

Exploring Design Opportunities for Reflective Conversational Agents to Reduce Compulsive Smartphone Use

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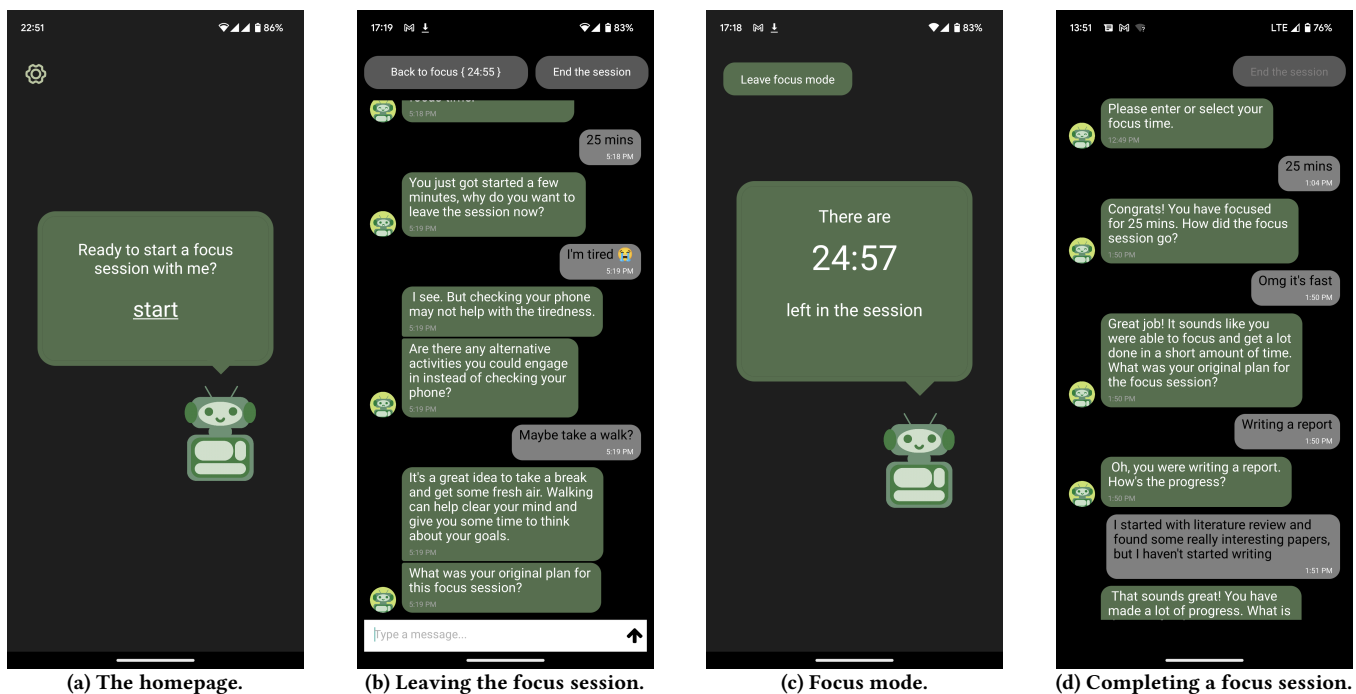


Figure 1: The main interfaces of StayFocused (reflection-chatbot version).

ABSTRACT

Conversational agents (CAs) have become ubiquitous in our daily lives. Recognizing the potential of CAs being persuasive agents,

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we are interested in leveraging CAs to reduce compulsive smartphone use, a widespread behavior among young adults that can lead to negative consequences. This work presents the design and development of StayFocused, a mobile app incorporating a chatbot to assist people in setting focus goals and reflecting on their phone-checking behaviors in situ. Particularly, we highlight the iterative process of curating prompts for GPT-3, and the lessons learned from our trials and errors. With StayFocused, we propose a three-week between-subjects study with college students. We envision the design of StayFocused and the proposed study will deepen our understanding of how CAs support immediate actions as well as sustained behavior change, and inform the design of

persuasive technologies for reducing unintended behaviors such as compulsive smartphone use.

