using the website.
		Disappointment and impatience	Having complaints towards the program, thinking it not useful, decide to reduce the engagement in intervention because already feeling well or feeling too disappointed with the contents.
	Positive feedback	Interest and confidence	Confidence in the program, interest and expectation in the lessons.
		Good reflection	previous experience of CBT, suggestions to the program, thinks the program is useful/helpful
	Communication	Communication	Discussing calling schedule with coach, reasons for falling behind, response to reminder/check-in, discussion on lesson progress, providing information

I identified several notable themes from the coding process, relating to the application of CBT principles and the potential barriers in engagement, which will be discussed below.

3.4.1 Depressed Feelings Affect Activities and Cause Negative Thoughts

One of the first steps in CBT was to improve awareness of one's depression and avoidance habits that worsen the emotion. Many participants had self-denial thoughts due to their low efficiency and failure in completing tasks. Procrastination was a common problem among these older adults, and the sense of anxiety and guilt from not completing the work made them more depressed and tired. This vicious cycle need to be acknowledged and broken, which many participants became aware of. For example, FTMT1868 wrote in a message:

> *"It's obvious to me that I have an addiction to video games and tv that are ruining my life (plus I never learned coping skills). Both make me tired and the more tired I become the more I watch/play/nap, the less I get done and more worthless/guilty/negative I feel." [FTMT1868]*

After the first few days learning about CBT and re-understanding oneself, most participants recognized the pattern they were trapped in and determined to change the situation. It might not always have led to successful results, but it was a good starting point:

> *"I need to break the cycle…… Just the idea of setting goals and making simple changes seems so overwhelming. I guess it's best to focus on simple changes first." [FTMT1868]*

3.4.2 Successful Examples of the Application of CBT Principles

There were many participants who reported positive feedback in messages to the coach or in the interactions with peers, noting that by practicing the CBT coping strategies, they were making real progress in breaking avoidance cycles and interrupting harmful thinking patterns, which improved their moods and emotions. For instance, while many participants initially suffered from procrastination, some were able to make plans and take actions as the behavioral activation treatment suggested and obtained a sense of accomplishment, like in the following message:

> *"I read the lesson after I went to exercise and ran some errands. I got irritated with a family member after I got home and started to tank. I had intended to start some framing for a show I'm having next month. I sat around for a while and then realized I was just stewing, so I got up and got four new pieces framed. i felt much better." [FTMT1674]*

Another successful example is how FTMT1885 overcame the anxiety and worry related to telephone calls to her oldest son, because of their alienated relationship and the fear of hearing bad news. But later, she wrote the coach a message that she was able to call her son because of the cognitive restructuring. She realized that she had a harmful thinking pattern that in which she imagined the worse scenario that her son was leading a worse life than before and still considered her as an irresponsible mother. But then she came up with a challenging thought that there was high possibility that her son was doing well. She realized the only thing to end the anxiety was to take action, and she was very glad to find out the true situation:

> *"He sounded really glad to hear from me. He's doing well and told me all about what's going on in his life. All positive. If I call weekly maybe his ups and downs won't seem so stark as they do when some time has passed since we*

spoke... I will say I have over 50% control over how he responds to me." [FTMT1885]

The positive outcomes from the original study could also serve as evidence that CBT lessons were at least assisting the beneficial changes.

3.4.3 Previous Experiences of CBT Can Be Related to Engagement

Despite the positive themes of CBT application, I also found some negative cases. Some participants were overwhelmed by the amount of lessons, some were frustrated by difficulties practicing CBT strategies, and others expressed disappointment when they did not find content that met their needs. Quite a few participants said that they could not smoothly come up with alternative thoughts when practicing cognitive restructuring, and many people just left that section blank in the practice. FTMT1633 was an extreme example because she later decided to discontinue working with the program:

> *"I tried to use the support questions for Creative Alternative Thoughts, but I can't come up with anything. Guess I need more direction. Much of my worrying/anxiety is regarding my mom and her care, and I seem to be sort of stuck in the worry mode. Just can't seem to come up with alternative thoughts." [FTMT1633]*

Another topic that I have noticed is that several participants mentioned that they had experienced the CBT or practiced similar strategies for years, and therefore were disappointed that the intervention did not teach them new things. Among these group some even believed the CBT strategies could not be useful because they had tried them before and failed.

