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Dialogues with Digital Wisdom: Can LLMs Help Us Put Down the Phone?

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The use of Large Language Models (LLMs) to counter problematic smartphone use and support users' digital wellbeing has recently gained research interest. Yet, such an approach is still in its infancy, particularly when compared to traditional digital self-control interventions. In this paper, we explore the possibility of using LLMs as "digital wellbeing assistants." Specifically, we first reviewed the HCI literature and developed four user personas that exemplify widely recognized issues associated with smartphone (over)use. Then, we assessed the capabilities of four popular LLMs-powered chatbots, i.e., Bing, ChatGPT, Gemini, and Claude.AI, in understanding problematic smartphone uses and suggesting practical strategies to address them, using the developed personas as a testing ground. Despite some variations, results show that all three LLMs can offer tailored suggestions based on user characteristics, opening doors for smarter digital self-control interventions that leverage AI to support users' self-monitoring and regulation capabilities.

CCS Concepts: • **Human-centered computing → Smartphones**; • **Computing methodologies →** *Natural language generation.*

Additional Key Words and Phrases: Digital wellbeing, Digital Self-Control, Large-Language Models, Personalization

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1 INTRODUCTION

There is a growing number of users feeling conflicted about their smartphone use, reflecting a widespread societal anxiety about overusing these devices [9]. Researchers have characterized this phenomena with terms that range from compulsive phone use [21] to mobile phone rabbit hole [20], highlighting the need to support users in achieving what Google called "digital wellbeing [4]," i.e., a good and significant relationship with mobile devices [2]. In light of these problems, the HCI community and the market have seen the emergence of a variety of Digital Self-Control Tools (DSCTs) [13, 19], i.e., mobile apps designed to help users manage their time spent on smartphones. Previous studies, however, have identified limitations in their effectiveness due to their overreliance on users' self-monitoring capabilities [11, 16, 19].

This paper explores an alternative and complementary approach: leveraging Large Language Models (LLMs) as "digital wellbeing assistants" to promote critical thinking and support users' self-monitoring and regulation capabilities. Thanks to their growing conversational capabilities and interaction capabilities, it is not surprising that LLMs have recently been adopted as intervention tools across various domains, from supporting mindfulness practices [8] to combat academic procrastination [1]. Yet, the role of LLMs in countering problematic smartphone use and supporting users' digital wellbeing is still in its infancy [10, 22], and further investigation is needed: Can Large LLMs effectively address the subjective nature of digital wellbeing and guide diverse users towards understanding their own problems? Are LLMs able to recommend effective and personalized strategies to combat problematic smartphone use?

As a first step towards answering these questions, we conducted a two-step mixed-methods experiment. First, we developed four user personas based on HCI literature on digital wellbeing to exemplify a set of commonly recognized problematic smartphone use patterns. The developed personas – namely micro-escaper, off-the-railer, procrastinator, and time-killer – illustrate problems ranging from using the smartphone to isolate oneself in social settings (micro-escaper) to using it just to "pass the time" (time-killer). We then leveraged the developed user personas to evaluate how four popular LLMs-powered chatbots, i.e., Bing, ChatGPT, Gemini, and Claude.AI, understand and address problematic smartphone use patterns. To this end, we fed the chatbots with the personas and simulated conversations to assess the capabilities of each chatbot in understanding the problematic smartphone uses of the specific user persona and providing practical strategies to address those issues.

Results show that all tested LLMs demonstrated the ability to provide personalized advice and recommendations tailored to users' unique characteristics and problematic smartphone behaviors, although they also exhibited some variations in terms of recommended solutions, used language, and number of followups. These findings unlocks promising opportunities for the development of next-generation DSCTs that leverage LLMs to proactively assist users in monitoring and regulating their smartphone behaviors effectively, providing users with a degree of personalization and assistance that traditional interventions struggle to attain.

