An Analysis of Usage and Reporting Patterns in a Mobile Health Application

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Abstract. The use of mobile applications (apps) as a tool to monitor health-related parameters is now a common practice. Connected to wearables or stand-alone, these apps usually track the user by retrieving relevant information from mobile embedded sensors but also may serve to get self-reported data. To make sense, these apps require that the user remains active in the use of the application, to get the most complete data records. Different aspects may affect the user's adherence level to the app, both personal characteristics (personality, motivation, etc.) and app design and technical features (attractiveness, usability, perceived usefulness, etc.). The aim of this paper is to explore user's adherence by analyzing users' behavior on the use case of an app which aims at helping track emotional states by using emoticons. The adherence analysis focuses on evaluate the real impact of notifications, which is the main strategy to incentive adherence in this case. The study analyzes four weeks of data from 20 young users, that have volunteered to use the app within the framework of a study on mental health. Based on a selected set of behaviour-related features, a clustering analysis shows two well differentiated adherence groups: the first one that use the app several times a day, while the second is less regular. Regarding notifications, they reveal to have different impact depending on the user group, being much more effective for very active users. Other adherence incentives must be designed to improve the continuous use of the application.

Keywords: Mobile Health · personal health · application · adherence · reminders · notifications · behaviour

1 Introduction

The World Health Organization defines mobile health (mHealth) as "medical and public health practice supported by mobile devices" [1]. Apps are a common and important component of mHealth systems; they have the potential of adding value to patient care, help improve the awareness on health status, promote behavior change to healthier lifestyles, etc. In the second quarter of 2022, there were around 54,600 and 52,400 medical apps (excluding wellness and fitness ones) in Google Play and App Store respectively [2, 3], after having increased significantly over the last seven years. Industry experts believe

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that by 2030, mobile apps will be embedded within standard treatment protocols for most diseases and conditions, and widely used in preventative care [4]. Mobile health applications can effectively support diagnosis and clinical decision making, make predictions on risk or detect a normal patters, provide support towards healthy behavior change, provide information to handle chronic diseases, etc.

How to improve apps' user experience and increase perceived usefulness is key to enhance adherence and leverage mHealth services. In this context, the aim of the paper is twofold: to understand how to optimally measure application adherence from usage features and analyze the impact of reminders/notifications as a tool to promote adherence, depending on the user profile and the context of application use. To do so, we will analyze usage data of a mobile application designed for youngsters to track their emotions (which is thought to be an enabler of a mHealth system that supports psychological tuition). The structure of the article is as follows. Section 2 contains a review of the state of the art on adherence techniques for mobile applications and their effectiveness. Section 3 describes the supporting technology that has been developed to provide the mHealth service for mental health. Section 4 compiles relevant details regarding the user study, the resulting data collection, and the chosen adherence-related features. Also, this section gathers results and its analysis. Section 5 concludes the paper and shows the future work.

2 State of the Art

Technology acceptance is related to perceived usefulness and perceived usability (Technology Acceptance Model, Davis, 1989). Particularized to mHealth [5], perceived usefulness is related to the fact that the use of the mobile application brings real and noticeable benefits to the user's health, and perceived usability refers to the effort needed to use the app. Therefore, acceptance is linked to the app being free of effort for the user to use it, and to provide functionalities and usage targets for the application that can achieve tangible health benefits for the user. Adherence can be thus understood as a consequence of both the application perceived usefulness (and motivation) and usability (in [6], 22 studies on apps usability are reviewed, concluding that usability is one of the main barriers to the adoption of mHealth systems). Bidirectionally, it will also be an enabler to perceived usefulness: the user adheres to the app because he/she finds it useful, and the mHealth can provide meaningful feedback and advanced features on continuous data thanks to the regular app usage. In [7], frequency of use is perceived to be an important fact in user satisfaction. In [8], 69% of people who use a health app several times a day or more strongly agreed on its effectiveness.

Mobile health apps seem to be able to bring huge value to users and patients when integrated as part of a clinical pathway, but there is still room to scientifically demonstrate this hunch. Some studies have tried to measure the impact of mHealth (in many different fields, e.g. [9] for patients with Covid-19, [10] for patients with coronary heart disease, or [11] for pregnant women with urinary incontinence) by comparing a control group (using traditional treatment methods) and a test group using an app; apps provide monitoring, reminders, feedback, motivational messages, personalized goals, etc. In general, studies' conclusions show improved health results in the test groups, pointing out that mHealth may improve standard care. Nevertheless, the usefulness of these apps is not always perceived by their users. According to [8], where 46 apps were analyzed, almost 20% of the surveyed users disagreed or strongly disagreed that health apps help them with their healthcare.