> *"Recording daily activity will likely sharpen understanding of how I passed time, but recognition of how certain activities affected mood seem quite obvious-something I have known a long time. Why do it? Doesn't contribute to new insight." [FTMT1869]*

> *"Although these exercised may work well for some people, I didn't find them very useful. I found my own techniques (similar) to work much better for me. Even though I did not schedule them I did practice them." [FTMT1868]*

The reluctance is especially significant regarding the relaxation exercises. Some have commented that the audio files were not working for them or even had opposite effect, and they preferred their own strategies that had been adopted for years:

> *"The relaxation lessons have not been particularly helpful for a couple reasons. the woman's voice for the deep breathing is too directive and not calming. Secondly, for all of the lessons, because there is no background 'white noise', when a voice materializes from silence, I find it startling, which of course is quite the opposite of their purpose. Finally, I have been employing these techniques for well over twenty years." [FTMT1873]*

As mentioned in the results of the first aim, video watching was much less frequent than usage of the other features and tools. One possible reason might be that, the videos were used to demonstrate the relaxation exercises, and many of these older participants had already found their own strategies earlier in life and therefore chose to ignore this feature.

I think that the different attitudes towards the same intervention lessons demonstrated the difference in mastery of the CBT strategies. Previous experiences and knowledge of CBT largely influence the experiences and engagement in the current intervention. Participants who had learned similar strategies before were probably expecting new knowledge from the intervention, while those who had never tried the practice previously would need more basic instructions and encouragement.

3.4.4 Various Environmental Factors May Cause Low Engagement or Drop-out

For most participants who demonstrated the drop-out pattern, the data that they produced was so limited that I cannot discern the actual reasons why they stopped using the program. But from what they have written in response to coach's reminders, the common topics included physical disease, emergency of a close family or friend, travel or vacation, or just being too busy with work or life events. The influence of those environmental factors was often huge and rapid, but also hard to predict or prevent. Therefore, even though I believe environmental factors played an important role in user engagement, I cannot find effective solutions for these types of issues.

3.4.5 Website Design Influenced the Experiences of Users

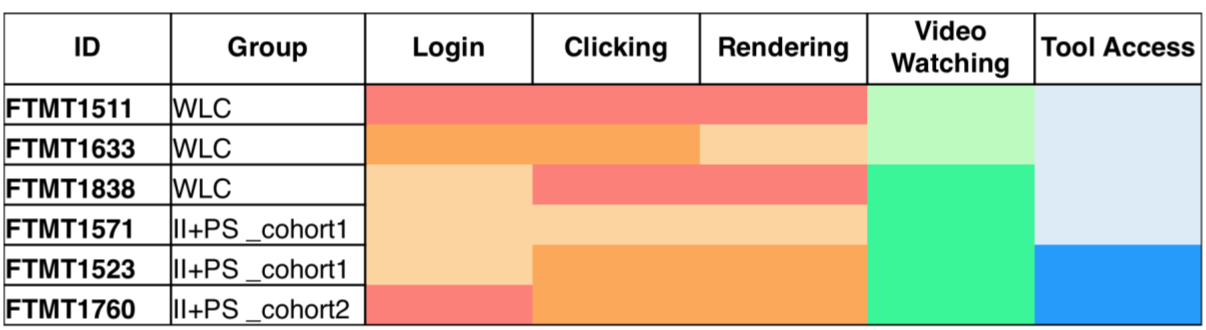
Many participants encountered technical problems, and I think these factors could be an important factor leading to disappointment in user experiences. Participants wrote in their messages or posts about the frequency of web pages not responding, failures in auto-saving the homework or messages, confusion when navigating the website, and repetitive false alarming about un-read lessons. These problems really made a great number of participants disappointed and tired:

> *"I did the first DO lesson and filled in my hour by hour activities for yesterday. When I got to the bottom and pressed NEXT, it would not go there. Frustrating!" [FTMT1633]*

"I've read every one of the lessons to date - several times - and they show as "unread. Can you tell me what I might be doing wrong?" [FTMT1868]

But I also found that even though the technical problems were seemingly the most-frequently discussed topic in the data, they rarely made the participants quit the intervention. I did not find statements saying technical problems made the participants quit the intervention. When I searched the engagement patterns of those who frequently reported technical problems, I found that they were not in the drop out pattern but could potentially be active users in many activities (Figure 19). It is possible that these participants reported problems because they were using the website actively. Thus, it appears that those who did not give feedback or complaints about an unstable website did not do so because they did not actively use the program or dropped out early. Additionally, I inferred that, partly because the coaches, peers, and technicians were enthusiastic to help, the support comforted most of the participants and earned their understanding.

Figure 19 - Meta-patterns for Users Frequently Reporting Technical Problems



Section 4 Discussion

The current study used multiple methods to characterize the engagement of older participants in MoodTech, and the results provided insights from both quantitative and qualitative perspectives. In this section, I will discuss the major findings pertaining to online engagement of older adults in MoodTech, offer suggestions for future intervention design, and discuss the methodological implications from combining multiple methods.

