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Push Notifications in Diet Apps: Influencing Engagement Times and Tasks

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ABSTRACT

Background: Smartphones have reached levels of popularity and penetration where they are now suitable for use in population health interventions. A key feature of smartphones is push notification or in app messaging service, which can be used to alert users to messages or instructions pertaining to an installed app. Little evidence exists as to the persuasive power of these messages.

Method: We conducted a 24-week live user evaluation of push notifications used in a behavior-based mobile app for a meal replacement program to understand the role of push notifications in persuading users to engage with self-monitoring tasks.

Results: User perception of the prompts were verified through questionnaires, which in conjunction with the interaction logs show that users were tolerant of multiple daily prompts. The decline in compliance to the tasks set, however, shows that while the participants did not object to receiving prompts, they were less likely to respond to them as the study progressed.

Conclusions: Push notifications and user tasks are appropriate mechanisms to engage users with mobile technology in the short term.

1. Introduction

The rate of chronic diseases in the developed world has been growing steadily in the last decades. Addressing the problem often requires a change in behavior and lifestyle, which is hard to achieve without ongoing external support. As the support that can be obtained from medical practitioners is often limited, more and more research is looking into the provision of information technologies to support people embarking on a behavior change program. These technologies apply a suite of persuasive tools to strengthen user engagement with the behavior change program and sustain steady participation.

The most common medium for the delivery of persuasive health interventions has traditionally been the Web. Prior evidence shows the effectiveness of online interventions in influencing user behavior—see encompassing literature surveys covering a broad spectrum of goals, technologies, and medical conditions (Acampora et al., 2013; Enwald & Huotari, 2010; Lehto & Oinas-Kukkonen, 2011; Lustria, Cortese, Noar, & Glueckauf, 2009; Norman et al., 2007; Vandelanotte, Spathonis, Eakin, & Owen, 2007; Webb, Joseph, Yardley, & Michie, 2010). Despite being generally effective, the very nature of online interventions is somewhat restricted, mainly due to two inherent limitations: the special attention that interaction with the interventions requires and the limited availability of reliable data reporting. Users are expected to remember to regularly interact with the sites facilitating the interventions and self-report their progress or conditions. As such, they may miss some interactions or report subjective or imprecise data, which may significantly deteriorate the effectiveness of the delivered interventions.

The mobile medium has the potential to successfully address the above challenges. Mobile phones are always on and always with the users, such that carefully designed interactions may require little cognitive effort and be completed "on the go". More importantly, the variety of sensors and technologies offered by modern smartphones substantially boost the accuracy, richness, and reliability of user data available to the mobile interventions. For example, consider the GPS, accelerometer, and gyroscope that can be leveraged to accurately estimate the amount, type, and duration of physical activity performed by a mobile user. These can be easily synchronized with additional devices, e.g., the heart rate and respiration monitors, which can use the mobile phone's communication capacity to report data on behalf of the user.

Mobile interventions can also be configured to gently nudge their users and increase their engagement with the health behavior change programs. Through text messaging, reminders, and monitoring tools, mobile phones can complement and enhance the online programs (Morak et al., 2008; Park, Kim, & Kim, 2009; Patrick et al., 2009). Early mobile phones were used as secondary communication mediums and were not considered core to the activities being encouraged. However, the smartphones and, particularly, native smartphone applications (in short, apps) have changed the role of the mobile phones in behavioral change interventions (Lathia et al., 2013). Hence, the ubiquity of smartphones means that they can act as the primary intervention devices, through

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which the content is delivered, the triggers for user interactions are sent, the necessary data is gathered, and user feedback is obtained.

In this article, we examine the role of tasks and notifications in a mobile app designed to support dietary change. We present a novel behavior-based mobile weight management program and application. The app builds upon a previously evaluated prototype app (Brindal, Hendrie, Taylor, Freyne, & Noakes, 2016; Freyne et al., 2010) and aims to support users on a Partial Meal Replacement Program (PMRP) diet by promoting self monitoring and reflection. The app is implemented as an interactive iPhone app that allows users to record food intake and weight data, provides feedback through graphical and textual mechanisms, and highlights the user progress toward their goals through visualization and rewards (see Figure 1 and 2). The app aims to strengthen user engagement through proactively prompting and reminding users to interact with the app several times per day. This is achieved by initiating self monitoring tasks, requesting weight updates and food intake recording, and reminding users of toward the desired weight loss goals.

While previous studies of health related text messages examined the overall contribution of mobile communications to the interventions (Brindal et al., 2016), here we examine user responses to tasks and notifications, and the resulting interaction patterns with the content and tools provided by the app. We analyze interaction logs gathered as part of a 24 week diet program. Our analysis shows that most users appear to tolerate receiving multiple notifications per day. We show that the combination of tasks and notifications drives an increased user engagement with the app at designated times, and with designated application components. We note a variety in the response rates to prompts sent at varying times of day, with higher compliance to prompts sent earlier in the day. We also note the differences obtained in the first 12 weeks of the program, when the participants were engaged with regular clinic visits, and the second free-living 12 week period. Qualitative analysis of users showed that 55% of users considered the notifications were good or helpful, with 13% users commending that notifications were well timed, and 20% commenting that they were too frequent or annoying after a while.

Thus, the contributions of this work are: First, we present the commercial grade native iOS application designed to support participants of a PMRP. Second, we report the results of a 24 week trial that evaluates the value of the application tasks and notification in supporting self monitoring.

2. Related work

Mobile Health (mHealth) applications are being developed in large numbers to satisfy high market demand in the diet and lifestyle space (Platt, Outlay, Sarkar, & Karnes, 2016). Dieters and exercise fans are keen to have convenient access to health information, recipes, self monitoring tools and more through their smartphones. Given that consumer demand has been a key driver in the design and development of mobile applications in this space, the commercial world rather than the academic world are leading the way in the development of mHealth applications (Shigaki, Koopman, Kabel, & Canfield, 2014). It is recognized that many apps designed in the obesity space do not incorporate theories or principles that could encourage behavioral changes (Hermawati & Lawson, 2013). Furthermore, research has identified the shortage of evidence-based research related to the short and longer term effects of application usage

Figure 1. App screen shots (a) Home screen, (b) Information Section, (c) Calendar View, (d) Meal diary.

