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Raising Awareness of Smartphone Overuse among University Students: A Persuasive Systems Approach

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Abstract: Smartphone overuse can lead to a series of physical, mental and social disturbances. This problem is more prevalent among young adults as compared to other demographic groups. Additionally, university students are already undergoing high cognitive loads and stress conditions; therefore, they are more susceptible to smartphone addiction and its derived problems. In this paper, we present a novel approach where a conversational mobile agent uses persuasive messages exploring the reflective mind to raise users' awareness of their usage and consequently induce reduction behaviors. We conducted a four-week study with 16 university students undergoing stressful conditions—a global lockdown during their semester—and evaluated the impact of the agent on smartphone usage reduction and the perceived usefulness of such an approach. Results show the efficacy of self-tracking in the behavior change process: 81% of the users reduced their usage time, and all of them mentioned that having a conversational agent alerting them about their usage was useful. Before this experiment, only 68% of them considered such an approach could be useful. In conclusion, users deemed it essential to have an engaging conversational agent on their smartphones, in terms of helping them become more aware of usage times.

Keywords: human-computer interaction; persuasive interfaces; conversational agents; behavior change; smartphone overuse; digital wellbeing

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1. Introduction

Nowadays, millions and millions of hours are spent on smartphones, making these devices the most popular Wireless Mobile Devices (WMD), due to their pocket size and accessibility. Smartphones have changed the way people think about mobile devices, since now it is possible to access the internet at any time and everywhere, and their owners use them not just for calling and messaging other people but also to browse the Internet, or check social media or the e-mail inbox, allowing and triggering them to go online every day [1].

Research shows that smartphone users can spend more than three hours per day and can reach out to their phones more than one hundred times each day [2–4]. Besides driving users into addiction, the overuse of a smartphone can drive them into a series of physical, mental, social, and sleeping disturbances [5].

Since companies' success can be measured by the time spent by their customers using their products, software designers compete for their users' attention. This motivates them to keep working on attention retention strategies and applying psychological principles as much as possible in software design [6]. The logic behind this is simple: the greater the number of users, the greater the number of accesses to their apps, resulting in more ingenious opportunities for companies to gather the attention of their apps' users and monetize their products [7]. In addition, smartphone users tend to underestimate their usage [8,9], when it could be in fact increasing due to these attention grabbing techniques, which shows a lack of awareness of the time they spend each day on their smartphone.

This uncontrolled capture of mobile users' attention can bring smartphone users into addiction, but this may be more prevalent among youth and young adults as compared to older adults and the elderly [10]. Nowadays, mobile device ownership is currently ubiquitous among higher education and college students (young adults), and these groups experience high cognitive loads in times of study and evaluations, becoming even more susceptible to companies' attention-grabbing strategies [11], which deserves our attention in helping to control or tackle this issue (See more at https://bit.ly/WysaApp, accessed on 28 November 2021).

In this paper, we present a mobile app that collects usage data and sends it to a conversational agent. The main goal is to send messages through this agent, triggering and managing a conscious conversation, to conclude whether this mechanism can reduce overall smartphone usage.

We present a study of this approach's feasibility. Self-tracking has an essential role in the behavior change process [12]. We present the design, implementation and evaluation of an app that achieved an average smartphone usage reduction of 81.3% in all experimental subjects. There was also a high perception of usefulness regarding the rationale of this mobile app.

2. Related Work

2.1. Smartphone Overuse

Besides the fact that abnormal use of the smartphone may vary according to personality factors [3], there is a consensus about the existence of smartphone addiction [5,10] that can harm users' wellbeing, including provoking social and mental health problems and irregular eating habits [13,14].

There have been some efforts to attenuate these effects of smartphone usage. Some of these strategies try to minimize the negative impact of smartphone overuse, through usage-tracking and self-control apps. In 2018, the top mobile operating system companies, Google and Apple, adopted these solutions in their devices, with the introduction of the Digital Wellbeing and Screen Time apps, respectively [15]. Some design features of these applications, however, are more popular and used than others [16].

There are few mobile applications with integrated chatbots focused on minimizing the impact of the user's stress, anxiety, depression, loss or worry (most of these associated with the smartphone overuse). Wysa [1] and InnerHour Self-Care Therapy (See more at https://bit.ly/InnerHour, accessed on 28 November 2021) are two such examples of mobile therapy chatbots. These apps, however, do not retrieve the smartphone's usage data to send alerts from their conversational agents in order to reduce usage.

Since 2015, there has been a sudden increase in the research output of chatbot or conversational agents, that can be understood in terms of the development of Artificial Intelligence and related technologies. Many of the existing studies focus on a technical perspective, such as how to surpass the Turing test. Accompanied by a lack of research from the humane and business point of view [17], they are not considered as yet, to the best of our knowledge, as a solution for the smartphone overuse problem. However, in 2018 [18]:

- 60% of millennials have already used them, of which 70% reported positive experiences.
- More than 50% of millennials who have not already used them say they are interested in using them.