Usually, adherence is studied by exploring motivation for app use, frequency of usage, perceived effectiveness and abandonment rate and reason (whether and why a health app was installed but its usage discontinued). How to improve adherence is still a challenge: it is not enough for an app to provide a great functionality; it is also important to guarantee usability while preventing app abandonment through adequate techniques. mHealth applications make use of a variety of design incentives to engage the user [8, 12]. They may include notifications and reminders, personalized goals and performance feedback. Existing literature is scarce with respect to the analysis of the effectivity of adherence mechanisms. In this article, we aim at summarizing the different strategies to apply, which include:

- *M1 - Provide relevant information:* Delivery of relevant information about health or disease.
- *M2 - Personalized goals:* Ensure motivation strategies to improve habits and health condition.
- *M3 - Performance evolution:* Provide feedback about the progress through motivational messages and other communication pills aimed to encourage the patient to keep improving.
- *M4 - Comprehensive data visualization:* Show evolution of self-data through graphs, notes, etc. In some cases, it is also allowed to export data.
- *M5 - Delivery of notifications/reminders:* Used to remind the user to input data, take medication, etc.
- *M6 - Community:* Social statistics, which may include rankings against a 'group' of interest (e.g., other users with similar circumstances) to show whether performance is over the average.

Moreover, we aim at providing some insights on the real impact of reminders in a specific use case, in order to gain knowledge on how to improve design for the users to better adhere the application.

3 Use Case: Emotions Tracking for Mental Health Support in Youngsters

Nowadays, young people reveal an increasing demand (and acceptance) of mental healthcare support. For a diagnosis, the time-to-doctor can take time, thus automated and semi-automated systems may be tools to facilitate and accelerate this process. Once under treatment, the digital phenotype collected by an app may serve to build personalized models of digital and physical lifestyles that may help identify anomalous behaviors on patients at risk, e.g., to trigger assistance alerts, modify the application workflow.

In this service context, we want to analyze users' adherence towards a mental health app, which is a key component on a digital health service for mental healthcare support for youngsters. The complete system is described below.

3.1 Context and System Architecture Overview

The technology solution has two main components. The first one is a mobile application for patients, which monitors their condition through passive data (information about their activity, collected directly from the digital device's sensors) and active data (emoticons representing feelings, directly reported by the users on the 'patient' side). The second component is a practitioner dashboard, that provides relevant information to the therapist during the sessions with the patient. The system is designed to provide full data sharing control through the app, i.e., patients must actively award access to their data during the therapy session and the access permission is kept ephemeral, only granted only during the session itself.

Through the mobile application, users can send reports (ideally several times a day) which consist of a simple choice of an emoticon that represents their mood, and information about where and with whom are they. Also, they can check on their history and get some complementary information about their activity data. Passive data (transparently gathered once consent is given) serve to generate a digital phenotype for users, considering their daily habits making use of the device sensors. For example, to monitor daily activity, we made use of the accelerometer and gyroscope measures, which allow us to analyze the number of steps taken by the patient. To calculate an estimation of the patients' circadian rhythm, we also use other information collected by the phone, such as the screen unlocking events (to determine interactions with the mobile phone) or the ambient light detected. Other characteristics analyzed with passive data are, for example, GPS locations or daily mobile phone usage.

The system backend provides storage, processing, and securitization features. Figure 1 shows the architecture of the mHealth system, with the three components stated above: the mobile application, for the user to register and send data; the dashboard for the therapist and the backend with storage for user personal information, emoticons and sensors data. A notification module is the one in charge of dispatching app prompts to applications users. Finally, a digital phenotype module oversees feeding the dashboard with relevant information for therapy.

3.2 User App and Adherence Mechanism

Figure 2 gathers some views of the mobile application interface in which the user reports an emoticon, also attaching context-based information on with whom and where the user is when reporting. The use of standard emoticons facilitates the identification of moods, although personal biases can apply on the choice of emoticons. The application design aims at being intuitive and easy to use. To incentive adherence, the application implements some of the adherence mechanisms stated above, in particular:

- *Performance evolution (M3).* For physical activity data, the app provides comparative information along the time. This feedback is very simple and not related to mental health as clinical related feedback and derived analysis are extremely sensitive.
- *Comprehensive data visualization (M4).* The patient can access a history of the emoticons sent and statistics of the digital fingerprint collected in the last 24 h.