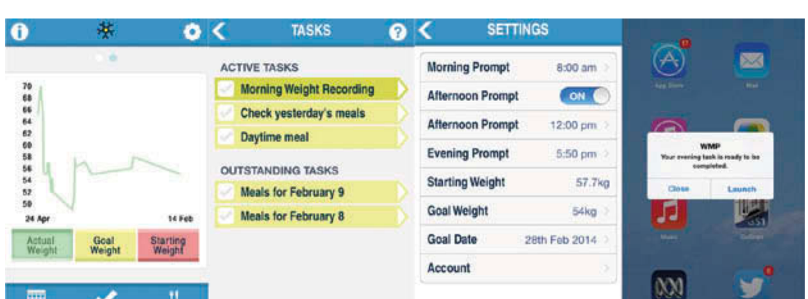


Figure 2. App screen shots (a) Weight tracker, (b) Task Menu, (c) Task configuration, (d) Prompt/reminder.

(Abroms, Padmanabhan, Thaweethai, & Phillips, 2011; Derbyshire & Dancey, 2013; Fry & Neff, 2009). Our work focuses on the design, development and deployment of efficacious mobile applications for dietary change to address the concerns and recommendations from leading experts.

Mobile phones are widely accepted as useful peripheral communication devices for a range of behavior change programs including diet management and obesity [8, 9, 10, ?], physical activity (Hurling et al., 2007; Prestwich, Perugini, & Hurling, 2009), mental health and social isolation (Vargheese, Sripada, Masthoff, & Oren, 2016; Whittaker et al., 2011), health promotion (Fry & Neff, 2009) and diabetes management (Yoon & Kim, 2008). The primary usage for mobile phones reported in the literature is as a communication tool, where messages (prompts, motivation, feedback requests) are send to an individual (Hermawati & Lawson, 2013). Due to their ubiquity, mobile phones provide real-time access to participants and change the modality of intervention from one where participants choose when to engage, to one where they are encouraged or prompted to engage. The realization of "just-in-time" or context sensitive communication can drive participants to do certain actions at certain times. Studies have shown that in the short term SMS was seen to have promising efficacy for the delivery of health behavior change interventions, by increasing adherence to the treatment program (Fjeldsoe, Marshall, & Miller, 2009). One such study focusing on the use of a text message-based phone intervention aimed at changing food intake and daily weight monitoring, was found to be effective for weight loss in the short (3 months) and longer term (12 months). Attrition on the program was 50% over a year period, but maintaining contact with the program was positively associated with weight loss success (Haapala, Barengo, Biggs, Surakka, & Manninen, 2009). Therefore prompting appears to be a critical component of mobile phone health interventions. Prior work proposes that electronic self-monitoring can be more effective than pen-and-paper recording (Burke et al., 2005), mobile phone messages can provide instant feedback (Cole-Lewis & Kershaw, 2010), make personalized feedback an easier possibility (Glanz, Murphy, Moylan, Evensen, & Curb, 2006), and utilize behavioral prompting (Fry & Neff, 2009). These factors make a strong case for the development of mobile apps in this space.

Research on the impact of notifications on human behavior has been conducted in online and mobile environments, with the most recent wave of research being coined *Interruptability Research*. Online notification research focusses on desktop notifications such as email pop ups and notifications from software applications (Cutrell, Czerwinski, & Horvitz, 2001; Gould, Brumby, & Cox, 2013; Iqbal & Horvitz, 2010; Mark, Voida, & Cardello, 2012; Renaud, Ramsay, & Hair, 2006). Notification use on mobile phones has become extremely popular with the proliferation of smartphones and tablet devices, with Pielot reporting in excess of 63 notifications being received by study participants each day (Pielot, Church, & De Oliveira, 2014). Notifications are commonly used to draw users' attention to an app or an event. Sahami et al (Sahami Shirazi et al., 2014) conducted a general investigation into notifications and discovered that notifications are generated by a diverse set of apps including messaging apps, clocks, news, games and mail and confirmed that users' value notifications despite their disruptive nature. The study showed a correlation between a users' perceived value of a notification and their response time, with important notifications being attended to faster than lower value notifications. The probability that users clicked a notification within five minutes of receiving is 83%, with a 50% probability of a click within 30 seconds. In their study messenger notifications were responded to fastest, with News apps having the longest click time. Fischer et al. (Fischer, Greenhalgh, & Benford, 2011), conducted a study that showed that users' receptiveness to a notification is determined by the users' interest in the notification content. In Pielot's study, an increasing number of notifications were associated with an increase in negative emotions; receiving more messages and social network updates also made their participants feel more socially connected. Their conclusion was that avoiding professional notifications could be achieved; when it comes to personal notifications approaches should focus on managing expectations.

The most recent wave of research in the interruptibility research area is focused on understanding when people are likely to be receptive to interruptions by considering individual daily patterns (Choy, Kim, Lee, Kim, & Motoda, 2016), location (Exler, Braith, Schankin, & Beigl, 2016) or psychological interruption research (Anderson, Heißler, Ohly, & David, 2016)

Pejovic and Musolesi (Pejovic & Musolesi, 2014) show that users' broad context, including their activity, location, time of day, emotions and engagement, determine different aspects of interruptibility and through an experiment of their Android app show that, compared to a context-unaware approach, interruptions elicited through our library result in increased user satisfaction and shorter response times. In a more recent study, Mehrotra et al (Mehrotra, Pejovic, Vermeulen, Hendley, & Musolesi, 2016) examined context such as physical (presentation, alert type, sender-recipient relationship) and cognitive factors (task complexity) impacted response times and perceived disruption of notifications. Interestingly, the study also highlights the substantial role of the psychological traits of the individuals on the response to notifications.

Few studies evaluate the efficacy of smartphone applications in the behavior change space. The combination of information access, digital self-monitoring, messaging, and the convenience of a mobile phone is expected to be a winning combination, but few have completed long term analysis of their usage. In our previous work we designed and deployed a behavior-based mobile application for weight loss, which provided information, tools, and exploited prompts or push notification as reminders to complete diet related self monitoring tasks (Brindal et al., 2013; Freyne, Brindal, Hendrie, Berkovsky, & Coombe, 2012). Our 8-week trial of the prototype indicated a trend toward better weight loss with an interactive support app with prompts relative to a control app with no prompts. Preliminary data suggested that the app could be an important adjunct to existing programs with the potential to protect against falls in motivation to stay on a diet and to improve positive mood. These psychological factors are seen to be important for maintaining engagement with the weight loss program and the subsequent weight loss.

In this work, we follow on from the initial study with a larger participant cohort and a commercial grade app. Here we focus on one particular app feature, to shed light on the true impact of communicating with participants through push notification messages.

3. Weight management program

3.1. Partial Meal Replacement Program and App

Commercial Partial Meal Replacement Programs (PMRP) have become a popular choice for people trying to lose weight (Heymsfield, Van Mierlo, Van der Knaap, Heo, & Frier, 2003) and have been shown to be successful in achieving weight loss in overweight adults (Noakes, Foster, Keogh, & Clifton, 2004). Participants following meal replacement programs are expected to replace a number of daily meals with pre-packaged formulated shakes or bars, eat one balanced daily meal, and snack on allowable foods between meals. We have developed a PMRP that uses a smart phone app as a support tool for weight loss intervention and encouraging self monitoring by users.