Chatbots are becoming known for their benefits, e.g., they are always available to perform a task that otherwise would not be possible or would take a longer time; they are also characterized by their correctness and impartiality [19]. This is because chatbots play an important role when the user wants to learn or develop skills in a language, for customer service in e-commerce websites, or for entertainment purposes [17,20]. However, they are not yet considered an ideal solution for smartphone overuse [19].

2.2. Nudge-Based Strategies

Our strategy is naturally rooted in so-called "choice architecture" [21,22] via the concept of nudges, in this case small messages sent by a chatbot that could make the user stop and reflect to proactively adapt his/her behavior.

In this context, we consider a 'nudge' as a specific form of choice architecture that changes people's behavior in a predictable way without hampering any options or significantly changing their economic incentives, thereby assuming a "soft" form of design-based control [21]. Studies of peoples' reactions and behaviors in the face of such nudges have been increasing exponentially [22], particularly regarding the decision-making hurdles affecting those choices, and ways to mitigate such hurdles. Nudging recognizes that users are frequently unaware of decision-making biases and can be affected by subtle differences in system design, for example, defaults, saliency of features, or feedback [21].

One of the most discussed aspects of these design strategies is related to privacy awareness [23]. Malandrino et al. discuss and exemplify this with a client-side tool that maximizes users' awareness of the information leakage extension, showing the power of customization to help users make informed decisions [23]. Our tool follows a somewhat similar approach but is adapted to a target base—university students—shedding some light into how a chatbot approach could influence the reduction of smartphone overuse while simultaneously maintaining high levels of awareness.

Another interesting approach and concept is presented by Guarino et al. [24] who describe alert and highlight mechanisms that can be used while maintaining full control and allowing users to make the final choice. Instead of using a conversation-based approach, they employ machine learning and sentence-embedding techniques with the primary goal of providing privacy awareness to users and, consequently, full control over their data during online activities [24]. Lettieri et al. [25] also elaborate on these aspects in the context of Digital Labor Platforms, one of the most relevant phenomena in the gig economy [25].

Guarino et al. [26] also describe a novel machine learning-based approach to classifying Terms of Service clauses, represented by using sentence embedding, in different category classes and fairness levels, which could be useful for future work if adapted successfully to nudging users into reducing smartphone overuse also.

On the other hand, there has been ample research studying the interplay between techno-regulation and techno-effects [27]. This ranges from topics, not only related to nudging, but also to affordances, scripts embedded in technological designs and even anthropomorphization [27]. The usage of a nudge-based approach in the form of a chatbot could be partially considered as a form of anthropomorphization, as textual messages mimicking the way we communicate in mobile phones elicit a similar human response.

Textual nudges have also been used to raise user awareness through salient and concise privacy notices, as described by Ebert et al. [25], as well as to create or enforce better privacy transparency for average users that do not read traditional privacy policies.

Researchers have also studied how to raise user awareness on the profiling capabilities and privacy threats associated with disclosing the user's location data [26]. Results show also how users perceive these questions. We did not follow this rationale, as our focus was limited to perceiving how our approach could mitigate smartphone overuse among university students, and to how useful would they find such an approach.

Other researchers have focused on how the location of users is processed in practice by the actors of targeted advertising ecosystems [27].

Pandey et al. present a similar approach to ours in the sense that they used AI and conversational agents to combat misinformation in the context of WHO recommendations during the COVID-19 pandemic [28]. They conclude that "a machine learning application delivering bite-sized vernacular audios and conversational AI is a practical approach to mitigate health misinformation" [28].

Finally, and more related to our specific approach, there have been some attempts at addressing these issues in the context of university students. For instance, Qasmi et al. [29] have studied how to raise student's awareness on biosecurity courses, and Aldawood [30] has shown that "ICT tools are influential in providing a sustainable structure for communication and information exchange to enhance human awareness" [30]. Mobile-based approaches have been designed and evaluated to engage new students in university orientation [31], where game elements were found to add value to the experience, and phone text messaging was found to have some positive impact on student participation [32,33].

3. Research Methods

Since conversational agents have not been widely used as personal digital wellbeing assistants, our novel approach intends to develop an Android app called <Anonymized> that collects real-time smartphone usage data, sends it to the conversational agent (via Dialogflow API) and, according to the usage data, triggers alerts to the user in the form of messages. These alerts intend to minimize the usage levels of the participants since self-tracking has a vital role in the behavior change process [12].

Besides the conversational agent messages feature, the developed application also has a floating widget that indicates when the user receives a new message from the chatbot, to avoid vibrations, LEDs or sounds and, consequently, without interrupting the user (since push notifications may compromise students' focus and attention [4]). When the user surpasses specific percentages of the defined goal, the application triggers a message that intends to minimize smartphone usage, according with the defined goal, like:

- "On the last hour, you unlocked the phone 15 times. What are you doing now?"
- "You've reached 50% of the total time on this device as defined on the settings! Do you want to take a break?"
- "You've reached the total time you set for today on your smartphone! Now it is time to read a book for the rest of the day of to do another interesting thing!"