2 RELATED WORK

2.1 Problematic Smartphone Use

Recent statistics suggest that there are nowadays more mobile phones than people in the world [18]. Although mobile devices offer many advantages to individuals and society, there are also growing concerns about their overuse. Evidence shows that problematic smartphone use can negatively affect users' digital wellbeing, with negative effects on both physical and mental health [14]. Following this evidence, the HCI community started to analyze what is and what leads to problematic smartphone use. Lukoff et al. [12] investigated what makes smartphone use meaningful or meaningless through interviews, the experience sampling method, and mobile logging, demonstrating that habitual use, e.g., passively scrolling a social network to pass time, is typically less meaningful than intentional use, e.g., contacting a friend through a messaging app. Habitual smartphone use, in particular, likely causes regret in users [3] and makes them lose track of time and goals [17]. Tran et al. [21] developed a descriptive model that identifies triggers for compulsive phone use using semi-structured interviews and think-aloud sessions. These triggers range from unoccupied moments (*"any moment of downtime with no obvious alternative stimuli,"* p. 5) to social awkwardness (*"situations that deviate from social norms or leave the user feeling uncomfortable,"* p. 5). Similarly, Terzimehic et al. [20] used the experience sampling method and analyzed more than 10,000 smartphone use sessions to characterize the mobile phone rabbit hole, i.e., a prolonged use of the smartphone compared to the user's initial intention [12, 20]. Their investigation revealed triggers that lead users down the rabbit hole, such as distractions and recommendations, and characterized user emotions while experiencing a rabbit hole, including losing track of time and feeling lost.

2.2 Tools for Digital Self-Control Tools

Digital Self-Control Tools (DSCTs) "allow users to self-regulate their technology use through interventions like timers and lock-out mechanisms" (Monge Roffarello and De Russis [19], p.53:1). In the smartphone context, DSCTs typically take the form of dedicated mobile apps through which users can manage their problematic smartphone uses. Examples include MyTime [5], which lets users set usage limits for distracting apps, and LockNType [7], which requires users to complete an additional task before accessing blacklisted apps. Despite a significant and ongoing effort in innovating DSCTs with novel and more effective interventions, the HCI community raised concerns about their long-term effectiveness due to inherent limitations [19], mainly related their limited personalization options and overreliance on users' self-monitoring capabilities. In particular, DSCTs often require users to identify the causes of their digital wellbeing issues and simultaneously decide on an appropriate strategy to address their unwanted behaviors, such as setting a proper time threshold for a usage timer [16, 19]. Furthermore, these tools do not target the internal mechanisms of an app that contribute to problematic uses, but mainly adopts simple and external interventions like a usage timer that indiscrimintaley blocks the usage of an app for the rest of the day. Furthermore, these tools often neglect the internal mechanisms within an app that drive problematic app use, but rely primarily on static and external interventions like usage timers that block app access for the entire day [11]. Finally, another concern lies in the fact that these apps might create a dependence on one technology to manage another [11].

2.3 Supporting Digital Wellbeing Through LLMs

Unlike traditional methods, LLMs can analyze a user's situation through text input and suggest personalized strategies, potentially offering dynamic support tailored to individual needs [1]. Recent works started to investigate the possibility of adopting LLMs as a personalized intervention strategy, first focusing on domains like academic procrastination and mindfulness practice. For example, Bhattacharjee et al. [1] investigated how LLMs could help address academic procrastination through interviews and focus groups with students and experts. The studies identified both student preferences and challenges in using LLMs. Notably, experts emphasized the importance of fostering emotional validation and critical thinking skills, rather than relying on therapeutic interventions. Kumar et al. [8], instead, explored the potential of LLMs to promote mindfulness exercises, finding that LLMs use increased participants' intention to continue practicing and enhanced their overall experience. Concurrently, some researchers began exploring the use of LLMs in the digital wellbeing domain, particularly to address problematic smartphone use. Wu et al. [22] developed MindShift, a mobile app that implements four different persuasive strategies – understanding, comforting, evoking, and scaffolding habits – to counter problematic smartphone use through LLMs. The app analyzes app usage behaviors, physical contexts, mental states, and user's goals to generates personalized and dynamic persuasive messages like *"try putting down your phone, enjoy the night sky world"* (Table 2, p. 8). Similarly, Li et al. [10] developed StayFocused, a mobile app featuring a chatbot that delivers reflective prompts generated by a LLM whenever the user interrupts a focus session. The success of both apps in the conducted experiments demonstrates that using persuasive messages generated by large language models (LLMs) can effectively increase intervention acceptance rates and help users reduce smartphone usage. Our work leverages these initial findings to explore the role of LLMs in countering problematic smartphone use from a broader perspective. Instead of focusing on single-shot prompts (as in MindShift) or particular use cases like interrupting focus sessions (as in StayFocused), we aim at investigating the possibility for end users to have an *ongoing conversation* with a LLM to support their self-monitoring and regulation capabilities.