The app was designed to support dieters by educating individuals through the provision of program information, by encouraging self monitoring of food and weight by rewarding positive behavior, and by encouraging regular engagement with the app through notifications and prompts. The app was implemented as a native application for iPhones running iOS6 or later. The application used 3G cellular networks or WiFi to communicate with a web service and Parse database in order to record user data, log events, and deliver content.

Users could learn about general diet and healthy eating, familiarize themselves with dietary rules, and read topic specific tutorials in the Information section of the app indicated by the *i* icon on the top left hand side of Figure 1a. The app provided monitoring tools for weight and food, and communicated weight loss progress and compliance visually and through virtual rewards. The app used a medal-based reward system to recognize and promote compliance with the diet guidelines. Gold, silver and bronze medals reflected how well the recorded food intake meets a user's daily targets. A gold medal means that the guidelines were met; silver that intake was close to the guidelines; bronze that some progress toward the guidelines was made.

The app is novel in that it sets tasks for users to complete, which are set around key behaviors known to be correlated to weight loss. The motivation for the use of tasks is to engage with the user in an active way, reminding them of their commitment and to establish good behaviors around reflection and routine. Users received task prompts or reminders in the form of smart phone push notifications, as shown in Figure 2c). Within the app the task button flashed to attract the user's attention (see Figure 1a). Users could set the times that the notifications are received, and could deactivate the afternoon notification (see Figure 2d). Two task types were set: the first is a *Weight Recording* task and the second is a *Food Recording* task. Each morning the user was reminded to complete/review their dietary intake for the previous day, and to record their current weight. In the afternoon, users were asked to record that day's dietary intake, with a final task in the evening to update to their intake. Weight Recording tasks required users to enter their current weight, taking only a few seconds. Recording meals involves the selection of menu items from a short list of categories including *Program Meal, Non Program Meal, Meal Replacement, Program Snack, Mini Program Snack, Non Program Snack* and *Treat* as outlined in the program, taking typically one minute per task depending on what was eaten. If a user failed to complete an afternoon or evening task by midnight an *Outstanding Task* was created. A maximum of seven outstanding tasks (7 days) were stored.

3.2. Overview of the study

We conducted an efficacy trial of the PMRP including the app (Brindal et al., 2016). The study was approved by the CSIRO Human Research Ethics Committee and registered with the Australian New Zealand Clinical Trials Registry (ANZCTR registration number: ACTRN12613000547741). Participants of the trial were over 18, had self-reported BMI greater than 25 kg/m^2 (i.e. overweight), owned an iPhone, had access to scales and were willing to attend a clinic on seven occasions. The study included an active intervention period of 12 weeks, followed by another 12-week period. All participants embarked on identical dietary interventions, but different apps were tested in the trial: the app described previously and a basic app which containing information about the program only (i.e., no self monitoring tools or notifications). Participants were provided with meal replacement product during the intervention period. No other incentives or rewards were provided.

To ground the research presented later in this article, we first provide a brief overview of the relevant outcomes of the overall study. By Week 24, 57.5% of participants remained in the study. No difference in drop-out between the two app groups was observed. The large drop-out (n = 24) between weeks 4 and 8 corresponded with the cessation of the provision of free meal replacements. A majority of drop-outs were lost to contact with no reason provided (n = 35, 56.5%). A small portion (n = 7; 11.3%) identified gastrointestinal issues or difficultly with the diet as the reason for withdrawal.

Weight loss self-efficacy increased and remained significantly higher than baseline at week 24 ($16.85 \pm 2.93, p<0.001$) for both groups. Based on a cohort analysis of the trial, the mean decrease in weight from baseline to week 24 was 6.43 $\pm$1.06 kg for males ($p<0.001$) and 5.66 ± 0.70 kg for females ($p<0.001$). Overall, both apps supported participants and were successful in achieving significant weight loss and improvements in health outcomes over 24 weeks although engagement with the apps differed. Figure 3 shows the correlation between the duration of membership (time between first and last login) and the number of days on which the app was accessed. We note that those with access to self monitoring tools and notifications accessed the app more than those with program information only. Full details of the study can be found in (Brindal et al., 2016) .

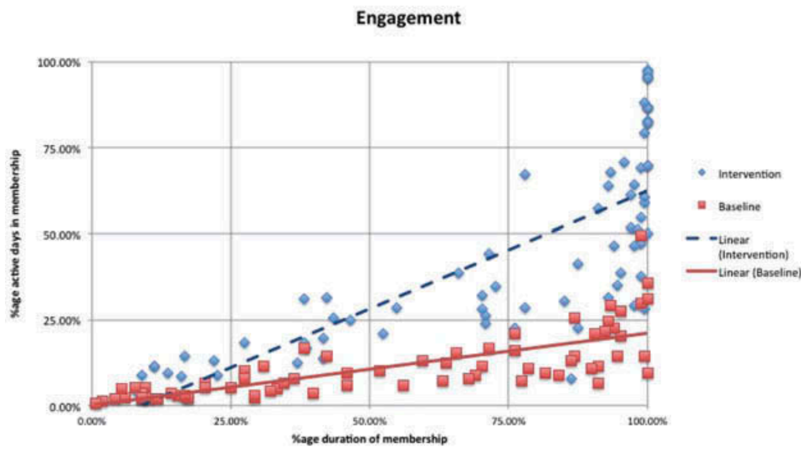


Figure 3. User engagement.

In order to evaluate the impact of the app notifications, we examined the usage logs gathered from users of the app with the notifications enabled ($n = 75$). 55 participants were female, 20 male. The average age of the participants was 48.57, the youngest participant was 21, the oldest—74. In this article, we report on observations and responses to tasks and notifications over time.

3.3. General application usage

Over the course of the trial (168 days), 75 users logged 12,613 app usage sessions, averaging 1 daily session per user. Figure 4 shows the portion of the population of active users who logged in any week. As expected we observed a reduction in app usage over the 24 weeks, but we note that after 17 weeks, half of the users are still engaging with the app. Figure 5 shows the proportion of users who used the app on a number of days (max = 168). We observe that 50% of participants logged into the app on 70 or more days. The remaining 50% used the app less frequently. When using the app we noted an average duration of sessions was 2.75 minutes. Figure 6 shows the distribution of the session duration. 47% of sessions were less than 1 minute long (average duration of these was 40 seconds) and almost 90% of sessions were 5 minutes or shorter.