These messages are in line with what users expect from previous studies on this topic [34]. The system's operation is summarized in Figure 1.

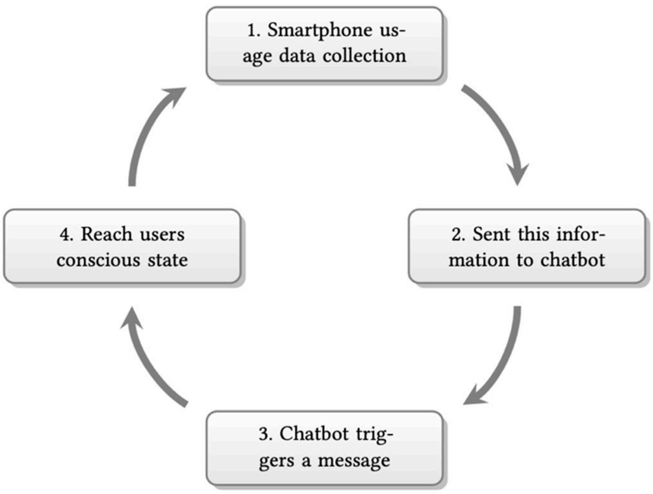
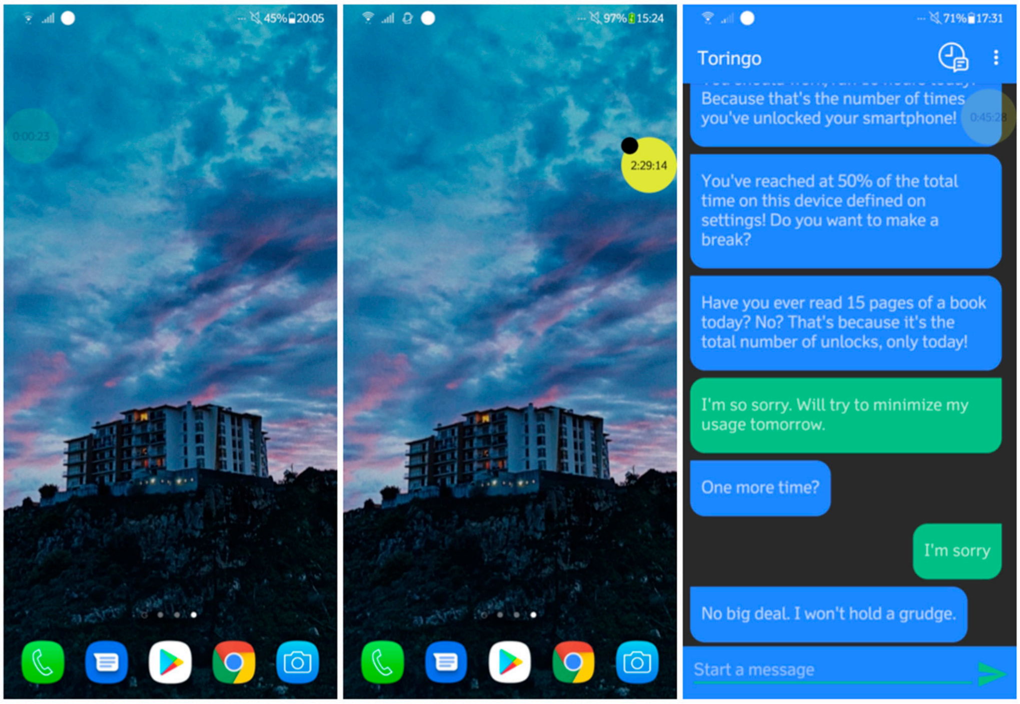


Figure 1. Step-by-step operation of the proposed application, which uses a conversational agent to mitigate the smartphone overuse problem.

The conversational agent's messages, instead of sending push notifications to alert the user to it, were shown through a black dot in the corner of the floating widget. In Figure 2, it is possible to see some images of the developed application, the floating widget and the chat activity. The messages are triggered according with smartphone usage, intending to change the user's behavior as soon as possible. For example, the user can receive an alert from the conversational agent when surpassing 50% of the defined goal for maximum total usage time in the settings of the app.



(a) (b) (c)

Figure 2. A floating widget that shows the user (**a**) the total time on screen (less than 50% of the defined goal), (**b**) the total time on screen (more than 50% of the defined goal) and with a pending message from the conversational agent, and (**c**) the prototype with answerable messages, triggered by the chatbot.

When the app is installed, the user is invited to activate the necessary permissions to start collecting the usage data for each day. Depending on this data and on the defined goal, the chatbot triggers messages, engaging the user and informing them of their smartphone usage.

