A Survey of Notification Designs in Commercial mHealth Apps

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ABSTRACT

Mobile health (mHealth) apps can support users' behavioral changes towards healthier habits (e.g., increasing activity) through goal setting, self-monitoring, and notifications. In particular, mHealth app notifications can aid in behavioral change through increasing user app engagement and adherence to health objectives. Previous studies have established empirically-derived notification design recommendations; however, prior work has shown that few mHealth apps are grounded in advised health behavior theories. Therefore, we wanted to examine if there was also a gap between recommendations and practice for mHealth notifications. We surveyed 50 mHealth apps and found a disconnect in several areas (e.g., tailoring, interactivity). Our findings show that mHealth apps can be improved to further support users' health goals. We discuss open research questions in the context of mHealth notifications.

CCS CONCEPTS

• **Human-centered computing → Interaction design**; • **Applied computing → Consumer health**.

KEYWORDS

mobile health, mHealth, notifications, alerts

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1 INTRODUCTION

The World Health Organization defines *Mobile Health* (mHealth) as the use of mobile and wireless technologies to support the achievement of health objectives [14]. Prior work has shown that mHealth applications (apps) can aid in personalizing treatment regimes, improving health education, and supporting users' behavioral change towards healthier habits (e.g., increasing activity levels, quitting smoking) (see [31] for review). mHealth apps can assist in behavioral change through many techniques, such as goal setting, gamification, self-monitoring, and notifications [31]. *Notifications* have been defined as a visual cue, auditory signal, or haptic alert generated by an application to help a user maintain information awareness [21, 33]. For the purpose of this paper, we concentrate on visual notifications generated by mHealth apps because they have been shown to aid in users' behavioral change through increasing app engagement [2] and adherence to health goals [16, 19]. App notifications have been effective in helping users achieve their health goals in various mHealth contexts such as mental disorder treatment [16], weight loss maintenance [18], and sleep [19].

While previous studies have focused on determining how to decrease the amount of app notifications to prevent distraction and annoyance [12, 22, 41], the context of mHealth requires a different approach. A main goal of mHealth is to increase adherence to health objectives, and notifications aid in keeping user engagement high to ensure better achievement of health goals. Therefore, the emphasis should be on how to design the notifications to relay the information efficiently and keep users engaged, instead of on decreasing the amount. Previous research has established empirically-derived notification design recommendations in mHealth, such as sending notifications based on the user's context (e.g., activity) [11, 20, 23, 25, 30]. However, prior work has shown that few commercial mHealth apps are either grounded in recommended health behavior theories or properly evaluated [30, 40]. Therefore, we wanted to examine if existing evidence-based design recommendations are being implemented in current mHealth apps.

For our study, we surveyed 50 mHealth apps from the Apple App Store and Google Play Store that had the capability for a user to self-monitor, set goals, and receive notifications. We downloaded and interacted with the apps for five consecutive days and transcribed each notification that occurred. We included notifications that appeared both outside the app (i.e., push notifications) and inside the app. For analysis, we qualitatively coded each notification based on 13 different dimensions (e.g., occurrence, content, purpose), and examined how the notifications related to evidence-based design recommendations. While we found that the mHealth app notifications aligned with existing recommendations in terms of the type of sentences (i.e., including statements over questions [24]), aesthetics [11], notification settings [23], and customization [33], we also saw a disconnect between current practice and recommendations in several areas. For example, the majority of mHealth app notifications did not include tailored content or interactive elements [13, 23]. Based on our findings, commercial mHealth apps can be improved to further support users' health objectives by taking into account research design recommendations. We identify gaps between current practice in mHealth apps and existing notification design guidelines, and discuss open research questions in the context of mHealth app notifications.