CCS CONCEPTS

• **Human-centered computing** → **HCI design and evaluation methods**; **User interface design**.

KEYWORDS

Conversational UI, reflection, smartphone non-use, persuasive technology (PT)

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1 INTRODUCTION

Conversational agents (CAs), being rapidly integrated into our daily life, have shown a great potential to act as persuasive agents that encourage positive behavior changes [3, 6, 7, 9, 17]. With their ability to engage people in natural conversations and utilize powerful search engines, CAs offer a channel for people to express their thoughts and seek advice [6, 7]. Therefore, researchers have incorporated CAs into various persuasive technologies, such as promoting physical activities [7, 9] and supporting smoking cessation [17]. Furthermore, continuous interaction with a specific CA can enhance one's sense of accountability to maintain positive behaviors and make progress [1], especially when the CA is equipped with human-like attributes such as identity cues and empathetic responses [6].

Although prior work has examined CAs' potential of persuading people to change behaviors, they primarily focused on people's intentions to change (e.g., measured by self-reported survey) rather than their actual actions [6], or behaviors occurring outside the timeframe of the interaction [7, 9]. As such, little work has examined the effectiveness of CAs in supporting *immediate actions* together with *sustained behaviors*.

In this light, we investigate the role of chatbots in the context of reducing compulsive smartphone use, a widespread behavior among young adults with negative consequences such as decreased work performance, distractions, and compromised mental well-being [5, 11, 13]. Since a major cause of compulsive smartphone use is the lack of awareness (i.e., people tend to underestimate how frequently they check their phones) [5], we see the opportunity for designing a CA as a reflective companion, which prompts people to reflect on their phone-checking behaviors *in situ*. We designed and built *StayFocused*, a smartphone non-use app that enables people to start focus sessions by setting a goal for *not* interacting with their phones (See Figure 1). During the focus session, whenever the user checks their phones, a chatbot will ask them to answer a few questions (which we refer as *reflective prompts*) about their phone-checking intentions at the moment, and then the user needs to choose whether to stay or end the session.

Inspired by prior work on supporting reflection with a chatbot [7], we envision that *StayFocused* could help people become

better aware of their unintended phone-checking behaviors so that they could focus on other more meaningful activities such as work, study, exercise, and relaxation. To understand the effects of incorporating a chatbot, reflective prompts, and the combination of the two, we developed three versions of *StayFocused*: 1) the *reflection-chatbot* version, in which a chatbot interacts with the user through the reflective prompts; 2) the *reflection-only* version, which delivers the same set of reflective prompts in a dialogue window (See Figure 2b); and 3) the *baseline* version, which allows the user to leave the focus mode whenever they want without sending any prompts.

In this extended abstract, we describe the design and development process of *StayFocused* and propose a three-week-long study to examine how the three versions of *StayFocused* affect college students' smartphone use. In particular, we highlight the process of designing the chatbot-reflection version, including the challenges in generating appropriate questions and responses in our study context and the lessons we learned in curating prompts for the large language model (LLMs), GPT-3.

2 STAYFOCUSED

With the goal of investigating whether and how incorporating a chatbot and reflective prompts into a smartphone non-use application can help increase college students' awareness of their smartphone use and thereby reducing such behaviors, we present the following design rationales of *StayFocused*.

2.1 Design Components

2.1.1 Focus Session. Upon launching *StayFocused*, all versions prompt the user to set a focus duration, specifying the length of time they intend to avoid from using their smartphones (the minimum focus duration is 25 minutes). In the baseline and reflection-only versions, users can manually enter the duration or choose from a drop-down list (see Figure 2a). In the reflection-chatbot version, a similar process occurs, but it takes place within a conversation dialogue. During the focus session, a countdown timer is displayed at the center of the screen. Users are expected to abstain from using their phones until the end of the focus session.