In addition, the floating widget is also used to share the total time spent on the smartphone. For this reason, the user can define the maximum usage time they would like to spend as a goal in the app (this information is considered by the chatbot to raise user awareness), where its color changes accordingly, as Figure 3 shows. It can also be dragged to any corner of the screen, and during inactivity its transparency is set to 80% so as not to disturb the user while using other apps. This feature reveals itself as important since previous research has pointed out that users tend to agree with the idea of helping them regulate their usage style [34].

Figure 3. Floating widget's colors when the user surpasses 50% (dark yellow), 75% (orange) and 100% (red-maroon) of the defined maximum total usage time, respectively. Before achieving 50% of the defined usage time, the widget is predefined to appear as green. For this example, a two-hour goal by the user was considered.

One of the goals of this app is to make the chatbot, from the users' perspective, "someone" reliable, trustworthy and who transmits a feeling of friendliness/loyalty. It was also intended to choose a color palette that does not stimulate peoples' brains. Research concluded that being presented with the color blue lowers blood pressure, stimulates creativity and stifles hunger, blue being associated with feelings of loyalty, sincerity, trustworthiness, calmness and serenity [35–37]. Findings also showed that the autonomic nervous system and visual cortex were significantly less aroused during blue than during red or white illumination, causing greater relaxation, less anxiety and less hostility [38]. This mobile application intends to be used for very short periods of time, in order to enjoy these blue color benefits.

3.1. Software Architecture

Today, there are many development platforms and implementation options (e.g., via Software as a Service (SaaS)) on the internet that allow the building of a personalized chatbot with many different features, which can be integrated into various platforms [39]. There are several messaging platforms—Messenger, Telegram, Viber, Kik or Slack—that allow the integration of chatbot agents. However, the main goal of this project was to develop an Android app that could receive usage data from the smartphone and trigger messages through a chatbot agent.

Understanding humans is not an easy task for machines, since there are many nuances and subtle ways for humans to communicate, with complex linguistic patterns and rules, and this is not very easy to replicate artificially. NLP stands as a sub-field of AI, a linguistics and computer science for human language processing. NLP is concerned with how machines can process and analyze large amounts of natural language data efficiently, using standardization through a series of various techniques, such as converting text to lowercase or correcting spelling mistakes [20].

Generally, these principles are present in conversational agents, which can be built, for example, by different markup languages, e.g., Artificial Intelligence Markup Language (AIML) and Synthetic Intelligence Markup Language (SIML, programming language libraries, such as the Natural Language Toolkit (NLTK) from Python, or scripting languages, such as ChatScript and RiveScript that generally encode rules for questions and answers. Besides that, there are also development platforms, some of them implemented as a SaaS (e.g., Pandorabots, Botsify, Chatfuel, Mobile Monkey, Dialogflow), that split the testing responsibility between the service provider (who receives inputs, tests them, and takes action, sending outputs which are appropriate and realistic for each situation) and the client (who evaluates the ease of use and the effectiveness of task accomplishment) [39].

Since smartphone overuse is the main concern and almost three-quarters of smartphone users have an Android OS, Dialogflow was the choice for the Conversational Agent Platform. In addition, Firebase was used for the backend server-side. The authentication process is made with known credentials, provided, for example, by Google, Facebook or GitHub instead of inserting credentials and personal data, avoiding a possible user experience bump. The application has an authentication system that allows users to access their data in a secure way and multiple times, provided by the Firebase Authentication SDK. With this SDK, it is only necessary to choose one or more authentication providers, and then the system handles the rest of the process. In this application, only Google Sign-In was used, since Android smartphones have Google accounts associated with this.

The Realtime Database is a cloud-hosted NoSQL-based database in JavaScript Object Notation (JSON) format that works differently from a traditional SQL database: all the code is on the client- side and not on the server-side, and there are no database access tiers. It intends to be responsive, allowing the building of a real-time experience that serves a high number of users, since it provides synchronization with all the connected devices, and data is still available when there is no network connectivity, through a local cache [40].

The App Distribution tool allows distribution of the app for trusted testers effortlessly, organizing the app releases by version. The process is straightforward, only requiring uploading of the *.APK file of the version we want to test, and adding of the testers to make them available for downloading of the application.

The Android project was organized according to a conventional MVC architecture. The final system architecture is summarized in Figure 4.