4. Persuasive tasks

Focusing on the persuasive power of prompts and tasks, we analyzed the prompt times, user responses, and activities driven by the tasks. As previously discussed, users were given weight and food recording tasks, two or three times a day, and tasks were brought to the user's attention via a push notification or *prompt*. The morning prompts reminded users of their weight recording task and to confirm their food entries for the previous day. The afternoon and evening prompts asked users to complete their food recording tasks. Note that while the afternoon task was always generated by the app, users had the option of being alerted to this task. The

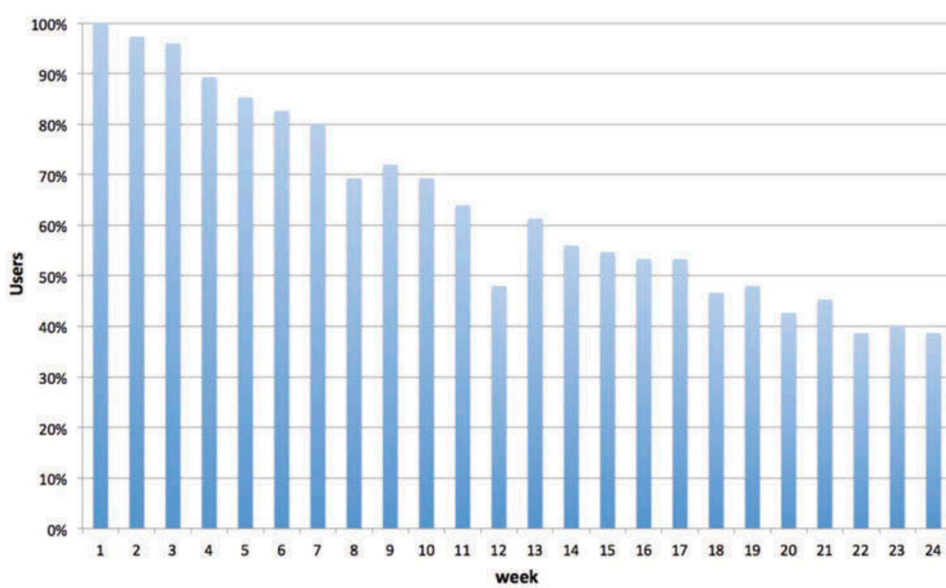


Figure 4. Active participants per week.

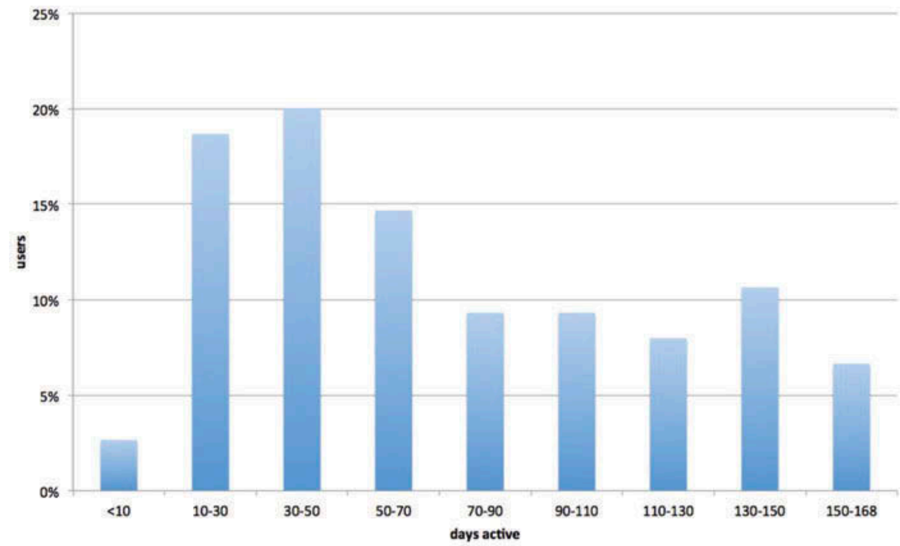


Figure 5. Number of active days.

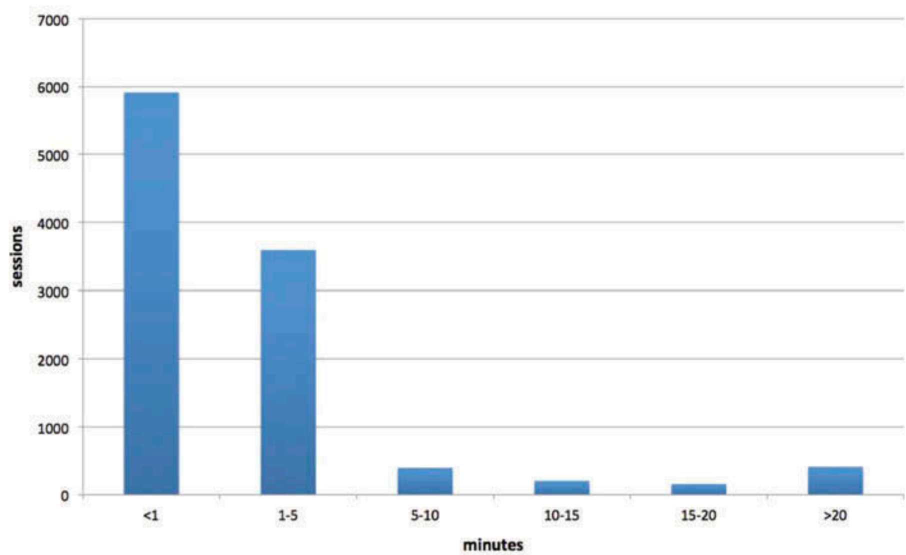


Figure 6. Session statistics.

ability to disable this task was provided to ensure that if the system was generated too many tasks for users, this feature could be controlled and would not negatively impact the study overall. Some users took this option, and we note that more afternoon prompts were disabled in the first week than at any other time, as shown in Figure 7.

46% of the 30,279 tasks set were successfully completed by participants. Figure 8 shows that completion rates overall falling from 47% to 36% and then to 26% in weeks 1, 2, and 3, respectively. By week 12 less than 10% of tasks are being adhered to. We observed differing completion rates for the morning, afternoon and evening tasks, with 26% of all morning tasks being completed, 13% of all afternoon tasks and only 8% of all evening tasks being completed. We note vastly different completion rates for tasks as the study progresses (Figure 9a-c), showing that the effect of prompts to persuade users to complete tasks (i.e., self monitor) wears off. Note that the decrease of the prompt completion rates is steeper than the attrition rate observed in Figure 4, showing the combined effect of user attrition and the weakening power of the prompts to motivate logging. We observed a 66% task compliance rate for morning weight tasks, 49% compliance for afternoon food recording tasks and 27% compliance for evening food recording tasks in week one, highlighting the differing response levels to the task types in the same time frame. The compliance rate for all tasks decreases as the study progresses, but the higher compliance to morning tasks far outperforms either of the food recording tasks.