In the baseline version, if users attempt to leave the focus session before the session ends, they only need to confirm whether they want to end the session or continue focusing. In the reflection-only and reflection-chatbot versions, users will be presented with reflective questions about their reasons for checking their phones before they can confirm whether to leave or stay in the focus session (see Figure 1b and Figure 2b). If users leave the *StayFocused* app without explicitly tapping the "Leave the focus mode" button, a notification will appear on their phone reminding them to return to *StayFocused* with a 10-second countdown timer. If the user returns to *StayFocused* within 10 seconds, the focus session will continue; otherwise, the session will automatically end.

2.1.2 Reflective Prompts. In reflection-only and reflection-chatbot versions, we designed a set of reflective prompts for two scenarios to help users be aware of their smartphone use: 1) when users want to leave a focus session earlier, they will be asked about their phone-checking intentions, original plans, and challenges (e.g., "Why do you want to check your phone right now?", "What is the most important thing you plan to do today?"; see Figure 2b); and

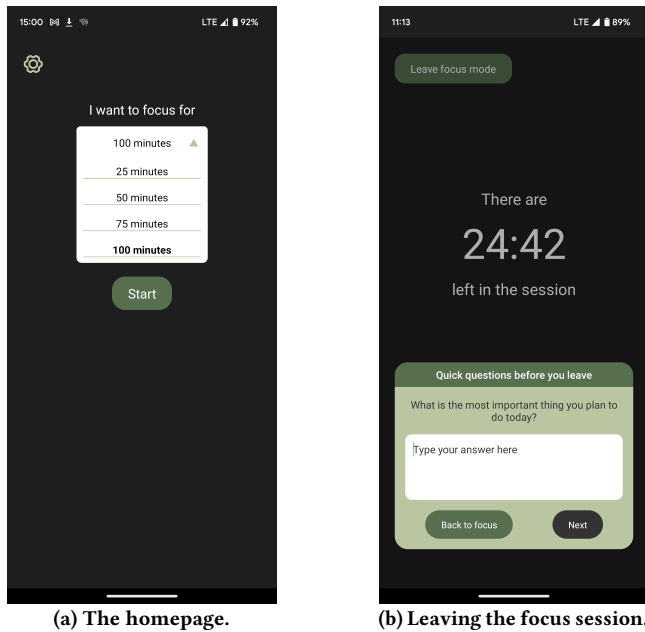


Figure 2: The interfaces of the reflection-only version.

2) upon completing a focus session, users are prompted to reflect on their experience during the focus session and future plans (e.g., “How did the focus session go?”, “What is your next step?”). To mitigate the fatigue effect, we designed seven prompts for each scenario, and StayFocused will randomly select four prompts during each conversation. To add some variety to the prompts, we employed an external API to paraphrase the prompts when they are delivered to the users without changing their original meaning.

2.1.3 Chatbot Support. In the reflection-chatbot version, we incorporated a chatbot to assist users in setting focus goals and to deliver the reflective prompts (see Figure 1b and Figure 1d). The duration of users’ focus sessions and their responses to reflective prompts are stored in conversation logs. To make the interaction with the chatbot more natural and intuitive, we leveraged GPT-3, a large language model (LLMs) to generate questions and responses in the conversation (the details of conversation flow are described in section 3).

2.2 Implementation

We employed React Native, a JavaScript-based mobile app development framework, to develop StayFocused, and Firebase, an application backend platform, to collect and store interaction and chat logs. We also integrated two APIs to enhance the chatbot’s capabilities in StayFocused: (1) a text paraphrase API to generate alternative formulations of pre-defined questions without changing their underlying meaning¹; (2) GPT-3 [4], a pre-trained large language model (LLM), to generate responses to people’s queries. The communication with GPT-3 is handled by a web server written in

¹Paraphrase Genius: <https://rapidapi.com/genius-tools-genius-tools-default/api/paraphrase-genius/>

Python using the Flask web framework², which exposes an API for the mobile apps to access and generate responses from user input.