4.1 Characteristics of Older Adults' Engagement with MoodTech

Older adults with depression are a special population in psychotherapeutic interventions because the complex influence from physical diseases, frailty and cognitive impairment make it hard to assess the efficacy or feasibility of interventions (Kok & Reynolds, 2017). Even when cognitive behavioral therapy has been widely applied into online psychotherapeutic interventions, older adults are relatively underrepresented in these studies, and their experiences are not well-assessed (Crabb et al., 2012; Knowles et al., 2014). In the current study, I endeavored to examine the unique characteristics of older adults in terms of how they engage with this online CBT program MoodTech.

I observed great diversity in engagement behaviors, both in individual activity types, as well as in the meta-pattern graph. The user behaviors were different in the three types of social interactions, especially in terms of the number of actions sent out by the individuals. The nudge networks were least active probably due to the lack of substantive content in the action, and the lack of similar features on popular social network sites. The delivery forms of the intervention did not have a clear association with the distribution of the patterns (Figure 5), suggesting that peer support features did not have an obvious influence on the other aspects of the intervention such as learning lessons and practicing skills.

By learning the lesson contents and accessing tools, many participants reported to coach and peers or expressed in thought records that they were more aware of their problems and more alert to triggers around them. The actual changes in behaviors were less often reported since the CBT strategies in the intervention focus on changing intrinsic avoidance patterns and thinking patterns, which is a cognitive change that in turn stimulates behavioral and emotional changes. But a few people reported real progress in breaking avoidance cycles and harmful thinking patterns, which improved their moods and emotions.

Negative attitudes or beliefs may come from frustration with practice or boredom from familiar materials. For novices who encountered difficulties, support from coaches and peers is valuable, but for those who have already been exposed to CBT or practiced similar strategies before, a better solution could be providing novel content and encouraging deeper thinking, because repeat practice might cause negative responses or reinforce biased thoughts that the strategies are not useful. For many older users, the problem was not the failure of CBT principles, but the fact that they had preconceptions that prevented them from practicing the strategies correctly. Lack of engagement was the cause of unsatisfactory outcomes, not the converse. If participants never carefully learned the lesson and still kept on being trapped in the negative cycle, they were more likely to blame themselves or others, rather than to seek solutions. It is very hard to break deep-rooted opinions, especially in older adults who have experienced a lot and constantly reinforce harmful thinking patterns. As far as I know, previous studies have studied reluctance in seeking face-to-face treatment (Doherty et al., 2012; Sharry, Davidson, McLoughlin, & Doherty, 2013), but have not examined skepticism towards the CBT protocol or other biased beliefs that could impact engagement.

Overall, engagement behaviors of older adults are hard to predict, but can potentially be influenced by technology use habits, contents of interactions and previous psychotherapy experiences.

4.2 Intervention Design Suggestions

Consistent with many previous studies about engagement and user experience, I also recognized that usability issues, such as navigation and stability of the website, were important complaints that were expressed in communications between participants and coaches, as well as among the participants themselves. The possibility of feeling frustrated or annoyed could lead to drop-out or low engagement, which would have a negative impact on the perceived benefits and actual outcomes of online CBT interventions (Earley et al., 2017). Most of the issues in MoodTech were related to website design process and would hopefully be improved in future iterations.

During the analysis of networks, I found that the design of comments was not convenient. As shown in the Figure 1, the system treated all comments as responses to the original posts. Even though the comments were shown in order, it was not clear which comment (or the original post) the sender was commenting on. Thus, this design blurs the boundary of sender and recipient. Also, there was a limit to the number of words per post or comment, which made some participants have to respond to their own posts to make a complete statement. Therefore, the networks created in the current study did not completely depict the relationships in those interactions. If in the future, the comment feature were altered to specify the senders and recipients of the comments, the networks could be rendered more precisely in analyzing the social interactions.

I now discuss the implications for tailoring the intervention to different subgroups of participants. In MoodTech, I discovered subgroups that were expecting novel content from intervention, subgroups that needed better explanations of CBT, subgroups that were actively using social interaction features, and subgroups that were not interested in social interactions. It might be helpful to classify participants by characteristics such as, technology use habits, social network interests and previous psychotherapy experiences, in addition to demographic characteristics. This information can be collected through surveys or questionnaires at the beginning of the study to facilitate personalization of the intervention.