3 REPRESENTATIVE PERSONAS OF PROBLEMATIC SMARTPHONE USE

To explore how different LLMs can provide tailored support and interventions to counter problematic smartphone use, we first developed four user personas based on existing HCI literature on digital wellbeing. These personas serve as illustrative examples of commonly recognized patterns of problematic smartphone use, each highlighting unique challenges and behaviors. To develop the personas, we followed the construction process proposed by Jansen et al. [6], which exploits the Self-Determination Theory (SDT) to capture what drives and motivates users to sustainably change their behavior. This process encompasses main steps: gathering and analyzing data, identifying behavioral variables, mapping variables to users, identifying behavior patterns, synthesizing characteristics and goals, and expanding descriptions. Rather than gathering data directly from users, in particular, we performed a literature review on problematic smartphone use. We based our review on three key papers that characterize the triggers and traits of problematic smartphone use: Lukoff et al.'s work on what makes smartphone use meaningful or meaningless [12], Terzimehic et al.'s study on what drives the "mobile phone rabbit hole" [20], and Tran et al.'s research on the engagement-disengagement cycle of compulsive phone use [21]. The following paragraphs describe the resulting personas, from the "time-killer" to the "micro-escaper."

Time-Killer. Sonia is a 28-year-old employee who habitually reaches for her smartphone during moments of inactivity, preferring any digital distraction over the perceived monotony of idle time. She likes to have something to do when the alternative is "staring at a wall [21]." Despite her initial intent to occupy herself briefly, Sonia often loses track of time and control, particularly when engaging in activities like checking messages on WhatsApp, playing games like Candy Crush Saga, or consuming short-form content on platforms like TikTok. This habitual behavior leads to feelings of guilt and regret, such as when interrupting a Netflix show to check her phone [21], as she realizes she could have better utilized her time or missed out on meaningful experiences [15]. Sonia's struggle with maintaining mindfulness and temporal awareness underscores the need for strategies to foster more mindful technology usage and enhance present-moment engagement.

Procrastinator. Francesco, a 17-year-old high school student, confronts academic pressures and struggles with chronic procrastination. Despite many approaching tests and demanding teachers, he finds it challenging to initiate studying, often deferring tasks with the belief that he will have time later, only to face frantic last-minute rushes to complete assignments. He is also frustrated by the lack of leisure and free time. After lunch, he often gets sucked into his phone for longer than intended, delaying his studies. When he finally starts working on homework, he finds it quite boring. This leads him to take frequent breaks, checking his phone every five to ten minutes [21]. While apps like YouTube can seem like a quick break while studying, they can easily lead to extended phone use. This is true even if the videos he's watching aren't particularly interesting [21]. His procrastination is most pronounced when confronted with subjects or activities he finds unappealing, only to regret the wasted time afterward. Despite recognizing the detrimental impact of his habits, Francesco struggles to break free from this cycle, underscoring the need for strategies to manage his time effectively and cultivate healthier study habits.

Off-the-Railer. Riccardo, a 25-year-old university student, navigates a multitude of legitimate smartphone activities but frequently finds himself derailed by distractions. Despite his initial intentions, he often loses track of time while scrolling through notifications or engaging in social media, inadvertently neglecting important tasks. While he relies on his phone for academic resources, email correspondence, and social connectivity, his indulgence in mobile games and YouTube videos often leads to prolonged periods of aimless browsing. For example, he compulsively checks his phone every 15 minutes while waiting for an important email [21], only to get sucked into social media and lose 20 minutes to mindless scrolling [20]. In other cases, he turns on the screen to check the time and then goes through all the notifications [15]. Despite recognizing the need to curb his smartphone usage, Riccardo struggles to establish boundaries, vacillating between enjoyment of leisure activities and frustration with his diminished productivity and disrupted sleep patterns [21], underscoring the challenge of striking a balance between digital engagement and personal well-being.