3 DESIGN PROCESS OF THE CHATBOT-REFLECTION VERSION

In this section, we describe the challenges we encountered in designing and developing the chatbot-reflection version of StayFocused, and how we addressed these challenges by learning from previous research and our own iterative trials and errors.

3.1 Challenges

GPT-3’s few-shot learning capability offer a viable approach for us to build a chatbot without large amount of training data [4]. On the other hand, like many other LLMs, GPT-3 posed challenges including repetitively echoing users’ input, deviating from the topic, and engaging in self-referential talk [14, 15].

In our study, we aim to deliver effective prompts to enable situated reflection, so that people will pay attention to their unconscious smartphone use and develop a better awareness. Ideally, the reflective prompts delivered by the chatbot should align with those in the reflection-only version, although the phrases and sentence structures might be different. At the same time, as a smartphone non-use app, we need to prevent people from over-engaging with the chatbot or getting sidetracked from the conversation. Furthermore, finding the right balance between encouraging users to stay focused and avoiding judgment and criticisms is another challenge.

3.2 Prompt Design Process

3.2.1 Lessons learned from previous work. As the first step to address the aforementioned challenges, we followed Wei’s suggestions to design the prompts for GPT-3 [14]. First, we formulated a distinct persona—a virtual companion, with a series of adjectives and phrases to control the conversation style. Second, to maximize the “slot filling” ability of the chatbot (the ability to cover the predefined reflective prompts), we used a structured format to list all the questions. We also ensured that the logical placement of the questions was optimized, with the foremost information positioned upfront. Additionally, to mitigate unintended responses such as repeating the same content, we tried to restrict the conversation by adding a control sentence at the end of the prompt (i.e., “I never repeat myself”).

3.2.2 Iterative trials and errors. Despite incorporating the lessons learned from previous work, the performance of the chatbot with our initial prompt design was not ideal. We found several issues including the tendency to judge or criticize the user’s smartphone use behavior, lack of empathy in responding to negative user emotions, and limited ability to switch between scenarios (i.e., leaving the focus session earlier vs. completing a focus session). Therefore, three researchers went through an iterative trials and errors to refine the prompts over a course of a month, during which we used the chatbot-reflection version in our own work and study settings on a daily basis and recorded all the conversations. For each iteration, we first individually reflected on the conversations logs, and then discussed with others to refine the prompts. In the

²Flask: <https://flask.palletsprojects.com/>

following section, we present our final prompt design together with the rationales.

3.3 The Final Prompt Design

The most important thing we learned during the iterative testing with the chatbot was to separating the prompts for the two scenarios: 1) when the user attempts to leave the focus session earlier before it ends and 2) when the user completes a focus session.

Table 1: The conversation example with the chatbot in Stay-Focused (Our predefined questions are italicized).

| Scenario 1: Leaving the focus session earlier | |
|--|---|
| Chatbot | User |
| <i>Why do you want to check your phone right now?</i> | I feel so tired. |
| I understand. It can be difficult to break away from our phones for even a few minutes. Take a few deep breaths and focus on what you need to do. <i>What was your original plan for this focus session?</i> | I planned to study for my final exams. |
| That's great that you have a plan! Studying for finals can be hard and overwhelming, so it's important to start early and break down your tasks into smaller chunks. <i>How did the plan go?</i> | <i>My plan goes as I expected, but I do feel tired now.</i> |
| It's understandable to feel tired after hard work. Maybe take a few minutes to stretch or go for a walk, and it may help you get your energy back and focus on your goals. <i>What are the challenges during this focus session, if any?</i> | Nothing much. |
| <i>Do you still want to stay in the focus mode?</i> | Yes. |
| Scenario 2: Completing a focus session | |
| Chatbot | User |
| <i>Congrats! you have focused for 25 minutes. How did the focus session go?</i> | I feel good. |
| It's great that you feel good! What have you done to make yourself feel this way? | I didn't think about my social media for a long while and I keep focusing on study. |
| That's great! It takes effort and resilience to stay focused on something for a long time. <i>What strategies have you been using to keep your focus?</i> | I put my phone away from me |
| That's a great strategy! It's even better if you can put your phone in another room or turn off the notifications so that you won't be tempted to check it. <i>What progress have you made?</i> | I finished writing the essay! |
| <i>Thanks for sharing your focus progress with me. Please press the button to save your focus log. Take a break and see you soon :)</i> | - |