4.3 Methodological Implications

To my knowledge, there has not been a study of engagement using visual analysis, network analysis and qualitative analysis at the same time. Each method provided a special perspective on engagement and combining these methods afforded a richer depiction of engagement from different angles. Visualizations are powerful tools for analyzing diverse data types, compare multiple participants, and search for patterns. Studying differences between members of a network can be helpful for identifying the subgroups of participants who are more comfortable with social interactions, and qualitative analysis provides rich detail of subjective experiences and facilitates understanding of the reasons behind external behaviors. I also tried to make results from multiple methods complementary to each other.

For example, compared to the statistics presented in tabular form in Table 2 and Table 24, the network analysis was a more intuitive and effective way to identify active users and study the extent to which members interacted with one another. It also helped us discover that there were participants in the cohort who never initiated an interaction by themselves but were involved in networks through others' comments, likes or nudges. On the other hand, as for the dimension of time, static networks did not facilitate the study of sequences and temporal changes in the activities, but I was able to study these phenomena through the individual online action visualizations.

The participants demonstrated considerable variability in patterns of engagement. It is almost impossible to use one type of data to represent online engagement, and it can be difficult to perform statistical methods on a heterogeneous set of variables. Visual analysis, in this regard, can be a useful method because it can combine multiple data and support intuitive reasoning (Caban & Gotz, 2015). Visual analysis can serve as an alternative way to explore online engagement and yield unique insights than more commonly used summative measures. I used visual analysis to investigate several types of log data and detect different patterns of use, then create a meta-pattern graph to search for subgroups. Specifically, the visualizations can allow comparison of all the participants in the same temporal scale and numerical scale (y-axis). It is also a powerful tool to detect those exceptions and edge cases that did not typically fit into the definition of patterns.

The qualitative results were also helpful to contextualize the results from quantitative or visual analytic methods. Besides interpreting meta-patterns, qualitative evidence could also be used to explore details in every visualization pattern. For example, the fact that relaxation guidance videos were not often accessed was not only because they were introduced in the later part of the CBT lessons, but also because many participants had their own relaxation strategies or had doubts towards the materials provided in the program.

It is a challenge to synthesize different results and also maintain the richness of individual experiences. Without qualitative materials, I might not be able to understand the reasons behind the external behaviors. The qualitative analysis results described heterogeneous experiences of the intervention and helped me understand the results from quantitative and visual analysis. Therefore, it is important that well-designed qualitative data collection and analysis should be included in CBT trials, so that researchers can determine what the underlying causes are relating to engagement and other outcomes.

Section 5 Limitations

There were various limitations of this study. One of these is that the analyses were conducted on data generated during the intervention, and the application of CBT principles in some participants could merely reflect short-term improvements. It was not possible to investigate whether there were sustained gains from the intervention due to this limitation of the data collected. Also, given the sample is rather small in MoodTech (45 participants who participated in the online intervention), the findings of this study are exploratory and cannot be generalizable to larger older populations without further validation.

Methodologically, the meta-pattern of engagement was a novel method and could have oversights or defects. The interpretation of the meta-patterns could be difficult, and even with qualitative analysis I was still not able to confidently use simple definitions to describe the characteristics of the participants or explain their behaviors. The meta-pattern graph can be expanded to include more variables of other forms of engagement, and the explanation of the pattern distribution needs more evidence.

Consistent with the underlying premise of qualitative approaches, it is inevitable that there is some subjectivity in the defining of patterns. Identifying patterns in visualizations requires subjective judgment such as how many types should be defined and why this graph was categorized into this pattern. There will always be some parts that do not perfectly fit the pattern model but focusing on nuances would result in more patterns and make the data harder to summarize. Thus, during this process, it is unavoidable that some information be dismissed, and, the edge cases in pattern identification need more discussion.

One final methodological limitation is that due to time limitations, crossover examination of results from the different aims was not fully conducted. It is possible to use qualitative analysis to more richly contextualize the differences in engagement patterns identified through the visual analysis, and in social interactions, as observed in the network analysis.

Section 6 Conclusion

In this study, I investigated engagement using multiple methods. First, I studied user engagement by characterizing individual and group behaviors. I identified patterns in multiple engagement variables and then developed a visualization to facilitate comparison of meta-patterns of engagement. I examined the application of CBT strategies and found factors that could be used to identify subgroups among participants. Engagement behaviors of older adults can potentially be influenced by technology use habits, degree of interest in social interaction, and previous psychotherapy experiences. Future intervention designs may take these factors into consideration and tailor interventions for different subgroups of participants, as well as improve the usability to meet the needs of older adults.