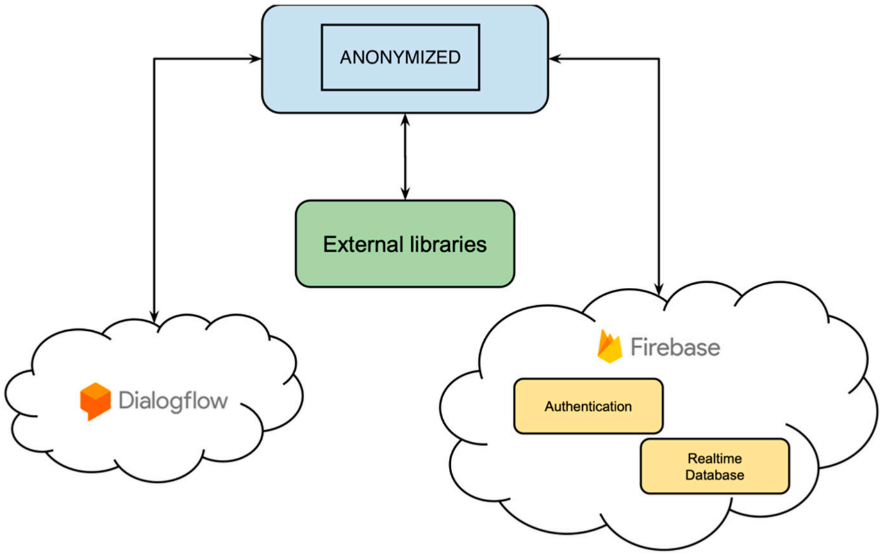


Figure 4. The developed app's system architecture.

The mobile app developed uses the getTotalTimeInForeground method from Android OS class to collect the usage data, returning these data, for each user, filtered by application and day.

The usage data that is intended to be collected is as follows:

1. The timestamp when the user unlocks the smartphone's screen;
2. The timestamp when the user locks the smartphone's screen;
3. The usage data for each application installed in the smartphone;
4. The total number of seconds that the smartphone's screen was interactive.

To know how much time the installed applications were used for during previous days, a special permission called Usage Access is requested from the user.

Some conversational messages are presented in the revised Section 3.1. The chat has a 50-message history limit. It is intended for users to spend the least amount of time possible on the app and so the user is not allowed to indefinitely scroll through all the exchanged messages with the chatbot. This decision was based on the known literature, according to which infinite scroll is one of the persuasion techniques intended to increase engagement with smartphone screens by users.

The conversation was designed by the authors, strongly based on existing, similar apps and the literature. There are essentially two stages: **Initiation** and **Use**. For instance, during **Initiation**, when the user successfully logs in, some messages that intend to welcome the user are triggered, introducing the conversational agent:

- Welcome, $username! My name is <ANONYMIZED> and I'm your digital wellbeing assistant! Glad to meet you!
- After activation, you can go to Settings and set how much time you want to spend each day. Then, I will do my work!

During the **Use** stage, some examples include:

- You've reached $usagePercentage (%) of the total time on this device as set in the settings! Do you want to take a break?
- Today, you received more than $numberOfUnlocks notifications. Don't you want to change the strategy of your notifications or block some of them?
- You've been using your smartphone for $numberOfMinutes minutes straight. Let's take a break?
- You've unlocked your smartphone more than $numberOfUnlocks just today! Aren't you worried about this number?

- Yesterday, you used the smartphone for 3 h. At the end of a year, this corresponds to nearly 45 days using it. Let's change these numbers.
- Over the last hour, you unlocked the phone $numberOfUnlocks times. What are you doing now?
- You've reached the total time you set for today on your smartphone! Now it is time to read a book for the rest of the day or to do some other interesting thing!
- Have you ever read $numberOfUnlocks pages of a book today? No? That's because that's the total number of unlocks, only today!

To illustrate an example of a possible, actual conversation with the chatbot we include below an excerpt (user input is in italics):

- Welcome John! Can you go to Settings and set how much time you want to spend each day. Then, I will do my work!
- *OK.*
  (. . .)
- John, you've unlocked your smartphone more than 23 times just today! Aren't you worried about this number?
- *I'm not worried.*
- OK, but for instance yesterday, you used the smartphone for 3 h. At the end of one year, this corresponds to nearly 45 days using it!
- *I will think about it.*

3.2. Procedure

The methodology described in Table 1 was adopted for each participant in this study. The subjects' smartphone usage data was returned in JSON by Firebase's Realtime Database and analyzed with a custom script developed in JavaScript.

Table 1. Evaluation stages for the digital wellbeing conversational agent.

Stage	Time Period	Duration
1. Usage data collection	28th September—11st October	2 weeks
2. Pre-questionnaire	12nd October	5 min
3. Application	12th October—25th October	2 weeks
4. Post-questionnaire	26th Oct.	5 min

The study was undertaken for four weeks, between 28 September and 25 October 2020, during an abnormal period—a pandemic crisis.

The usage data was collected using the Realtime Database from Firebase in JSON format, and then was filtered by JavaScript functions and analyzed by plotting charts. The app was uninstalled after the end of the study protocol, on the 26 of October.

3.2.1. Usage Data Collection

In the first two weeks, a specific mobile application intended only to collect smartphone usage data, without influencing or conditioning the subjects' smartphone usage in this study, was developed. To collect this data, the app only needs to be run two times, for two minutes each time. While the subjects had this application installed, the collected usage data were not shared with the subjects, so as not to influence their smartphone usage behavior or their responses to the first questionnaire.

3.2.2. Pre-Questionnaire

To validate the efficiency of the proposed application, it was important to know the subjects' own perception of how much their smartphone usage was before the proposed application was installed (pre-questionnaire).