We conjecture that there are two possible explanations for the lower uptake of the evening prompts. The first is associated with the similar nature of the afternoon and evening prompts. Since both of them referred to the food recording

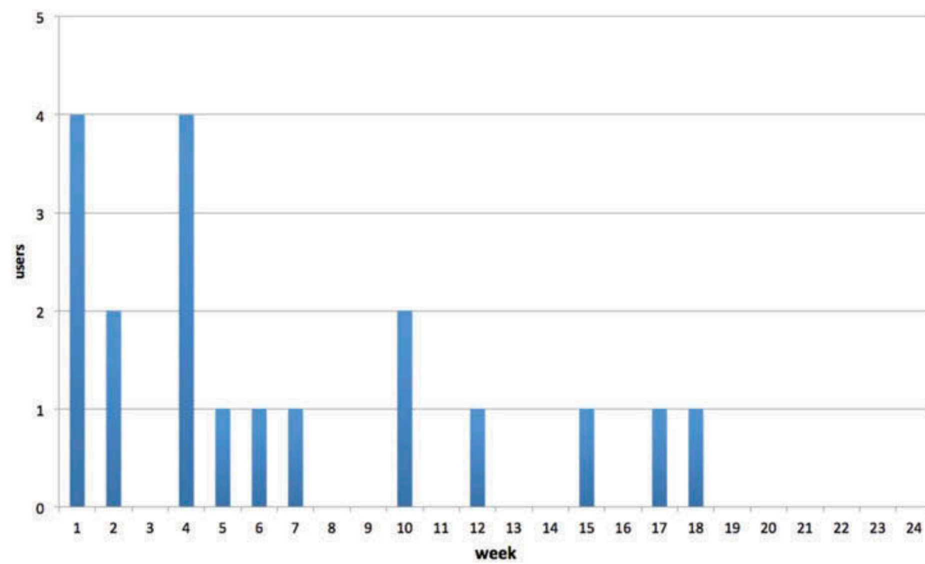


Figure 7. Disabled tasks.

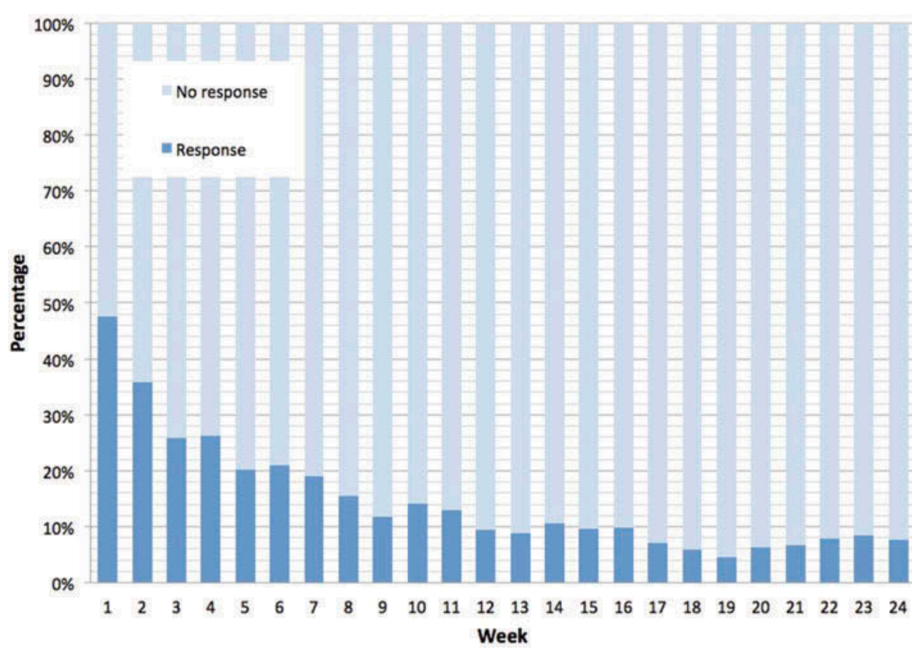


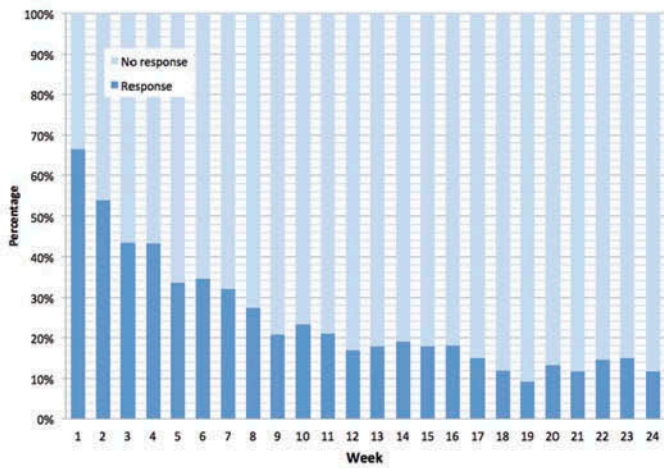
Figure 8. Task compliance rates overall.

task, users could complete only one of them and ignore the other. Unless completed, the afternoon task was positioned higher in the list of *Active Task* (see Figure 2), such that the users were more likely to complete the afternoon task rather than the evening task. Finally, our tasks expired at midnight and so the window of opportunity to complete the evening task was shorter than that of the afternoon and morning tasks. All of this taken into consideration, if participants may only have responded to one of the food recording tasks—either afternoon or evening—the sum of the completion rates for both is still lower than the completion rate for the weight task. It could be the case that weight tasks were easier to comply with, or that tasks delivered in the morning were more persuasive to users.