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Appendix

Figure 20 - Engagement Trajectories (Castro et al., 2017)

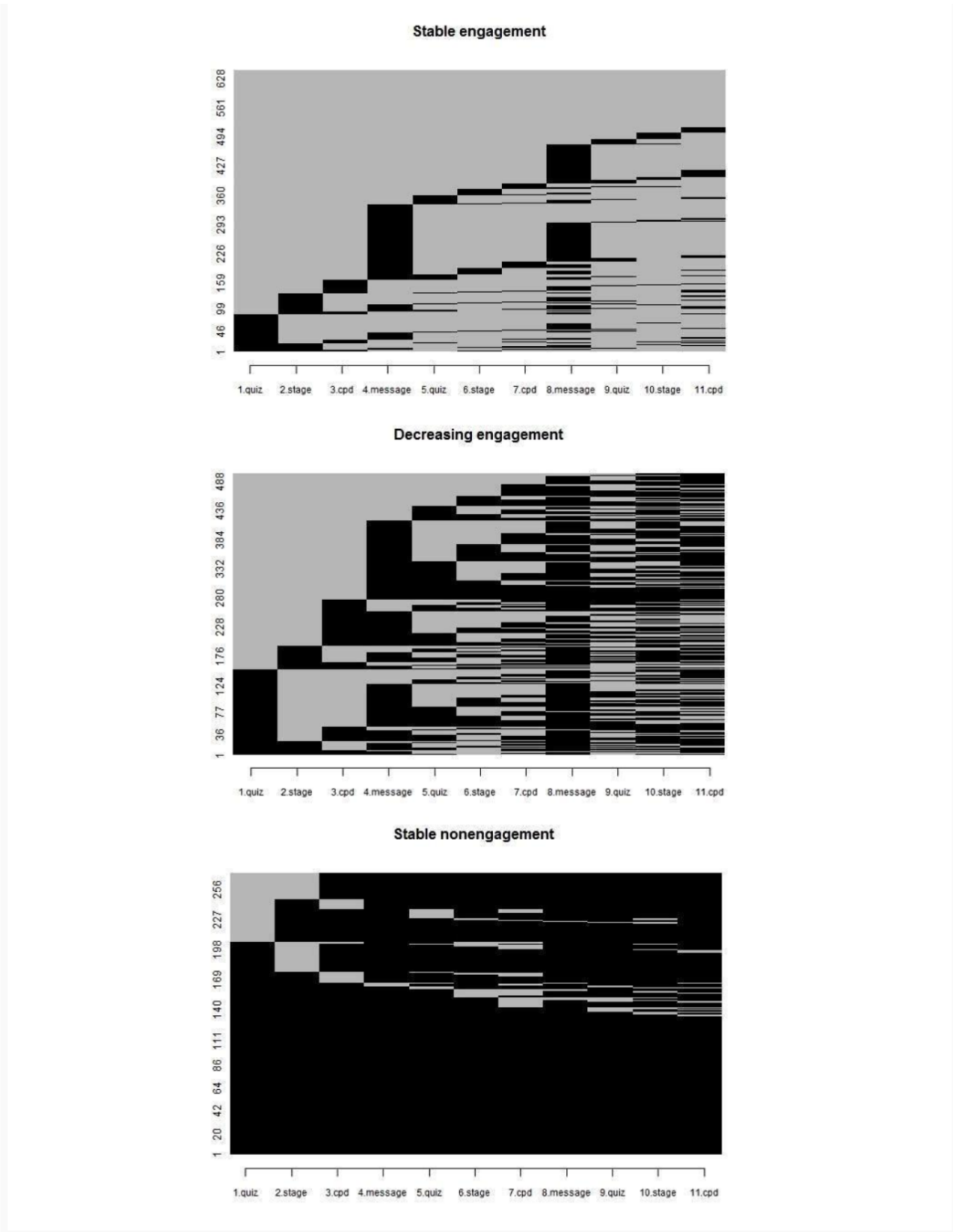

Figure 3. Individual engagement trajectories within each of the three clusters. Rows represent participants and columns represent the 11 prompts that could be answered by the participants. Black boxes represent nonreplies, and gray boxes represent replies.

Figure 21 - Navigation Graph (Morrison & Doherty, 2014)