3.2.3. Developed Mobile Application

Then, during the two final weeks, the proposed application was installed on the subjects' smartphones. As already mentioned, the main goal of the developed application is to collect the usage data for each subject and use it to trigger alerts in order to decrease smartphone usage. In this app, subjects know how much time they spend each day on the smartphone, through the floating widget.

3.2.4. Post-Questionnaire

A questionnaire was shared before installing the app (pre-questionnaire) and after the study's period (post-questionnaire), to understand the subjects self-perception, which would be compared with the app's collected data. In the post-questionnaire, we also asked about users' perception of the app features. Both questionnaires intend to collect qualitative data.

3.3. Participants

For this study, 16 subjects were recruited, with ages between 18 and 24 years (M = 21.4, SD = 2.0) and with a balanced gender representation (male: 56% (9), female: 44% (7), other: 0% (0)), who were at that time students in the University of <Anonymized>. These participants were all using Android smartphones, whose API had to be greater than 24 (Android 7.0), since this was an application restriction. In Table 2 it is possible to see details of the recruited subjects' profiles, including which of them regularly use usage-tracking applications.

Table 2. Participants' profiles.

Subject	Gender	Age	Already Has Usage-Tracking Apps?
U1	Male	24	No
U2	Male	22	No
U3	Male	20	No
U4	Male	20	Yes
U5	Male	18	No
U6	Female	20	No
U7	Male	24	Yes
U8	Female	20	No
U9	Female	19	No
U10	Female	24	Yes
U11	Female	21	No
U12	Male	23	No
U13	Male	20	No
U14	Female	22	Yes
U15	Male	22	No
U16	Female	24	No

The ethical requirements inherent to empirical research and data collection were met through the presentation and signing of free, prior, and informed consent protocols, which described the purpose of the study and the type of data collected.

4. Results and Discussion

The initial evaluation's results suggest that the approach is indeed effective in reducing smartphone usage. 81.3% of the subjects reduced their smartphone usage, when comparing the period before—weeks 1 and 2—and during the use of the developed mobile application—weeks 3 and 4. Comparing the evolution of smartphone usage data of the average of all users throughout the four weeks, a reduction of smartphone use was noticed, as Figure 5 shows. Using an ANOVA with repeated measures and with a Greenhouse-Geisser correction, the mean scores for the usage time were statistically significantly different ($F(1, 15) = 13.099$, $p \approx 0.003$). Post hoc tests using the Bonferroni correction revealed a reduction between the phone usage from pre-testing to post-testing of 36.95 $\pm$ 10.21 min/day.

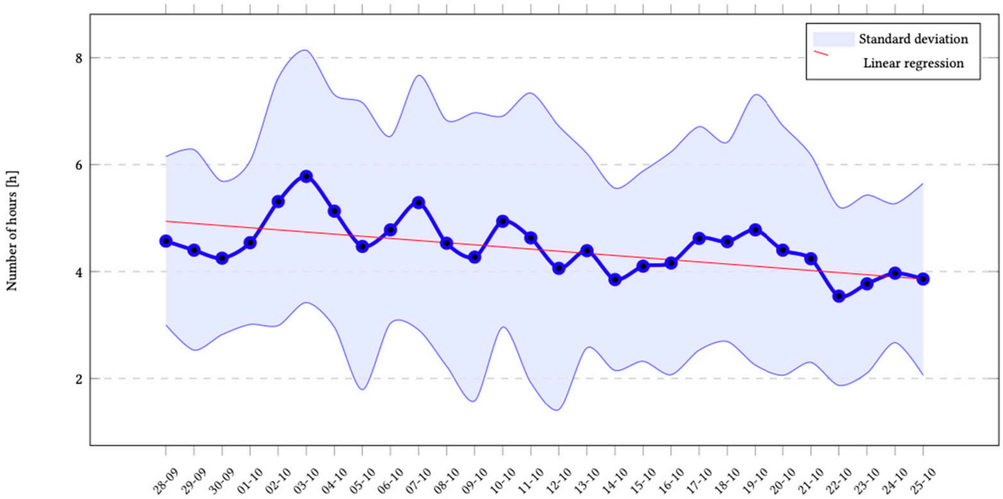


Figure 5. Average usage data, for each user, filtered by day. It is possible to observe that the linear trendline decreases, which indicates a reduction of smartphone use over the time. Filled blue areas as standard deviation.

Although subjects showed a decrease in their smartphone usage, there were some for whom activity increased. This increase, however, never exceeded the groups' average decrease (36.95 min). Interestingly, all subjects who mentioned that they already had usage-tracking apps showed a reduction in smartphone usage.

When talking about smartphone use, it is also important to compare, for each user, the real usage data with their perception. Therefore:

- In the pre-questionnaire, their perception of how much time they spent on average, on the smartphone during the last seven days, i.e., between 5th and 11st October, was asked about.
- In the post-questionnaire, how much time was spent on average, on the days that <Mobile App Name> was used, i.e., between 12nd and 25th October, was asked about.