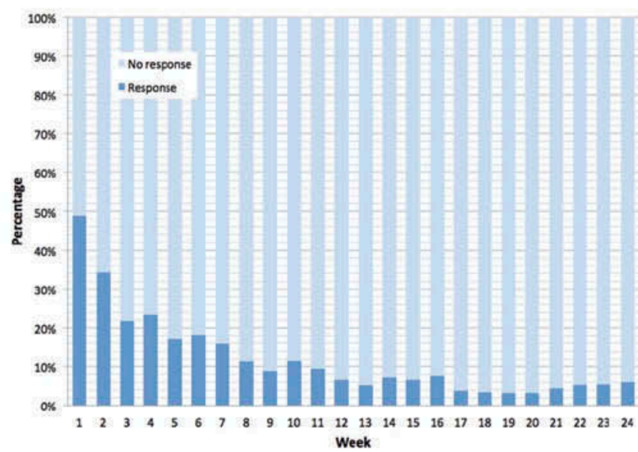
4.1. Persuasive prompts

The purpose of the prompts was to remind users to self monitor both their weight and food intake through the tasks. The user interaction logs allowed us to identify user sessions, where the application was launched directly from a prompt. Surprisingly, only 4.2% of sessions were initiated directly by the prompts. Further investigation showed that if the user's smartphone had been locked, the process of entering the PIN code hid the prompt and users tended to launch the application through the app icon rather than locating the prompt in the notifications menu.

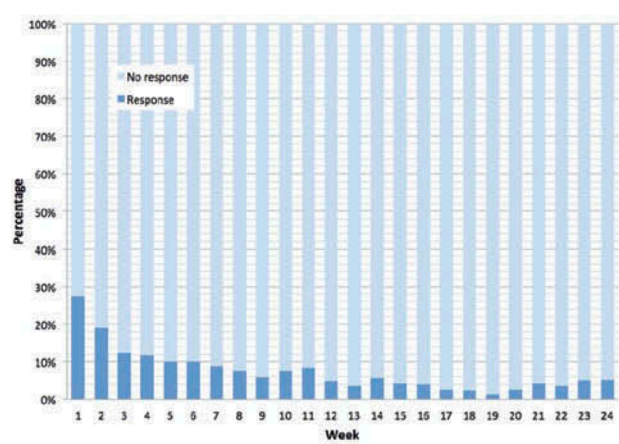
The application had default times set for the three daily prompts which could be updated by users, to a more



(a) Task compliance rates - Morning tasks



(b) Task compliance rates - Afternoon tasks



(c) Task compliance rates - Evening tasks

Figure 9. Task compliance at different times.

convenient time for the. Logs show few people deviated from the defaults. 79% of morning prompts were sent between 8:00 and 8:30, close to 90% of afternoon tasks were sent between 14:00 and 14:30, and 83% of evening tasks were sent between 20:00 and 20:30. The highest variability of prompt times was observed for the morning prompt. The impact of the prompts on the observed app activity clearly comes through in Figure 10, which illustrates the overall distribution of sessions over the 24-hour period. Three peaks of activity are clearly visible in the plot, and their time slots mirror the morning, afternoon, and evening prompt times. The activity in these slots is about double the activity observed for other times. Thus, we conclude that the use of prompts as reminders to complete tasks offers an effective persuasive mechanism that drives traffic to the app and serves as a reminder for self monitoring at the desired times of day.

The morning prompt reminds users to weigh themselves and record their daily weight each morning. Figure 11a shows users' response time to the morning prompt at hourly intervals. The average response time for the morning prompts stands at 4.85 hours. We see that 27.0% participants recorded their weight within the first hour of receiving the morning prompt, and 40.1% participants recorded their weight within the first two hours of receiving the prompt. Taking a closer look at the first hour after the prompt (shown in the inset graph in Figure 11a), we note that a total of 12.2% of users completed their weight recording task within 15 minutes of the prompt. This indicates that the morning prompt effectively motivates users to record their weight.

We note two minor peaks in the weight task completion time in the main graph in Figure 11a that correspond to 6 and 12–13 hours after the prompt. Given that most morning prompts were received between 8:00 and 8:30, the 6 hour peak corresponds to the 14:00–14:30 time slot and the 12–13 hour peak to 20:00–22:30, which coincides for many users with the arrival of the afternoon and evening prompts. Thus, we conjecture that while the morning prompt asking a user to complete the weight recording task is the most persuasive one, asking the user to complete other tasks later in the day reminds them of the outstanding morning tasks and persuades them to complete them.

The afternoon and evening prompts request users to complete their food recording tasks. Both prompts requested users to complete their diary for the day until that point. As mentioned earlier, the most popular times for the evening and afternoon prompts were 14:00–14:30 and 20:00–20:30, respectively. Figure 11b refers to the afternoon prompt and demonstrates two clear peaks when the food recording tasks are submitted: within 1 hour (the breakdown of the first hour is shown in the inset and shows the dominance of the 15 minutes immediately following the prompt) and 6–7 hours after the prompt. Again, we note that the second peak correlates in many cases with the arrival of the evening prompt. We observe that slightly more tasks are submitted 6–7 hours after the prompt, showing that more users submit their food recording task, having received the evening prompt. We hypothesize that this often happens because prompts received around 14:00 are not as convenient to respond to due to work or study constraints, such that users postpone the task until the evening, when they have more time. The average response time for the afternoon prompts is similar to the morning prompts—4.37 hours.

Figure 11c shows the response times for the evening prompt, where the average response time is substantially lower—1.25 hours. We note that in this case the distribution is fairly different—over 60% of evening tasks are submitted within

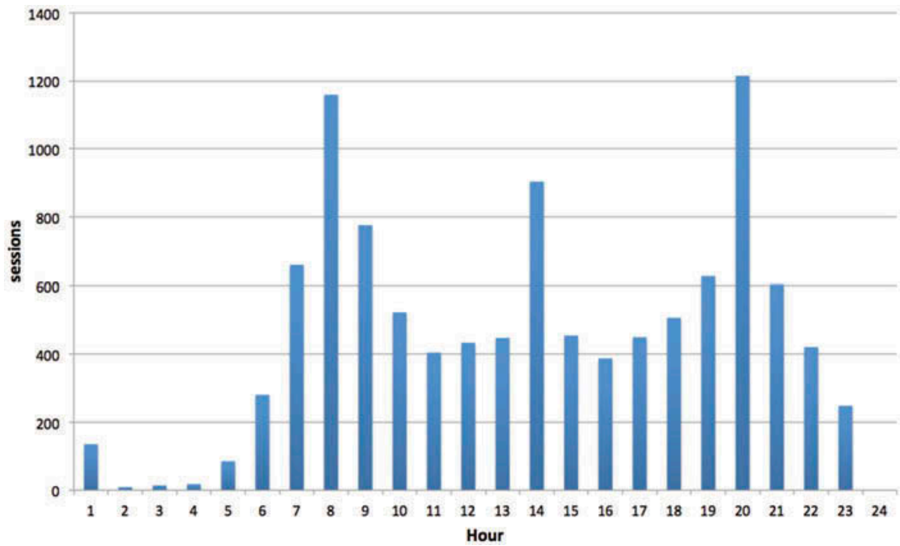


Figure 10. Session times.