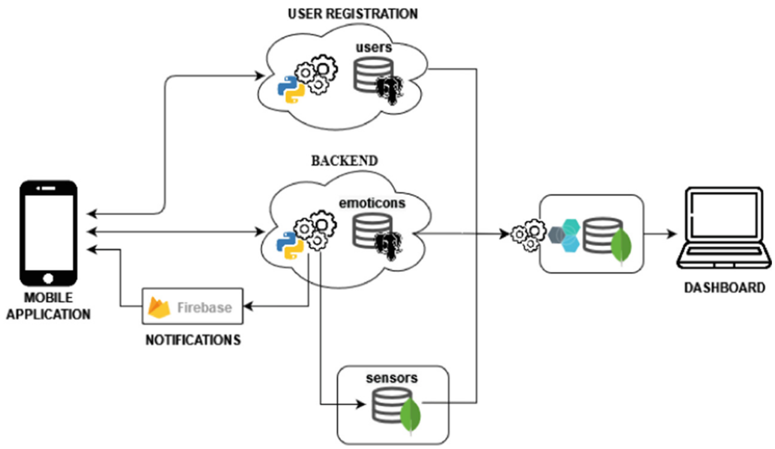

Fig. 1. Architecture system.

- *Delivery of notifications/reminders (M5).* Notifications are the main mechanism chosen to keep the user active in the app. The system sends several daily notifications to encourage users to report their emotional state. In this implementation, five prompts are delivered as shown below (Table 1).

Table 1. Hours when users receive notifications.

Notification	N1	N2	N3	N4	N5
Hour	9:00	11:00	14:00	17:00	20:00

3.3 User Study

Between October 2020 and March 2021, 20 young users (between 16 and 24 years of age, M = 20.06, SD = 2.54, 78% were female) seeking for mental healthcare assistance volunteered to use the beta app for a trial period of one month thanks to the call of a European organization providing services for youth. Users were people without any specific diagnosis on mental health diseases, but with interest in being able to access tools for their self-management and with standard skills on mobile devices usage.

4 Data Analysis

On these data, we carried out a general analysis on the generated data volume per user during a period of maximum 4 weeks, computing the number of records (a record is a timestamp with a sensor id and its value). Apart from volume and frequency (how many

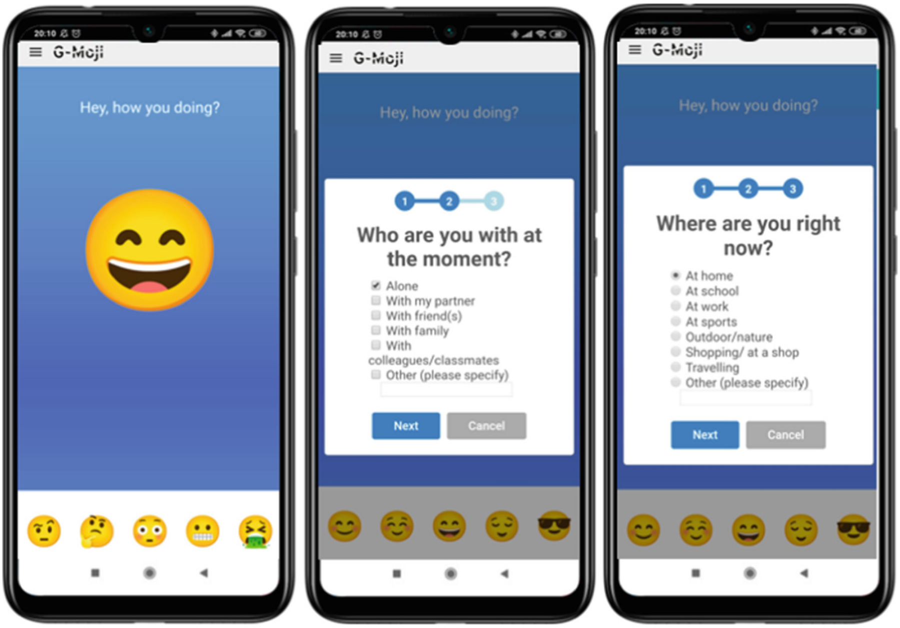

Fig. 2. Emoticons reporting interface of the application.

and how often), we also processed information about where, with whom and when emoticons reports were provided. And, being interested on the effect of notifications, we divide the day into slots (Fig. 3) to calculate the number of emoticons sent within each. We also computed the time difference between the notification was received and the user time to send a subsequent emoticon (average reaction time to the five notifications), as can be seen in Fig. 4. We following analyze the different user profiles in terms of app usage, the context in which users were reporting active data and some analysis on the notifications' effectiveness. To sum up, the data collected for the analysis can be grouped as follows.