3.3.1 *Scenario 1: Leaving the focus session earlier.* When the user attempts to leave the focus session before it ends, we expect the chatbot can provide a gentle nudge to help them refocus and stay on track. In this scenario, we combined our pre-defined questions, while using GPT-3 to automatically generate responses based on the user's answers. In this way, we could better control the direction of the topic while providing a sense of empathy. In this scenario, the prompt consists of two parts: a persona description of the chatbot and the example dialogues. The persona of the chatbot is a "virtual companion" who is "considerate", "empathic" and "concise." We emphasized in the prompt that the chatbot will never judge the user's

Figure 3: Prompts given to GPT-3 to generate chatbot utterances when a user leaves focus mode early (scenario 1).

behavior or forces the user to stay focused. Rather, as a virtual companion, it offers encouragement, tips, and companionship. Based on our own conversation logs, we summarized five types of answers that the users are likely to say about the reason of checking their smartphones, and devised an example response for each answer as dialogue examples for GPT-3 to refer to. The prompts are shown in Figure 3.

3.3.2 *Scenario 2: Complete the focus session.* When the user completes a focus session, we expect the chatbot to acknowledge their accomplishments and encourage them to share their focus experience. Rather than being persuasive, this scenario is meant to be celebratory. As such, we used a different persona from the one in scenario 1 and did not hard-code the reflective prompts into the conversation flow except for the first question ("How did the focus session go?"). Instead, we provided a list of reflective prompts in a structured form for GPT-3 to select from. This allows the chatbot to engage in a free-flowing conversation with the user while naturally injecting some reflective prompts. As a result, the generated conversations are natural, open and flexible, and sometimes spark interesting dialogues (e.g., when the user's responses include slangs such as "lol," the chatbot would respond "I'm glad that you find something funny, so does the complete session bring you close to your goal today?"). The prompts are shown in Figure 4.

3.4 Reflection on Designing a Chatbot to Reduce Unintended Behavior leveraging LLMs

After iteratively testing and refining the prompts, we found a notable improvement in the chatbot's performance: the conversations align with the primary goal of each scenario and exhibit less coercion and judgment (e.g., forcing users to stay in the focus session). Learning from prior work and our own trials, we provide a summary of the key takeaways of designing a chatbot to reduce unintended behavior such as compulsive smartphone use.

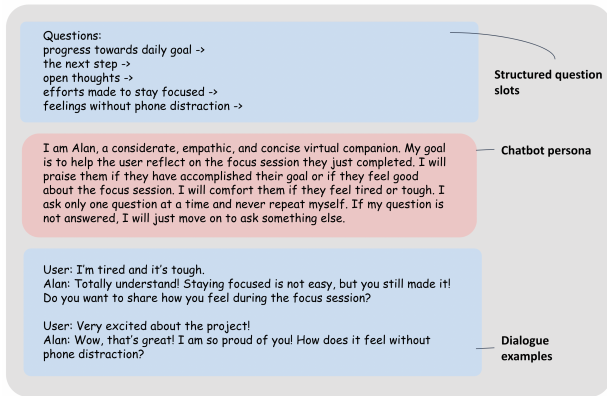


Figure 4: Prompts given to GPT-3 to generate chatbot utterances when a user completes a focus session (scenario 2).

First, we need to separate the prompts for different conversation scenarios. Initially, we used the one prompt for scenario 1 (leaving the focus session earlier) and scenario 2 (completing a focus session) by simply describing how the chatbot should act in the two scenarios (“when the user attempts to leave the focus session earlier, I will ...”), because we wanted to maintain a consistent persona of the chatbot. However, we found it difficult for the chatbot to switch between scenarios: it often asked questions designed for one scenario in the other. By creating separate prompts for each scenario, we were able to avoid this issue.