2 RELATED WORK

2.1 Benefits of mHealth App Notifications

Smartphones have potential for achieving health-related purposes due to portability and ease of use [4]. Mobile health (mHealth) apps have been shown to help users change their health behavior through personalized goal setting and self-monitoring [31]. In particular, by utilizing push notifications (e.g., as reminders for tasks), mHealth apps enable users to more easily self-monitor to achieve their goals of behavioral change. App notifications also increase users' engagement with the apps and their adherence to health objectives [2, 16, 19]. Prior work has demonstrated the effectiveness of text-based notifications on users' engagement in mHealth apps. Bidargaddi et al. [2] analyzed mHealth app engagement over 89 days with 1,255 participants and found that sending a push notification with a tailored health message resulted in more app interaction within the next 24 hours than not sending notifications. Patrick et al. [27] investigated the effect of text-based interventions on helping users lose weight over 4 months. The participants who received text-based tailored notifications 2-5 times a day instead of printed material lost more weight. While prior work has shown that mHealth notifications help users with behavioral change through increasing user engagement and commitment [2, 16, 19], notifications may also create dependencies on technology instead of supporting habit formation [29]. Therefore, it is important to consider the design of notifications, in order to support user engagement and habit formation while avoiding dependency. Prior research studies have suggested certain notification design recommendations, such as sending notifications based on the user's context [11, 20, 23, 25, 30], tailoring messages to the specific user [3, 13, 23], varying content [15], and allowing for user customization (e.g., changing the amount) [17, 23, 33]. However, prior work has found that few commercial mHealth apps are grounded in health behavior theories [30], so, by extension, it is also unclear if notification recommendations are being followed in mHealth apps.

2.2 Existing mHealth App Reviews

Previous studies have reviewed different behavioral change features of existing mHealth apps [7, 32, 37]. Vlahu-Gjorgievska et al. [37] examined 10 mHealth apps supporting diabetes self-management to identify social support features. The authors found that all of the apps provided self-monitoring features, while only a few of them implemented social support features. Coulon et al. [7] evaluated 60 stress management apps for evidence-based behavioral change strategies, such as goal setting, engagement, social support, and self-monitoring. The authors found that only 32 apps included at least one strategy. Schmidt-Kraepelin et al. [32] investigated 1,000 mHealth apps for gamification elements. They found that game mechanics highly preferred by users, such as points and levels, were not often implemented.

The studies above investigated various behavioral change features in mHealth apps, but did not examine notifications. Stawarz et al. [34] reviewed 229 medication reminder apps. The authors found that most of the apps used time-based notifications, instead of considering the user's activities. In another of Stawarz et al.'s studies [35], the authors reviewed 115 habit formation apps. They found that most of the apps provided self-tracking and reminders, but only three of them supported routine creation using event-based cues. Although the previous studies listed above examined notifications, they either focused only on a specific context or did not conduct an in-depth investigation. We surveyed and used 50 mHealth apps covering a range of health themes to examine current notification designs (e.g., content, personalization).

3 METHOD

To examine how notifications are utilized in current mobile health (mHealth) applications, we surveyed 50 mHealth applications (apps). We (1) identified 50 mHealth apps using a systematic search process, (2) iteratively generated a coding scheme of notification dimensions based on prior work, (3) downloaded and interacted with each app for five days using a set of defined information criteria, and (4) coded each notification that appeared using our coding scheme.

3.1 App Identification

In order to select a representative sample of mHealth apps, we started with an updated version of Xu and Liu's database of mHealth applications [42]. The database consists of apps found in the "Health & Fitness" and "Medical" categories from both the US Apple App Store and US Google Play Store. At the time of our study, the database contained 78,734 iOS apps from the Apple App Store and 44,517 Android apps from the Google Play Store. Similar to prior work [32, 35], we excluded apps that had missing information in the database, that were not free, or that had fewer than 10 user reviews (leaving 4,855 iOS apps and 13,045 Android apps). After the initial exclusion criteria, we applied four keywords to the app descriptions to find apps relevant to our study context: "notif" (capturing notification, notify, etc.), "remind", "alert", and "text message." To further simplify the subset, we focused on widely used apps by only including apps that had 500 or more user reviews and that were *successful*. We used Schmidt-Kraepelin et al.'s [32] definition of *successful*, which is apps with 3 or more stars. After filtering out the apps, we had a subset of 131 iOS apps and 460 Android apps.