1 hour of receiving a prompt, unlike the 27.0% and 22.1% observed for the morning and afternoon prompts. As shown in the inset graph, over 30% of the completed tasks were submitted within 15 minutes of receiving a prompt. As discussed earlier, the reasons underpinning this difference may lay either in the greater time availability in the evening or in the daily expiration of tasks that allows less time to complete them. We note that the response times for tasks decreases from 4.87 hours in the morning to 1.25 hours in the evening.

We note that users establish relatively stable patterns with respect to their response times. For example, consider the distribution of response times to the morning prompt, computed separately for weeks 1–6, 7–12, 13–18, and 19–24 of the study, as shown in Figure 12. We observe little variability in the response times: between 25% and 30% of tasks are submitted within 1 hour of the prompt and the differences are also minor across later responses. A similar observation holds also for the afternoon and evening prompts. This suggests that users establish at the beginning of the study their routines for interaction with the app, and these routines hardly change over the course of the study.

Having observed the higher completion rate within 1 hour of a prompt, we recall that the completion rate for the evening prompts (8%) was substantially lower than those observed for the morning and afternoon prompts (26% and 13%, respectively). One could argue that because of the daily expiration of the tasks, users who typically complete tasks many hours after a prompt cannot complete them in time. Thus, we examined the task completion rates for all users within 4 hours of receiving a prompt, the time typically allowed for the evening prompts before they expire. Figure 13 shows the portion of completed tasks when limiting submissions of tasks to a 4-hour window, separately computed for weeks 1–12 engagement period and week 13–24 period.

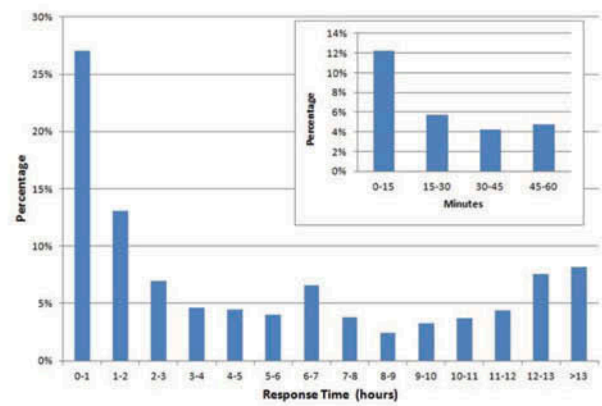
We observe that 59.5% of evening tasks completed, compared to 50.1% of morning and 52.4% of afternoon tasks completed, were completed within 1 hour during the first 12 weeks, as shown in Figure 13a. This suggests that in the evenings, when users have more time, their responses to prompts are generally quicker than in the morning or afternoon. During the free-living period, the completion rates for the morning and afternoon prompts increase to about 61%, as shown in Figure 13b. We also note that the completion rate for the evening prompts drops down to 37.3% during the free-living period.

In general, the analysis of prompt response times has shown us that while many users are immediately spurred to action or take action within 1–2 hours, for many the receipt of a second or even third prompt for an alternative task can be a motivator to comply. We also note that when a short time frame is given to respond, as in the case of our evening prompts that users tend to respond more quickly than when they have many hours to complete a task.

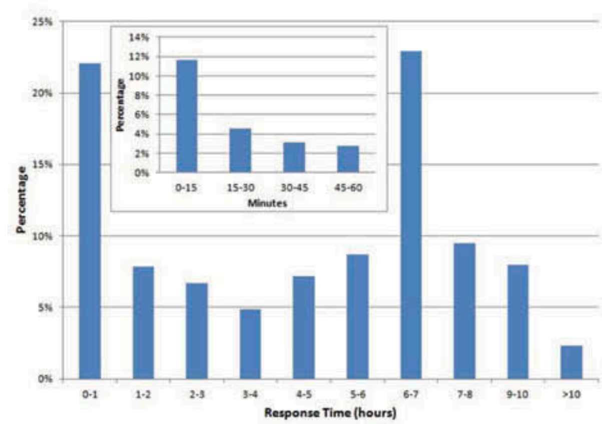
4.2. Qualitative analysis

Finally, participants were asked two open-ended evaluation questions, to capture their experience with the program: "How did you find the frequency and timing of the prompting feature?" and "Please describe any feature that you thought was particularly helpful with keeping you on track with your weight loss". 45 participants answered these questions and their responses were coded according to common themes.

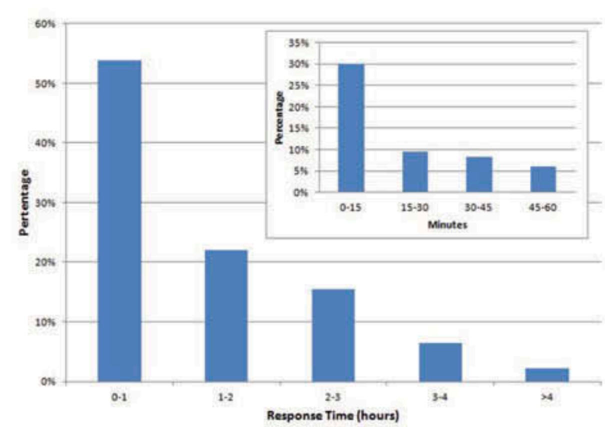
In response to the frequency and timing of the prompting feature 19 participants responded that notifications were "good" and a further 6 considered them "helpful/useful for keeping me on track". 16 respondents commented specifically on timing: 6 described notifications as "well timed", 5 as "too frequent", 4 as "annoying after a while", and 1 said that the app "prompted too much early on but enough in later stages". The remaining comments were singular comments that did not fit with the themes identified. When asked to describe features that were particularly helpful for keeping them on track with weight loss, 42 respondents in the intervention group cited the app. In comparison, only 2



(a) Morning Prompt Response Times



(b) Afternoon Prompt Response Times



(c) Evening Prompt Response Times

Figure 11. Morning vs afternoon vs evening prompt response times.

participants in the control group (app without notifications or self monitoring) found the app helpful.

5. Discussion and conclusion

This article reports on a live trial of a meal replacement program including app and personal support. Our analysis provides insight into the use of notifications and tasks to drive compliance with tasks known to promote positive behavior toward weight loss. The data collected as part of this study allowed us to take a previously unseen, in-depth look at the use of push notifications in health related mobile apps and users tolerance toward notifications for this purpose and feedback on frequency and timing of said notifications.