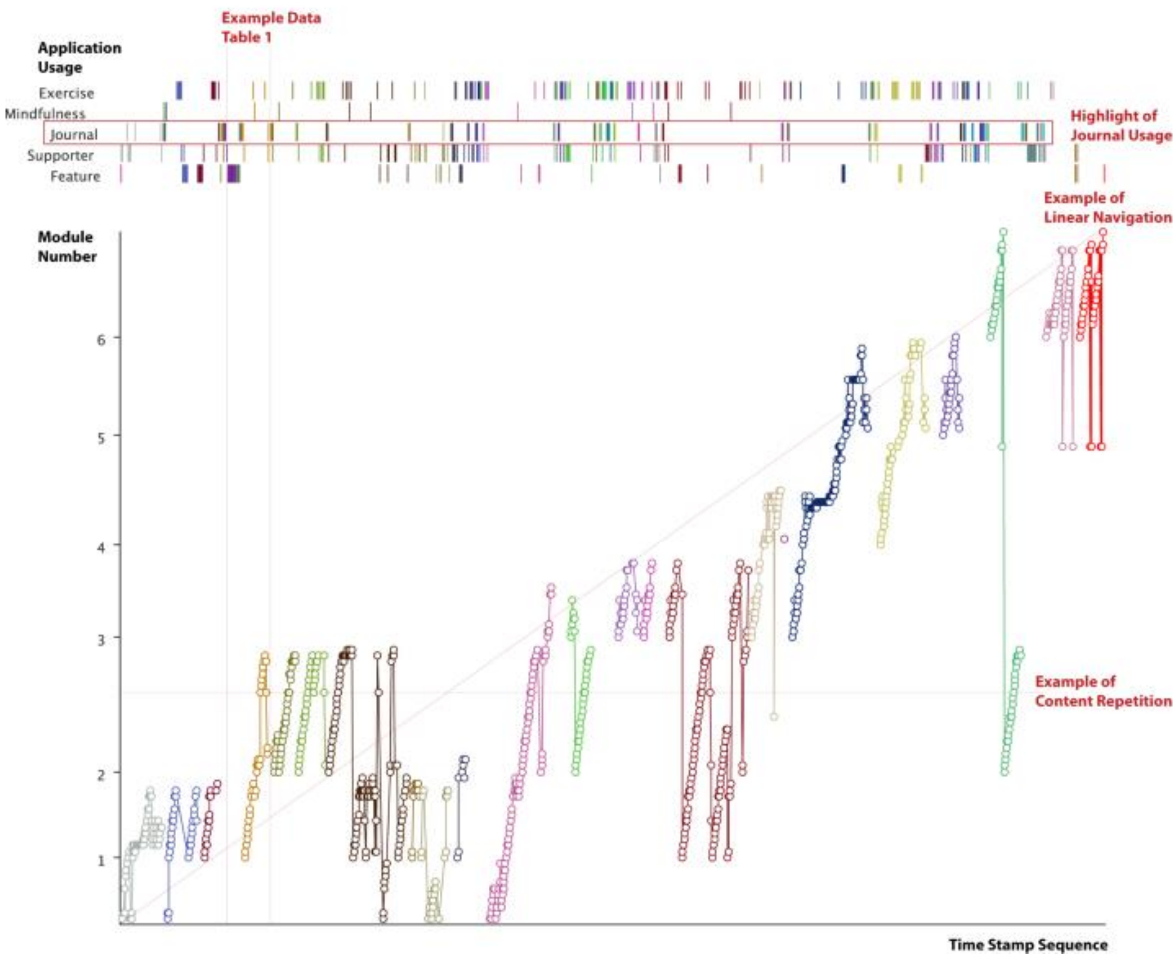

Figure 22 - Patterns of Use Trajectories (Morrison & Doherty, 2014)