From this subset, we identified 25 iOS apps and 25 Android apps to survey by randomly selecting the apps and confirming they met our final inclusion criteria: they were in English, available to download at the time of analysis, included notifications, not

Table 1: Themes of the 50 Mobile Health Applications.

App Theme	Count	App Theme	Count
Fertility	9 (4 Android, 5 iOS)	Blood Pressure	4 (2 Android, 2 iOS)
Weight	9 (5 Android, 4 iOS)	Workout	3 (2 Android, 1 iOS)
Medication	8 (3 Android, 5 iOS)	Smoking	2 (2 Android)
Water	7 (3 Android, 4 iOS)	Health Routine	1 (1 Android)
Baby & Pregnancy	6 (2 Android, 4 iOS)	Vision	1 (1 Android)

geared towards healthcare professionals, and focused on the goal of behavior change (i.e., tracking and setting goals). If the same app was chosen in both the iOS and Android subsets, the app on the platform that had more user ratings was included. Table 1 shows the themes of the 50 mHealth apps.

3.2 Notification Coding Scheme

We developed a coding scheme of notification dimensions based on prior work [3, 13, 23], shown in (Table 2). The majority of the codes were drawn from Muench and Baumel's [23] list of notification dimensions for patient-centered health interventions. To ensure the code set was reliable, we refined the codes in an iterative process. We randomly chose 6 apps (3 iOS and 3 Android) from the subset that were not part of the final 50 apps. Two researchers independently interacted with all 6 apps for five consecutive days and coded the notifications that occurred. After the five days of coding, a discussion of disagreements and agreements led to refinement of the coding scheme. We added extra codes to capture notification dimensions that were not represented in the first coding scheme (e.g., creating notifications). Our final coding scheme included 13 dimensions focused on the occurrence, content, and personalization of the notifications.

3.3 App Usage and Analysis

For surveying the apps, the list of 50 apps was randomly split between the two researchers who did the initial coding (i.e., 25 apps per researcher). The two researchers independently used each of the apps for five consecutive days. To control for variation in notifications across apps, we established a set of defined information criteria to input into the apps. For example, we inputted specific blood pressure values and calories for the apps that focused on blood pressure or weight. In order to generate as many notifications as possible, we created the values to be equal to, under, and over current health recommendations. The five day usage period was broken down into: (Day 1) the values aligned with health recommendations, (Day 2) the values were under recommendations, (Day 3) the values were over recommendations, and (Day 4 and 5) no values were input to resemble a user either forgetting or becoming disinterested. For example, for apps that pertained to blood pressure, the values on the first day aligned with the US Department of Health & Human Service's recommendation of an ideal blood pressure (e.g., 120/80), while they were under on the second day (e.g., 85/55) and over on the third day (e.g., 230/100) [26]. For days one through three, the two researchers input values in the morning, afternoon, and night following the set information criteria. The researchers independently transcribed and qualitatively coded the notifications that appeared both inside and outside of the apps (i.e., push notifications) along the 13 dimensions in the coding scheme (Table 2). After the two researchers finished coding, the entire research team examined the frequencies of the codes and discussed how well they aligned to current notification recommendations.

4 RESULTS

After interacting with the 50 mHealth apps, we had accumulated a total of 1,405 notifications (916 iOS). For our analysis, we excluded notifications that focused on rating or promoting the applications (n = 15). Therefore, we had a total of 1,390 notifications for analysis. We found that the mHealth app notifications align with recommendations on including: statements over questions [24] (i.e., content type), aesthetics (e.g., images, different font sizes) [11, 24], notification settings [23, 33], and notification customization (e.g., changing the time, turning on/off) [17, 23, 33]. For the purpose of this paper, we focus on the notification dimensions in which the mHealth apps did not align with existing design recommendations or in which prior work has not included specific design recommendations.