- *Adherence data:* total emoticons sent, total active days, maximum consecutive active and maximum consecutive inactive days.
- *Context of sending emoticons:* total reports from home, total reports outside, total reports alone and total reports with company.
- *Hours of sending emoticons:* total reports sent in the following time slots.
- *Notifications feedback data:* Average reaction time to the five notifications and its standard deviations

4.1 Analyzing App Usage Patterns: Are There Different Types of User Profiles?

The average number of passive data per user was $\eta = 107{,}262$ records ($\sigma = 91{,}257$). This large difference of data volume among users is due to the explicit permissions to

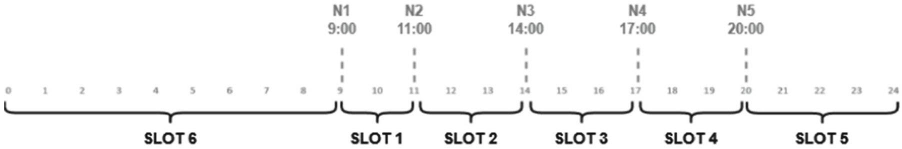

Fig. 3. Time slots in the day according to notifications

Fig. 4. Reaction time to the notifications

sensor data access on the Android/iOS and the time that the application has been up and running. The volume of active data (emoticons) is much lower, as expected. The total number of records per user ranges from 9 to 115 (with an average of $\eta = 65$ records per user, $\sigma = 50$). This variability in the number of reports is related to the adherence itself, i.e., the frequency for the user to report emoticons.

Taking as a basis both volume and frequency of reports, we can distinguish two different types of users. On the one hand, a group of 7 users (U0–U6) who report emoticons every day of the trial, not showing any period of inactivity (days with not even a single emoticon reported), and with a high average number of daily emoticons ($\eta = 4.74$ emoticons/day, $\sigma = 0.24$). On the other hand, the rest of users (U7–U19), who are less methodical, show inactivity periods (even of a week time) and report less emoticons in the active days than the first group ($\eta = 1.10$ emoticons/day and $\sigma = 0.47$). This split was confirmed by a cluster analysis carried out after a Recursive Feature Elimination on 29 features from each user, summarized previously.

4.2 In What Context Do Youngsters Use the Application?

As mentioned above, and as shown in Fig. 2, when users send an emoticon, they are asked two questions: where and with whom they are. Thanks to these questions we can evaluate the influence of the environment on the emoticons reporting. In addition, the context of use is generally not significantly different between the two groups. As shown in Table 2, emoticons reported from home 63.5% in the first group and 50.6% in the second. Work stands out as the next most common location, representing 15% of the emoticons registered, but with differences between groups: 7.8% for first group and 29.6% for second group. In addition, most emoticons were sent when users were alone, 56.3% and 40.8% respectively. The rest were recorded with family, partners, friends, or work colleagues. For example, the reports with co-workers are very similar with percentages of emoticons sent at work, 7.8% for first group and 21.4% for second group (Table 3). The schedule for notifications may justify the registered data, although in that sense, it is needed to have a look to the responsiveness of the users towards the notifications.

Table 2. Percentage of answers about where they are when they send the emoticon.

Users	Home	School	Work	Travelling	Outdoor	Other
U0–U6	63.5%	1.7%	7.8%	4%	2.4%	20.4%
U7–U19	50.6%	1.4%	29.6%	2.6%	3.7%	12.2%

Table 3. Percentage of answers about who they are with when they send the emoticon.

Users	Alone	Family	Co-workers	Partner	Friends	Other
U0–U6	56.3%	15,3%	7.8%	3.2%	3.9%	13.5%
U7–U19	40.8%	15.9%	21.4%	8.5%	5.5%	7.7%

4.3 Are Notifications an Effective Mechanism to Encourage Application Adherence?

The application sends 5 daily reminders for a user to report an emoticon, at: 9:00, 11:00, 14:00, 17:00 and 20:00. We analyzed the percentage over the total of emoticons sent in each time slot between notifications (Table 2). We observed clear differences between users who report emotions every day and those who do not do it. Users showing greater adherence have a uniform distribution of emoticons throughout the day (with almost no night-time sending). Meanwhile, users with more irregular adherence send more emoticons in the first half of the day and their interaction decreases as the hours go by. In addition, these users send more emoticons at night (Table 4).