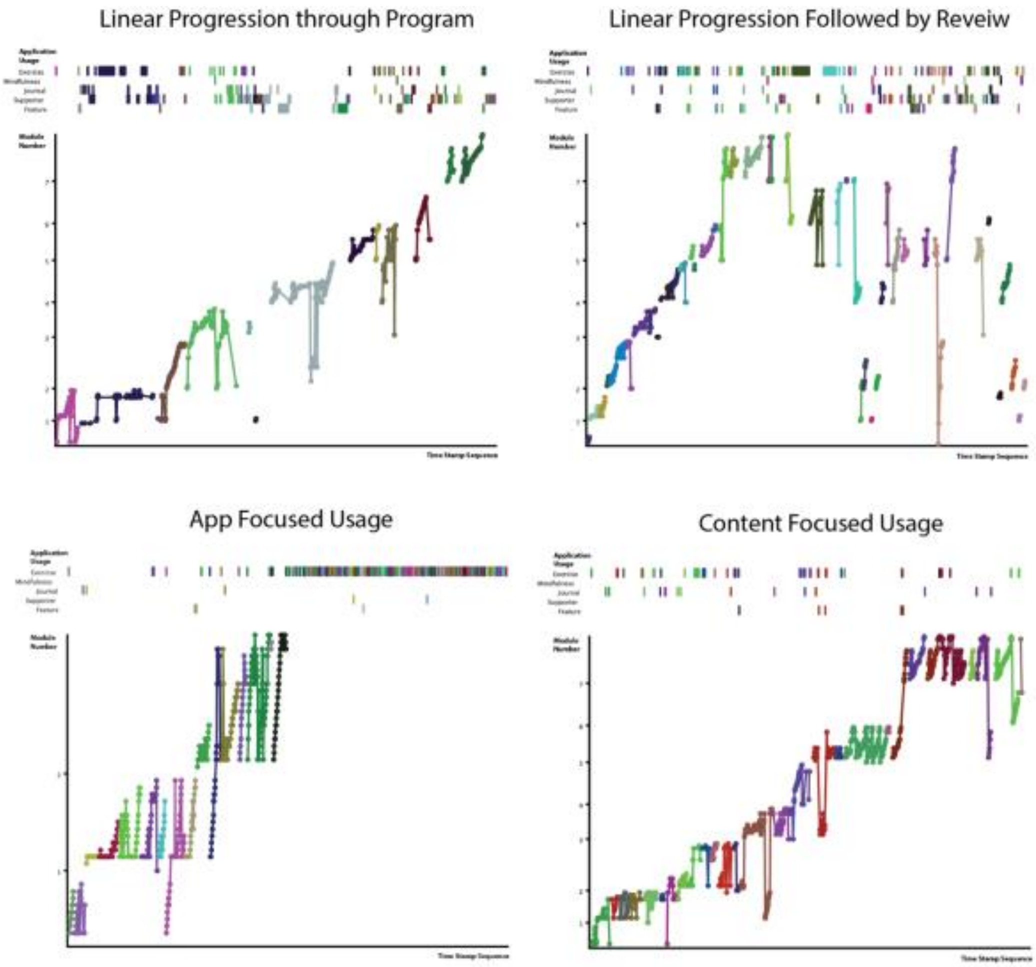

Figure 23 - Engagement Histograms (Lehmann et al., 2012)