4.1 Notification Occurrence

4.1.1 Occurrence (Does Not Align). The majority of the notifications (84.1%, n = 1169) occurred based on a time specified by either the user or the app. For comparison, only 10.4% (n = 145) of the notifications appeared because of interactions with the app (e.g., opening the app), and 4.5% (n = 63) were created in response to specific data the user inputted (e.g., "WARNING high blood pressure"). Only 4 of the apps (out of 50) did not include any notifications based on time. Prior work recommends basing the trigger of notifications on the user's activities and environment instead of fixed times [11, 20, 23, 25, 30]. Our findings show that current mHealth app notifications do not align with recommendations since we did not observe any notifications appear based on the user's context.

4.1.2 Frequency (Does Not Align). We analyzed the frequency of the notifications (i.e., daily, weekly, monthly). Since we only used each app for five days, we coded the notifications as weekly or monthly if the notification could be set to appear in that time frame. We found that 37.2% (n = 517) of the notifications were only capable of being enabled daily, 24.3% (n = 338) of the notifications allowed the user to choose between receiving the notifications daily or weekly, and 30.9% (n = 430) allowed the user to choose between daily, weekly, or monthly. Only 7.2% (n = 100) of the notifications occurred once. Almost all of the apps (n = 49) had notifications that appeared daily. For notifications, prior work suggests that more is not necessarily better and to consider the user's readiness

Table 2: Coding Scheme of Notification Dimensions.

Code Themes and Individual Codes
Notification Occurrence
Occurrence: Occurred due to the user's context, data, app interaction, the time [23]
Frequency: Occurred daily, weekly, monthly, or only once [23]
Notification Content
Notification Type: Appeared outside (i.e., push notification) or inside the app *(Created after initial coding)*
Content Type: Message was in the form of a statement, question, command, exclamation [23]
Content Purpose: Purpose was to remind, motivate, gather data, provide insight, tips, user reflection, feedback [3, 23]
Goal Type: Overall goal of the notification was short-term (i.e., requires immediate action) or long-term [23]
Interactivity: Incorporated a link, redirected the user, prompted a response, required acknowledgement [13, 23]
Tailoring: Contained the user's name, sex, body characteristics (e.g., weight), data [3, 13, 23]
Aesthetics: Included an emoji, font color, different fonts and sizes, bold text, highlighted text [1, 23]
Sender: Listed the app name, human support, personification (e.g., virtual character or coach) [23]
Personalization
Notification Settings: App included notification settings or not [23]
Customizable: User could modify the notification amount, time, context, content, type, or presence (i.e., on/off) [23]
Creating Notifications: App had default notifications or the user had to manually set notifications *(Created after initial coding)*

for change when determining frequency, such as increasing notifications if the user is more willing to change [23]. Most of the notifications we received were sent multiple times a day and none of the apps we surveyed considered the user's level of inclination to change.

4.2 Notification Content

4.2.1 Notification Type (No Recommendation). Over three-quarters (75.8%, n = 1053) of the notifications were push notifications, while only 24.2% (n = 337) of the notifications appeared within the app. While prior work has shown that push notifications are beneficial (e.g., increase usability and user retention [6, 28]), we are not aware of any recommendations regarding push versus inside notifications or the effect inside notifications have on behavioral change.

4.2.2 Content Purpose (Does Not Align). We did not see a lot of variety in terms of the purpose of the notifications. The majority of the notifications (89.6%, n = 1245) were aimed at reminding the user to do something (e.g., "Birth control reminder take a pill!"). The next more common notification purposes included providing insight (6.6%, n = 92), motivation (4.4%, n = 61), user reflection (4.1%, n = 57), and tips (3.2%, n = 44). Insight included messages based on the user's specific status or data (e.g., "Your coach says have a 340 Cal wholesome breakfast"), while a tip was a suggestion that did not take into account the user's specific status (e.g., "Remember keep a water bottle at your desk to drink regularly") [3]. Each notification could be coded with multiple purposes. Although the majority of the notifications were reminders, prior studies have found that reminders hinder habit development since the user becomes reliant on the notifications [23, 29, 35]. Also, prior work states that notification content should be varied to keep users engaged [15].