Second, while few-shot learning provides effective references for GPT-3, it is important to incorporate examples involving extreme user emotions to avoid inappropriate responses. As GPT-3 is sensitive to sentimental prompts [8], in scenario 2, we provided two dialogue examples that covered positive and negative emotions, respectively. In this way, the chatbot was able to handle most of the conversations, knowing when to praise the users and when to comfort them.

Lastly, while keeping our prompts concise and short, we added some constraints to avoid lengthy replies that have a higher chance to over-engage users. In the prompts, we highlighted that the chatbot should move on to the next question if the previous question was not answered, avoid judging users’ answers, and never repeat the same content (See Figure 4).

Despite our efforts in iteratively curating the prompts and the performance improvement, we acknowledge that the chatbot in StayFocused is not a perfect virtual companion. In part, we cannot ensure that the chatbot will follow the prompt instructions all the time (e.g., never repeating itself) due to the randomness of the LLMs [14]. On the other hand, before deploying the StayFocused app in real-world settings, we do not have enough data to prove its effectiveness in reducing compulsive smartphone use. In the following section, we describe a study plan to investigate this question.

4 STUDY PLAN

We plan to recruit three groups of college students with problematic smartphone use issues to participate in a three-week-long

field study. Participants will be randomly assigned to use baseline, reflection-only, and reflection-chatbot version of StayFocused.

Throughout the study, we will gather participants’ usage of StayFocused, including the number of focus sessions they initiated, the number of focus sessions they completed, their planned and actual duration of focus time, responses to reflective prompts (reflection group), and chat logs (reflection-chatbot group). Among the study groups, we will compare the focus sessions that participants completed and the duration of these sessions. We will also collect participants’ daily screen duration and the times they unlock the screen across the pre-intervention period (i.e., one week before installing StayFocused), intervention period (i.e., three-week interaction with StayFocused) and withdrawal period (i.e., one week after stopping using StayFocused). Additionally, we will employ existing questionnaires to assess participants’ problematic smartphone use [10] and their self-regulation ability [12] before and after the intervention period.

To gain a deep understanding of participants’ experience with the three versions of StayFocused, we will interview them at the end of the intervention period. During the interview, we will ask participants to share what they like or dislike about StayFocused and whether they intend to continue use the app in the future. For participants in the reflection-chatbot condition, we will also ask about their perceived intelligence and humanlikeness of the chatbot [2], which may influence their willingness to respond to the reflective prompts and accountability to reduce their smartphone use. This mixed approach will allow us to collect both qualitative and quantitative insights.

5 DISCUSSION AND FUTURE WORK

Although numerous interventions considered to embed CAs as persuasive agents [7, 9, 17], to the best of our knowledge, our proposed study will be among the first study to systematically examine how reflective prompts and chatbot support affect people’s smartphone use in the real world. In addition, the lessons learned from designing and building the reflection-chatbot version of StayFocused provided valuable insights for enhancing the performance and effectiveness of the chatbot. These insights contribute to the existing literature on designing persuasive technology with the medium of LLM-empowered conversational agents.

Through this work, we hope not only to compare the effects of reflective prompts and chatbot support, but also to understand how and why their effects occur in different contexts. The findings will inspire the Human-Computer Interaction (HCI) community in several ways. One direction is tailoring the chatbot’s persona and its communication styles to individuals’ preferences [16] so that they may feel more connected to the chatbot and thus be more motivated to change their behaviors. Researchers may also consider personalizing the reflective prompts based on people’s work routines, helping them more efficiently identify the common triggers of smartphone use. Moreover, our design of the chatbot with reflective prompts can be extended to other contexts to encourage positive behaviors (e.g., daily exercise) or reduce negative behaviors (e.g., smoking cessation). The chatbot’s ability to converse with people can also be further enriched after we collect sufficient conversation data from users.

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