Table 4. Percentage of emoticons sent in each time slot.

Users	9:00–11:00	11:00–14:00	14:00–17:00	17:00–20:00	20:00–24:00	24:00–9:00
U0–U6	18%	20%	20%	21%	19%	2%
U7–U19	26%	25%	22%	11%	7%	8%

Secondly, we analyzed the average time difference between a reminder and the next emoticon, to analyze the reaction time towards a notification, to correlate both reminder-emoticon (even if no cause-effect event can be directly inferred). As can be seen in Table 3, U0–U6 users send emoticons about 30 min after receiving the notification, while the rest of the users usually take more than twice that time. Then, the recording pattern in the first group could be therefore associated with a better response to notifications. Moreover, in the second group of users we perceive better feedback to notifications in the morning. For the notifications later in the day, users almost never respond within half an hour time (Table 5).

Table 5. Average reaction time to notifications and its standard deviations.

Users	N1	N2	N3	N4	N5
U0–U6	27 min. ($\sigma = 25$ min)	27 min. ($\sigma = 34$ min)	28 min. ($\sigma = 33$ min)	26 min. ($\sigma = 27$ min)	29 min. ($\sigma = 41$ min)
U7–U19	45 min. ($\sigma = 32$ min)	83 min. ($\sigma = 69$ min)	61 min. ($\sigma = 38$ min)	62 min. ($\sigma = 32$ min)	84 min. ($\sigma = 31$ min)

4.4 Determining Behaviour Types on Application Usage

The clustering analysis was only able to discriminate between two groups: users showing a high adherence to the application (group 1) and those reporting a more irregular use (group 2). Group 2's users reported fewer emoticons per day on average that Group 1's users, being more intense in the app usage during mornings/midday. Additionally, they registered periods of inactivity (e.g. not using the application over the weekends). Regarding company, both groups agree on the context in which they tend to use the app, with all of them being more active when they are at home and/or alone. Regarding the generation of notifications as an effective mechanism for application adherence, we found that users have responded to prompts in a 70% of cases (with a threshold of a maximum average of 60 min to determine the notification as effective), thus "typically" responding to notifications. Moreover, 30% of users responded to notifications in less than 30 min. Group 1's users almost always react to notifications and quite quickly. But Group 2's users do not always react (they apparently are more reactive for notifications delivered early in the day) and take longer to input data.

Although we explored the effect of fatigue over the weeks and the value of notifications for this, these results were not relevant because the second group of users did not have enough data and usually did not complete the four weeks of the study.

5 Conclusions

Although, from the retrieved data, users in our experiment can be classified into two main different groups, this short analysis shows the variability of usage patterns over the same application. Observing that periods of inactivity may differ between users, user profiling could be useful to model activity and usage intensity. The objective would be to design specific measures to foster adherence during inactivity periods and to guarantee timely reporting along the day. In this direction, notifications have been shown to be a key mechanism for their adherence: they do help to keep users active, but unfortunately seem to be more efficient with those users already showing higher adherence. For the more inactive user, notifications reveal to be useful but not sufficient. Corrective measures may include a) to facilitate notifications customization, thus their frequency, delivery context and timing is better for each specific user (adaptive and automated customization is also an option to consider); b) to better model the user motivation and expectations when starting the app, to enrich the operation context by adapting interfaces and adherence mechanisms; c) to include other adherence mechanisms that may explore rewards, group performance advice, etc.

In addition to the problems concerning users who did not complete the four weeks of data reporting, the study is limited by the number of users and the difficulties to directly communicate with them during the study and the limited amount of data. Within the study, there is also a weakness due to the lack of social data about users, which prevents analysis along these lines. Nevertheless, the study reveals that rough clustering and posterior classification can be enough for setting up a first strategy for notifications handling. In any case, it would be interesting to carry out a broader study with better access to users' demography and social data.

In this study we have not been able to measure the impact of using data as a support for clinical treatment, thus it is in our roadmap to conduct a study in a use case in which the app, in practice, is integrated in a clinical pathway. The fact of using the app for clinical follow up may substantially influence how adherence is considered from the design viewpoint.

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