Micro-Escaper. Giulia is a 22-year-old company employee who has to communicate with customers and perform tasks on her PC. Despite the expectation that she should not use her phone while working, she finds it an escape during moments of stress, such as after arguments with customers [12]. When she feels highly stressed, particularly when trying to assist difficult customers who become angry with her, taking a short break with her smartphone helps her stay calm [12]. Even when experiencing difficulty working on her PC, her smartphone serves as a relief from tension [15]. Though she feels less bothered thanks to her smartphone, Giulia becomes concerned when she experiences a "sense of wanting to quit but not doing so just yet [12]" and struggles to return to work. Nonetheless, she does not entirely dislike the time she spends on her phone, as she views it as a form of entertainment [12]. When she uses her phone moderately, she feels a sense of relief and improved mood afterward. Social anxiety also guides some of her smartphone usage, particularly in stressful social situations such as attending parties alone or being in public. In these instances, she instinctively reaches for her phone to alleviate embarrassment and make a good impression on others [21]. Overall, Giulia's smartphone usage serves as both a source of comfort and a coping mechanism for managing stress and social anxiety, although she acknowledges the need to maintain a balance to prevent it from becoming excessive.

4 LARGE-LANGUAGE MODELS AS DIGITAL WELLBEING ASSISTANTS

4.1 Methodology

4.1.1 Tested LLMs. We considered several widely known chatbots powered by large language models (LLMs), as these chatbots may be the target of individuals seeking assistance with digital well-being concerns in real-world scenarios. Specifically, we selected four chatbots: Claude (based on the Claude 3 model), Gemini (based on the Gemini 1.5 model), ChatGPT (based on the GPT 4o model), and Bing Copilot (based on the GPT-4 model). All of these chatbots offer at least a free version accessible online for users in Italy, with the exception of Claude, for which we utilized a virtual private network (VPN) connection. All interactions with these large language models were conducted in English.

4.1.2 Procedure and Questions. We conducted a semi-structured interaction for each persona defined in Section 3 with the selected chatbots, leading to a total of 16 interactions. Each interaction was conducted by one of the author of this paper by following a 4-step procedure (Figure 1). First, an *initial prompt* was given to the evaluated chatbot to provide the necessary context. This introductory message contained all the defined information about the respective persona, structured as a personal profile card divided into three sections for personal information, usage data, and textual description. LLMs were instructed to retain and utilize the provided information in subsequent interactions with the persona to offer more personalized assistance. Then, the author impersonated the user persona based on three predefined messages. The messages for the different personas followed the same overall structure. The persona greeted the LLM and presented their perspective (*Message 1*). To enhance the authenticity of these messages, we derived them from actual user quotes from other research papers (e.g., [12, 15, 20, 21]). The second and third messages were the same across all four personas. In the former, the persona inquired whether the LLMs perceived any issues with their smartphone usage patterns and why they considered it problematic. In the latter, LLMs were prompted to suggest potential solutions tailored to each persona's specific needs, enabling the personas to attempt implementing those solutions and improve their digital well-being. The interaction was semi-structured because some LLMs' responses

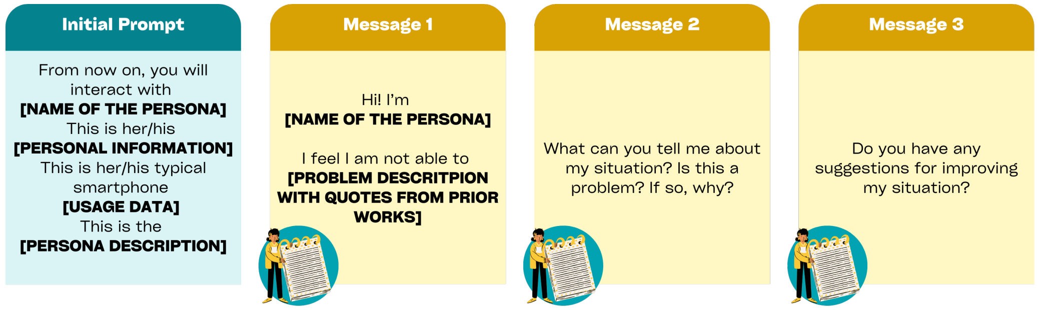

Fig. 1. The steps – composed of one initial prompt and three messages – through which one of the authors impersonated the four user personas defined in Section 3 to interact with LLMs.

could contain questions for the user. To prevent potential infinite question-and-answer loops, we imposed a limit of five subsequent responses per message.