4.2.3 Goal Type (No Recommendation). We examined whether the goals of the notifications were short-term or long-term. Short-term goal notifications required an immediate action item (e.g., entering weight), while long-term goal notifications focused on a behavioral change (e.g., "Hey it doesn't mean you've failed. Just work out how you can stop further slip-ups or relapsing altogether.") [23]. Our results show that 93.4% (n = 1298) of the notifications targeted short-term goals, 5.1% (n = 71) did not contain a goal, and only 1.5% (n = 21) targeted long-term goals. Even though prior work has found that setting short-term goals can be more motivating [38], we do not know of any recommendations on whether to include short-term or long-term goals in mHealth app notifications.

4.2.4 Interactivity (Does Not Align). Interactivity refers to the interactions a user could have directly with a notification, such as responding to the notification. Only 40.5% (n = 563) of the notifications included interactive elements. When examining interactive elements, we found the most common interaction was acknowledgment of the notification (e.g., tapping an "OK" button) (28.1%, n = 390). The least common interactive element in the notifications was inclusion of a link to take the user to another page or application (0.8%, n = 11). Including interactive elements has been found to be important for mHealth notifications in increasing user engagement [13] and the likelihood of notifications being attended to [23]. However, the majority of the notifications in our survey were not interactive (59.5%, n = 827).

4.2.5 Tailoring (Does Not Align). Tailoring notifications has been shown to increase engagement [23] and persuasively motivate users [3]. For tailoring, we recorded how many of the notifications included the user's name, sex, or other data such as the number of steps taken. Our data shows that only 32.6% (n = 453) of the notifications included tailoring. User data was used in 25.2% (n =

350) of the notifications, whereas 10.1% (n = 140) of the notifications included the user's name. Our findings show that current mHealth app notifications do not take into account prior recommendations of the importance of tailoring messages to increase engagement [13, 23] and meet the user's individual needs [17].

4.2.6 Sender (Does Not Align). We recorded the different types of senders (i.e., who or what sent the notification) that were specifically stated in the notification message. Possible senders that we coded for included the specific app name, human support (i.e., sent by a real person), or any personification with a virtual character or coach. Only 8 of the apps had all of the notifications list a sender, while 11 of the apps listed a sender for some of the notifications. Over half of the apps (n = 31) never included a sender in their notifications. In analyzing the specific notifications, 83.2% (n = 1157) did not include a sender, 12.9% (n = 179) listed the specific app name, and 3.9% (n = 54) included a personification. Our findings reveal that current mHealth apps disregard recommendations to include a sender. Including a sender can increase credibility, engagement, and can be more persuasive if perceived to be sent by an expert [23].

4.3 Personalization

4.3.1 Creating Notifications (No Recommendation). We examined whether the notifications had to be manually set or were already default within the app. The apps were split between only default notifications (n = 19), only manual (n = 14), and offering a mixture of default and manual (n = 15). In terms of the amount of notifications, there was an almost even split between default (51.9%, n = 721) and manual notifications (45.3%, n = 629). Although prior work has found that people rarely change default notification settings [15, 39], we are not aware of any recommendations on including default or manual notification settings, and whether they affect user engagement and behavioral change in mHealth.

5 DISCUSSION

We identify open research questions for mHealth app notifications through (a) exploring the disconnects between design recommendations and current practice and (b) recognizing areas that do not have clear design recommendations.