Regarding perception before using <Anonymized Mobile App Name>, Figure 6 compares the average usage time per day and perception from the pre-questionnaire for the same period. Considering the percentage change between these two data groups, the median obtained was -25.7%, which indicates a general underestimation of smartphone use by subjects (A Shapiro-Wilk test showed, at the level of significance of 0.05, that the data is not normally distributed ($W(16) = 0.7026$, $p < 0.001$). In this view, the median is the best measure of central tendency, since it is unaffected by extreme values in one direction). It is interesting to note that people tend to underestimate their smartphone use, since 68.8% of the subjects mentioned a lower value than the real one before using <Anonymized Mobile App Name>, which revalidates the same conclusions as those of prior research [8,9].

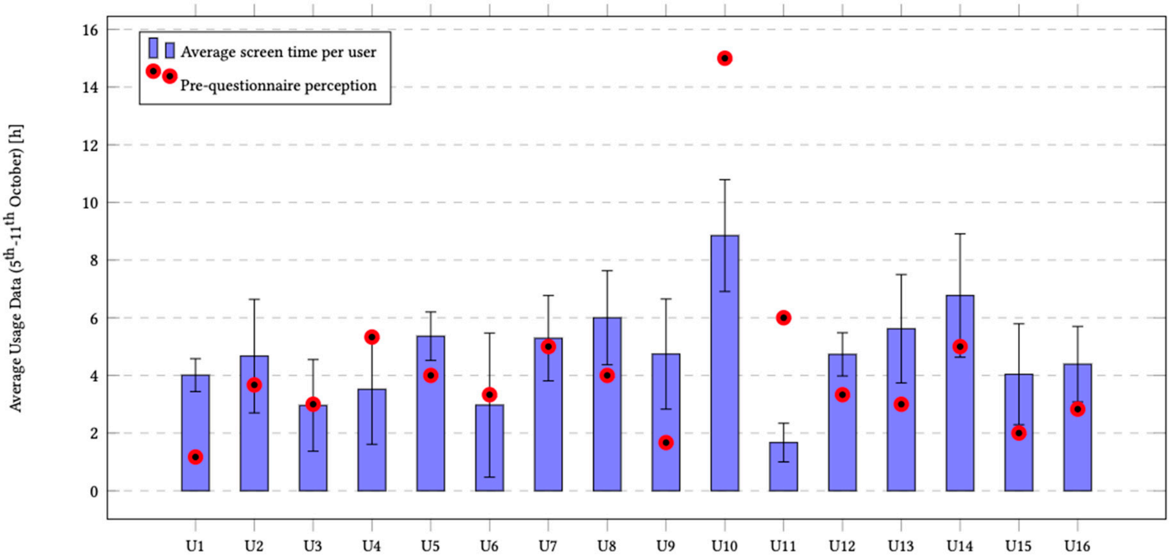


Figure 6. Average usage data, for each user, filtered by day, compared with their perception after filling the pre-questionnaire.

Concerning the period in which <Mobile App Name> was used, Figure 7 compares the average usage time per day for all users and their perception from the post-questionnaire for the same time period. Here, considering the percentual change between their perception and the real data, the median obtained was 10.31%, which indicates an overestimation of their smartphone usage (A Shapiro-Wilk test showed, at the level of significance of 0.05, that the data is not normally distributed ($W(16) = 0.8849$, $p < 0.05$). In this view, the median is the best measure of central tendency, since it is unaffected by extreme values in one direction). This could be attributed to an increase in awareness on the users' part while making a conscious effort to decrease their overall smartphone use. When considering the period after using <Mobile App Name>, their perception was more realistic: only 31.3% of the subjects underestimated their smartphone use (which could be explained by the fact the floating widget was constantly displaying total usage time).