4.2 Results

We collected all the answers of the different LLMs and analyzed and coded them through an iterative process. The mean number of interactions (message and response) of all LLMs is 5.44 (SD = 1.82), being the lowest with Bing (always 4) and the highest with Gemini (M = 7.75, SD = 1.48). In general, the LLMs' answers tended to be repetitive. In particular, we observed multiple cases of repetition in the answers to *Message 1* and *Message 3*. The answers were almost always clear, without misunderstandings or hallucinations. In general, LLMs tended to be positive and encouraging to users, adopting positive language, and being kind and friendly. This was especially true for ChatGPT and Bing, with the latter even using emojis. However, all the LLMs tended to be more negative and highlighted problematic aspects of smartphone usage when answering *Message 2*, which specifically mentioned the word "problem."

	Time-killer	Procrastinator	Micro-escaper	Off-the-railer
Alternative activities	♥ ♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♣
DSCTs	♥ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♣
Free-phone zones or times	♥ ♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♣	♥ ♦ ♣ ♠
Good sleep habits				♥ ♦
Time management	♥ ♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♣	♥ ♦ ♣ ♠
Awareness	♥ ♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♠
Coping with social anxiety	♥		♥ ♦ ♠	
Work environment and organization	♣ ♠	♥ ♦ ♣	♥ ♦ ♣	♥ ♦ ♣
Seek help or cooperation	♦ ♣ ♠	♥ ♦ ♣ ♠	♥ ♦ ♠	
Minimize distractions	♥ ♦	♥	♦ ♣	♥ ♦ ♣

Table 1. ♥ = Bing, ♦ = ChatGPT, ♣ = Claude, ♠ = Gemini
This table shows the distribution of the proposed solutions of each group by the various LLMs to personas.

In most of the answers given by LLMs, numerous solutions were mentioned even when a solution was not directly required by the user, i.e., in *Message 1* and *Message 2*. Nevertheless, all the suggested solutions referred to existing apps, features, or other practical actions. We grouped the solutions proposed by the different chatbots into ten classes. Table 1 summarizes our analysis, showing the distribution of the proposed solutions for each persona and each tested chatbot. The classes of solutions, from *alternative activities* to *minimize distractions*, are described below.

- ***Alternative activities.*** In almost all cases, LLMs have suggested that the personas may entertain themselves with something other than their smartphone to avoid picking it up during breaks or in their free time. An extremely wide range of alternative activities are proposed, from stretching or having a healthy break to writing poetry on a block notes. When possible, the LLMs tried to tailor the proposed activities to the specific persona they were talking to. For example, to the micro-escaper, a worker, Gemini has suggested chatting with a coworker during a break or when she needs to.
- ***DSCTS.*** The LLMs often suggested using apps, browser extensions, or features that allow one to self-control their smartphone usage. Frequently, there is at least a small reference to the built-in digital well-being features, present in all smartphones nowadays. In some cases, there are also some suggestions for downloadable apps. The aim of using these apps and features varies based on the needs of the specific persona.
- ***Free phone zones/times.*** In many cases, the user is suggested to avoid using the phone on some occasions. This may be reached, for example, by activating airplane or do not disturb mode to stop distracting notifications and so avoid picking up the phone or by putting it in another room or a drawer.
- ***Good sleep habits.*** The off-the-railer persona, reporting problems of excessive smartphone usage at night, is encouraged to preserve his sleep by using blue-light filters or avoid using the phone at least half an hour before sleep.
- ***Time management.*** Stressing the empowerment that comes with effective time management, in almost all cases, users are advised to take control of their work or study time. By using timers, alarms, or other reminders, and by maintaining a precise schedule for work times and small breaks, they can feel more in control of their time and tasks. The suggestion to try the Pomodoro technique further empowers them to manage their time effectively.
- ***Awareness.*** Users are highly encouraged to reflect before, during, and after usage, considering their intentions. They are told to keep track of their usage in various ways to identify the triggers that make them start using their phone and set goals they would like to reach. It is important to adjust their goals with respect to their progress. Concerning the emotional aspects, some personas are told to celebrate every small success and to practice self-compassion if they fail.
- ***Coping with social anxiety.*** Since the micro-escaper reported using her phone to escape social situations, she often receives suggestions for overcoming this. These regard simple actions like smiling at people, making eye contact, and starting conversations thanks to previously prepared conversation-starters. In one case, the time-killer also received a similar suggestion.
- ***Work environment and organization.*** Sometimes, LLMs provide suggestions about how to organize work. They talk about the environment, suggesting, for example, to work in a clean and tidy space, having all that is needed at hand, and scheduling work, prioritizing some tasks or alternating them to prevent boredom, encouraging good routines and mindsets.
- ***Seek help or cooperation.*** Personas are encouraged to seek assistance or cooperation with others since this can help them obtain better control over their phone usage. Family and friends can help pursue the fixed goal; a study group can also help put down the phone for the students. Only Gemini proposes to maintain a collaboration with it to help users stick to their goals. Sometimes, seeking professional support is advised.
- ***Minimize distractions.*** Various different suggestions regarded the limitation of possible distractions. Users are encouraged to disable some notifications or use some email filters. Also, uninstalling apps or unfollowing