5.1 Recommendations versus Practice

Through analyzing notifications from 50 mHealth apps, we found a disconnect between evidence-based design recommendations and current practice. We found that the notifications mainly occurred based on time, instead of triggering according to the user's context [11, 20, 23, 25, 30]. Stawarz et al. [36] conducted a survey with 1,146 participants to investigate remembering strategies for medication adherence. The authors found that relying on contextual cues such as routine events, locations, and objects is an effective strategy. They also suggested that adherence technologies should take advantage of relevant contextual cues. While prior work recommends focusing on context, open questions remain about **what specific contextual features would be the most effective** in increasing long-term engagement and adherence in mHealth apps. In addition to occurring based on time, most of the notifications appeared daily, sometimes multiple times a day. Although prior work recommends avoiding information overload in context-aware applications [17], it is not apparent what the exact frequency should be. Pham et al. [28] found that user retention was lower when notifications were sent every 3 hours instead of once or twice a day, but that was in the context of learning. There are still open questions in **how often notifications should be sent** to keep users engaged in mHealth. Also, it is unclear whether the frequency should differ depending on the theme of the app (e.g., medication, weight). Regarding the content, the majority of the notifications were reminders. Users can become reliant on reminders, which can hinder habit formation [23, 29, 35]. mHealth apps should vary notification content to keep users more engaged [15] and tailor it towards the specific user [3, 13, 17, 23]. The majority of the notifications from our study were not tailored to the users. We also saw a disconnect in the apps not including the sender or interactive elements. While using interactive elements in notifications can increase the likelihood of being attended to [23], there are still open questions in terms of **what interactive elements help the most with engagement** (e.g., external link or requiring a response).

5.2 Design Areas Without Recommendations

In our survey, we also found areas of notification design that have not been examined in prior work and therefore no clear design recommendation exists, such as the notification type. The majority of the notifications from our survey were push notifications, which prior work has shown can increase usability and user retention [6, 28]. Dolan et al. [10] found that push notifications helped patients remember to drink water and walk frequently after weight loss surgery. While push notifications can be beneficial, there are not any clear design recommendations on including **push versus inside notifications** or whether inside notifications can aid in behavioral change in the context of mHealth. We also did not see any clear design recommendations for the goal of the notifications and the method of creating the notifications. In our survey, the notifications mainly focused on short-term goals instead of long-term goals concentrating on behavioral change. Although short-term goals are more likely to be achieved than long-term goals [9], there are still open research questions on **how long-term goal notifications can affect behavioral change** in mHealth apps. Finally, we examined whether the notifications had to be manually set or were already default within the apps. We found a mix between default and manual notifications. In examining notifications for an app to help users with food intake, Freyne et al. [15] found that few people changed the default notifications, although the notifications could be customized. The authors also noticed a decrease in app engagement over time. Requiring users to manually set notifications may help in retention by encouraging the users to customize settings. Open questions remain about the effect of **utilizing default or manual notifications** on engagement in mHealth apps.

6 LIMITATIONS AND FUTURE WORK

Our work has several limitations. First, we coded a subset (i.e., 50) of existing mHealth apps and only considered free apps. Although other previous surveys of commercial apps also only included free apps [32, 37], it is possible that some pay-to-use apps may have triggered more targeted notifications. Second, we performed our study during the COVID-19 pandemic. As such, our coders went outside less often and performed fewer activities. It is possible that some app notifications were only triggered by specific user contexts that our coders never triggered. Third, our coders used each app for five days. Even though five days is longer than the duration of previous similar studies [7, 8, 32], we could have missed notifications due to the time frame. Finally, we acknowledge that not all of the design recommendations might be relevant to every app theme. For example, a HIV self-management app may want to include more private notifications that do not highlight its true purpose [5]. However, our goal was to provide an overview of mHealth notification designs. Future work can examine existing notification recommendations in different mHealth contexts.

7 CONCLUSION

We examined how app notifications from 50 current mHealth apps align with design recommendations from prior work. While the notifications aligned with recommendations in several areas (e.g., aesthetics, customization), we found more disconnects than alignments (e.g., occurrence, frequency, tailoring). We also identified open research questions in the context of mHealth apps, such as how long-term goal notifications can affect behavioral change. Based on these findings, there are significant aspects of the design of notifications in current mHealth apps that could be improved in order to increase user adherence and engagement, thus improving support for users to reach their health goals.

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