In designing the app we identified three time points for self-monitoring; the aim was to persuade users to weigh in each morning and to take stock of their food intake through the day. We generated tasks to match these desired behaviors and reminders to maximize compliance in the form of notifications. The primary aim was to create patterns and behaviors. Only 20% of our participants disabled the afternoon prompt through the app interface. User perception of the prompts were verified through questionnaires, which in conjunction with the interaction logs show that users were tolerant of multiple daily prompts. The decline in compliance to the tasks set, however, shows that while the participants did not object to receiving prompts, they were less likely to respond to them as the study progressed. The decline in completion of prompts was in line with the overall app interaction decline.

Compliance with weight tasks was higher than the food recording task compliance. As mentioned, this could be a factor of the time of day or it could be a factor of the task itself. Weight recordings could only be added for the current day, i.e., no previous days weights could be entered. Thus, the weight task could have been perceived as being more urgent or having limited completion time. This could have been strongly persuasive for users. Food recording tasks were less constrained. Food entries for previous days could be entered at any time, and there were multiple time points within each day when participants were reminded to log their food intake. Thus, little urgency was associated with the food recording tasks. It is worth noting that the weight task required the dieters to physically complete a task, whereas the food recording task simply required data entry. Despite the simplicity of the food recording task, its compliance was lower.

The analysis of response times to prompts shows a high level of variability in the time elapsed between the generation of a prompt and the completion of the corresponding task. This can be explained considering that people may not have their phones with them at all times or may have them set to silent mode. We also noted that most people accepted the default times for prompts rather than considering their lifestyle and daily routines and setting prompts accordingly. We noted that 20–25% of prompts sent for morning and afternoon tasks received a response within an hour window, in comparison to 60% of the evening prompts. We conjecture that people may be persuaded to respond more quickly to a task when a limited amount of time in which they can complete a task is in place. Again, this relates to the sense of urgency or limited opportunity to comply.

Overall, the analysis has provided us with an insight into the appropriate use of push notifications and tasks. We note that the delivery of three daily notifications does not appear to overly frustrate users; however, given the low compliance rates we suggest that the generation of multiple similar daily tasks may not be appropriate. We note that the persuasive power of prompts and reminders wears off after a while and suggest that the uniformity of the prompt times and the content presented

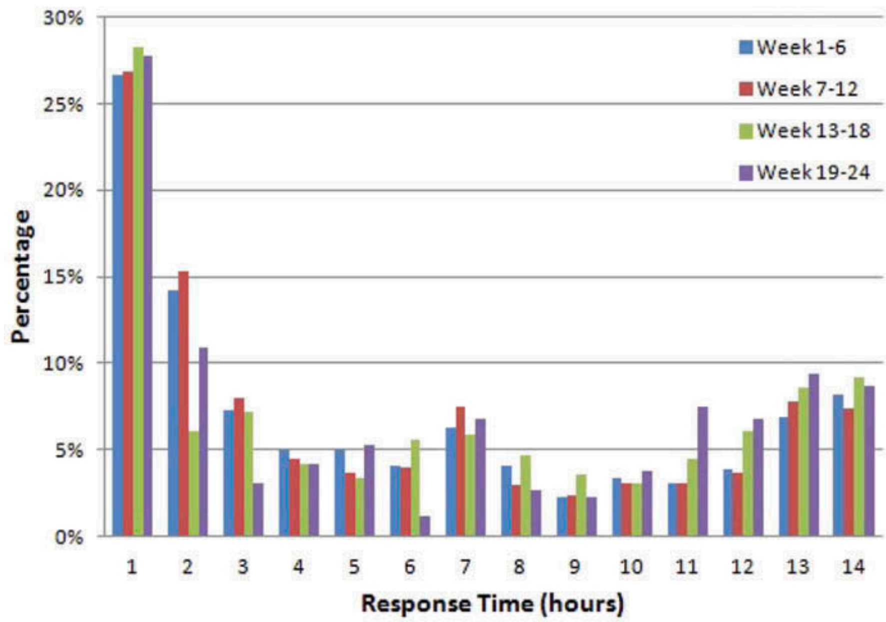


Figure 12. Response times to morning prompts over the course of the trial.

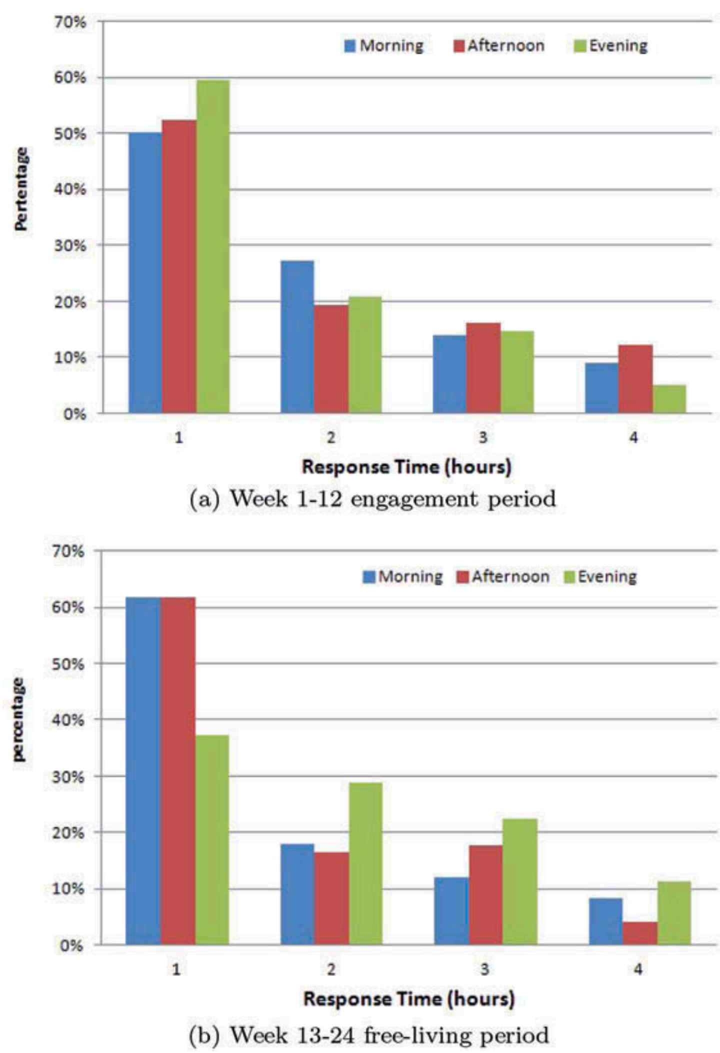


Figure 13. Response times to prompts within 4 hours.

should vary, to keep the user engaged. Finally, we note that the response times for tasks appear to decrease when the window of opportunity for task completion decreases and the number of reminders increases. We suggest that further experimentation is required, in order to understand the impact of setting short task completion deadlines on response times and completion rates.

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