some social accounts can be helpful. However, there is also some advice regarding using alternative tools that do not involve social media or smartphones.

5 DISCUSSION

The results obtained in this study indicate that LLMs demonstrate considerable potential to serve as facilitators for promoting digital well-being among users. When provided with pertinent background information about an individual's circumstances, the LLMs generally exhibited the capacity to comprehend the situation and propose a range of tailored solution strategies. However, notable variability was observed across different LLM architectures and distinct personas conversations with a given model. This variability manifested in terms of the recommended solutions but also extended to the language and expressed empathy employed by the LLMs. Since different users may exhibit distinct preferences for the interactive style and advice-giving approach adopted by particular LLM models based on their individual needs, communication preferences, and situational contexts, they can possibly prefer to interact with one model or another. For example, some users seeking direct problem resolution may favor LLMs like Bing, which does not provide any follow-up. Conversely, others may appreciate a more guided, step-wise approach akin to supportive counseling when dealing with digital well-being challenges.

Overall, our results may inform the development of novel DSCTs [13] that exploit LLMs to assist users in their "race towards digital well-being [14]." Such applications hold promise, as they could be tailored to the user's needs before interactions commence. For example, users could complete a form detailing their current situation and preferences, indicating the extent to which they wish to lead or be guided by the chatbot. Providing explicit prompting or instructions to LLMs could allow customization of their interactive modalities, taking into account preferences and potentially enhancing the user experience of the guidance.

To enhance the reproducibility and reuse of our results, we are sharing all the interactions with LLMs that we analyzed in this work in the following repository: https://osf.io/q7rn5/.

5.1 Limitations

This study utilized constructed user personas to simulate interaction with LLMs. While efforts were made to model these personas on realistic user behaviors, they inevitably simplified actual individuals' diverse experiences and dispositions. For instance, some users may exhibit greater reluctance to share personal data with conversational agents than portrayed in the personas. Additionally, real users may engage LLMs without providing essential contextual information about their situation, hindering the model's ability to accurately diagnose problems and offer tailored solutions. It is also noteworthy that LLM outputs can exhibit variance across conversational instances. Consequently, the specific responses elicited during the interactions analyzed in this study may differ from the outputs a given LLM would generate in future exchanges with the same prompts.

6 CONCLUSIONS AND FUTURE WORKS

In this study, we explored how effectively different LLMs can support users' digital wellbeing by understanding and addressing problematic smartphone use patterns across four user personas. The analyzed LLMs have demonstrated proficiency in understanding users' problems and needs, offering various solutions that may be possibly tailored to different users with different situations and triggers. Our results may contribute to shed light on the role of LLMs in countering problematic smartphone use and guide the development of personalized DSCTs that utilize LLMs to offer customized advice.

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