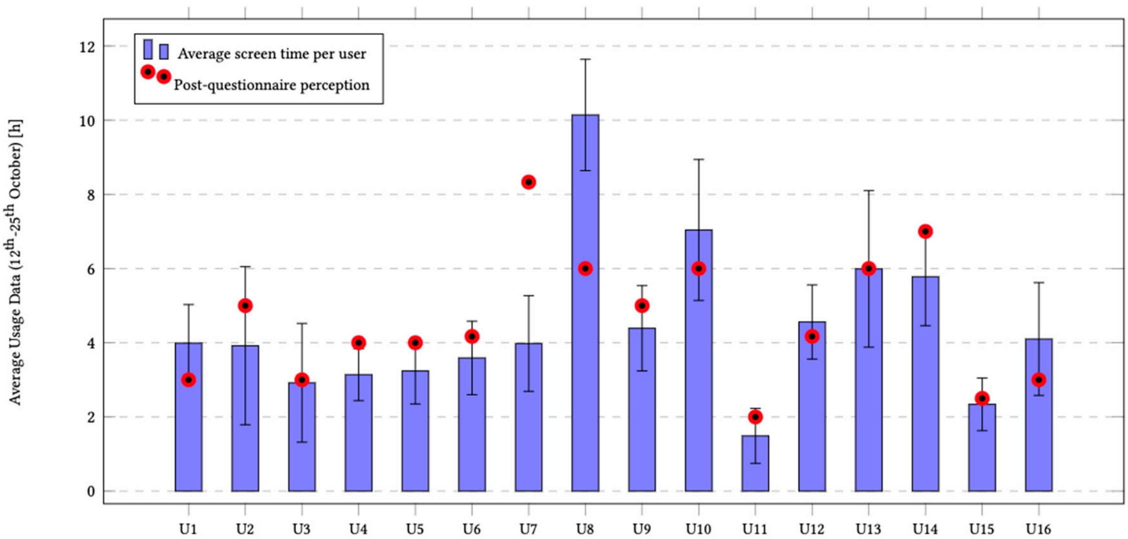


Figure 7. Average usage data, for each user, filtered by day, compared with perception after filling the post-questionnaire.

This study reinforces the notion that the user tends to underestimate the total time they spend per day, on average, on their smartphone, as was previously discussed by several authors [4,8,9,41].

In short, it is possible to conclude that, since subjects were more aware of their smartphone usage data, they were more realistic about their smartphone use. When comparing the perceptions of their usage with the real values, after using <Mobile App Name> it was revealed that the real value was only higher in five subjects out of the sixteen, i.e., only five subjects underestimated the time spent on their smartphones. This constitutes a decrease in half of the number of subjects underestimating their usage from the results of the pre-questionnaire (from eleven to five).

Qualitative Data

Other questions were given on the post-questionnaire, to collect the users' feedback about the <Mobile App Name>:

- 81.3% of the subjects considered as beneficial for their "smartphone behavior" having the floating widget always-on display, making sure that they know how much time they are using the smartphone for.
- 75% of the participants pointed out that the smartphone was used for study purposes: to read documents, assist video calls for classes, and to clarify doubts with friends—which revalidates the same conclusions as those of prior research [42], although Atas et al. (2019) reported smartphone use among university students to text and talk with someone, check social media and perform an Internet search, even during classes [11].
- Of the participants, 10% mentioned that having a conversational agent alerting them of their usage was useful, when before installing <Mobile App Name> that percentage was 68%.

Although smartphones can positively impact their academic performance through, e.g., the enhancement of learning skills and preparation and submission of assignments on time [42], it can also harm their performance, depending on how and where smartphones are used [13,43].

5. Conclusions

Self-tracking has an essential role in the behavior change process [12], which can be proved by an average smartphone usage reduction of 81.3% in all subjects. The floating widget possibly played an essential role in this reduction, since the total time spent on screen was always displayed, alerting users constantly and preventing an underestimation of the total time on screen. This was considered as a useful feature by most of the participants.

Of the participants, 75% said that the smartphone was used for study and educational purposes, which could justify the usage increases for some smartphone users, besides the fact that during the lockdown there was an increase in digital media consumption [44]. Since habit formation could have a significant part to play in digital wellbeing apps, it is essential to know the smartphone usage patterns for each user to set and trigger different messages, in order to improve efficiency. Smartphones allow us to do many different things, and since these patterns differ for each user, it is crucial to improve the personalization of the conversation agent messages.

Since push notifications could have a negative impact, 81.3% of the participants considered that the delivery method for conversational agent messages was not annoying. In this way, users do not know about those messages until they unlock—and not merely check—their smartphone. Interestingly, people can also underestimate the frequency with which they check the smartphone [8].

All participants considered the conversational agent messages as useful. On the other hand, most of them felt the conversational agent as attractive, by not sending too many messages per day. This can be an interesting conclusion, since the conversational agent did not result in people engaging in more smartphone use.

For future work, instead of developing tools looking at total time on screen, it would be interesting to develop the conversational agent for other situations, e.g., the number of unlocks or duration of each smartphone session, to give more and more personalized messages and consequently reduce smartphone use.

Study Limitations

Since for this kinds of study a minimal amount of personal data must be collected, gathering students who were available to participate was a demanding task. Users were not aware of the goal of the study: they knew that the only data being collected would be the amount of time they spent on their smartphones and the exchanged data with the developed app. The visual representation of the usage of time is shown, together with the chatbot, and in that sense this could constitute a confounding factor.

The sample size is not sufficient, nor is the sample design adequate for it to be representative of students at the University of Madeira. A non-probabilistic sample was built because we do not have access to the list of all elements. However, this methodological option responds to the objective which guided the study and gives us clues for more in-depth and generalizable studies.

The study had a limited time duration. This means that nothing can be claimed regarding the study's efficacy in the long term.

The functionalities of the chatbot can be improved and expanded (quick replies and psychological advice with help from experts, for example), as this is an experimental test that allows understanding of the positive impact that this could have on users' digital wellbeing.

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