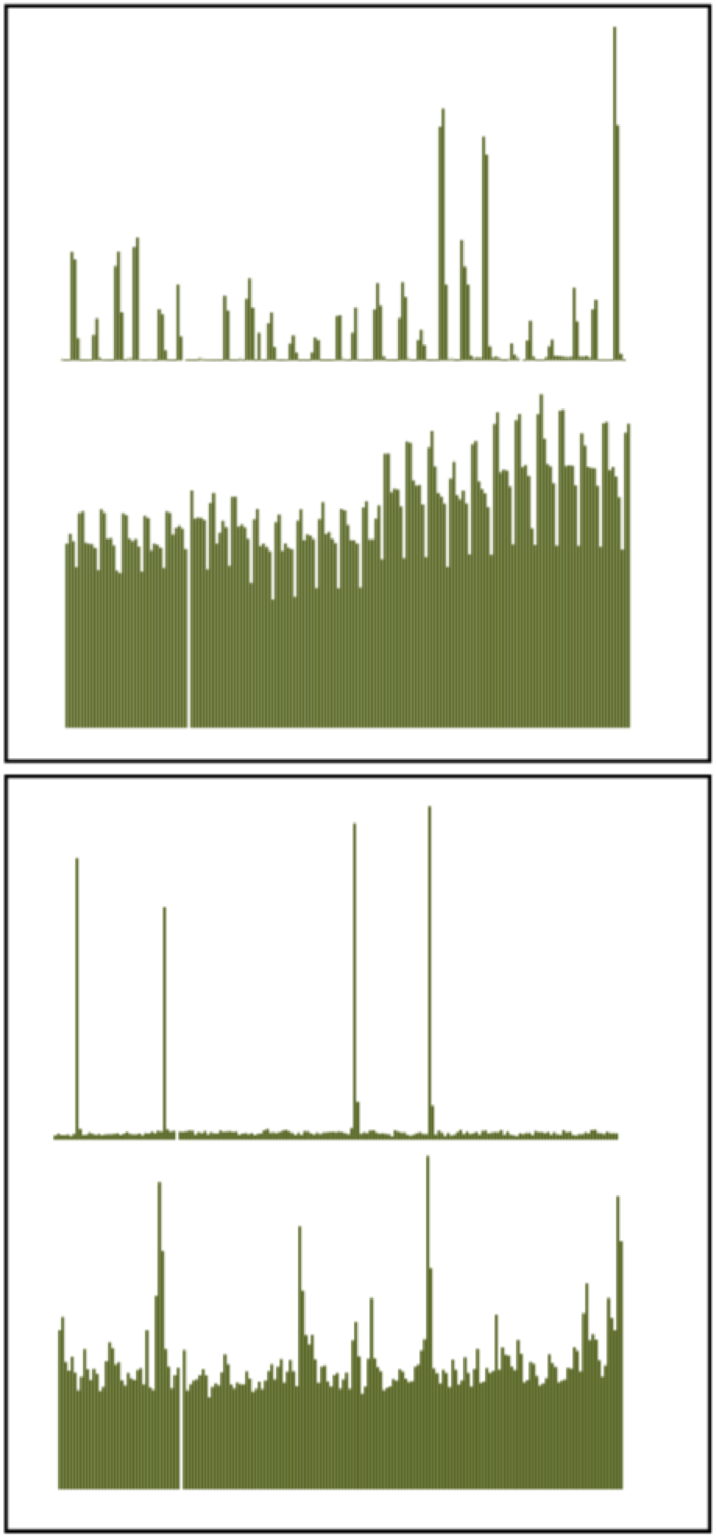

Figure 24 - Heatmap of Gene Expression Data (Wilkinson and Friendly, 2009)

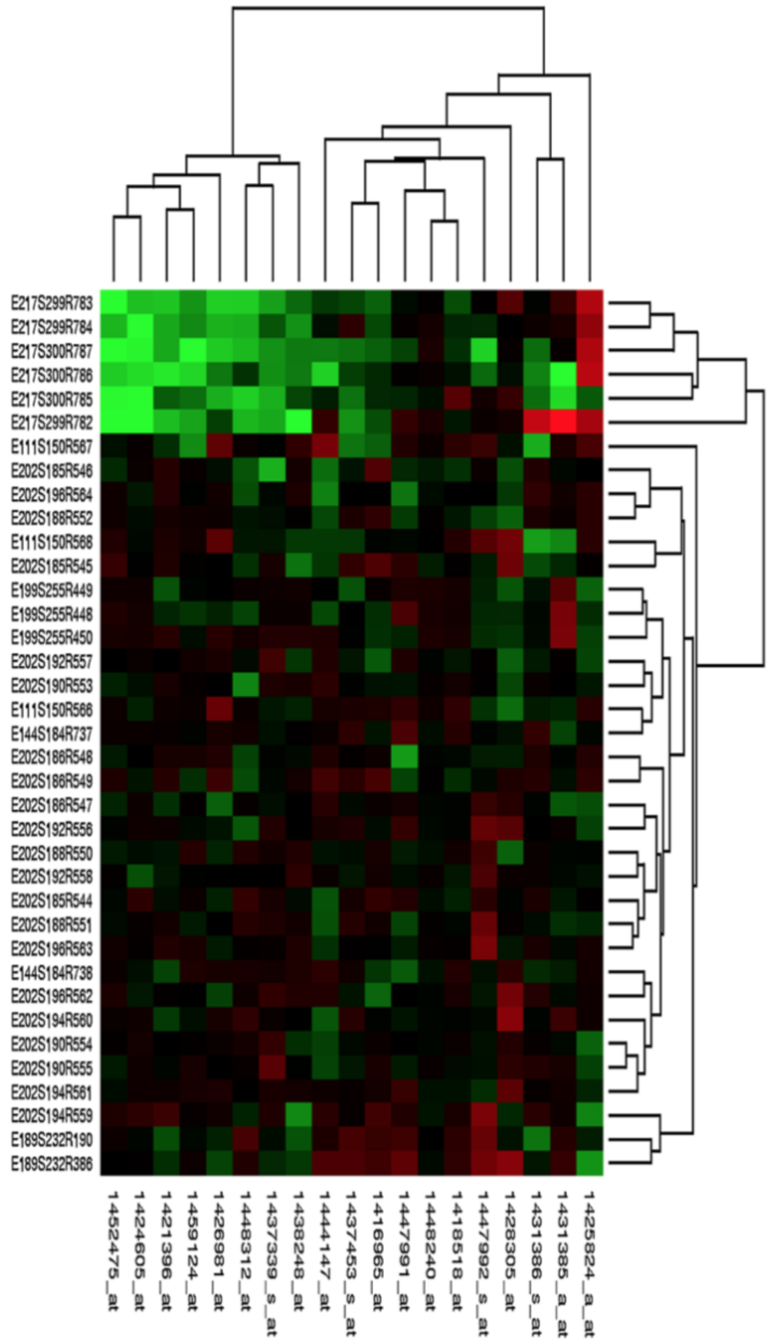

Figure 1. Cluster heat map from Andrade (2008), based on Eisen et al. (1998). The aspect ratio has been adjusted to make the pixels square. The rows (or columns) of a microarray heat map represent genes, and the columns (or rows) represent samples. Each cell is colorized based on the level of expression of that gene in that sample.