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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

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53 address the subjective nature of digital wellbeing and guide diverse users towards understanding their own problems?
54 Are LLMs able to recommend effective and personalized strategies to combat problematic smartphone use?

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

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

75 2 RELATED WORK

77 2.1 Problematic Smartphone Use

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

100 2.2 Tools for Digital Self-Control Tools

101 Digital Self-Control Tools (DSCTs) “allow users to self-regulate their technology use through interventions like
102 timers and lock-out mechanisms” (Monge Roffarello and De Russis [19], p.53:1). In the smartphone context, DSCTs

105 typically take the form of dedicated mobile apps through which users can manage their problematic smartphone
106 uses. Examples include MyTime [5], which lets users set usage limits for distracting apps, and LockNType [7], which
107 requires users to complete an additional task before accessing blacklisted apps. Despite a significant and ongoing
108 effort in innovating DSCTs with novel and more effective interventions, the HCI community raised concerns about
109 their long-term effectiveness due to inherent limitations [19], mainly related their limited personalization options and
110 overreliance on users' self-monitoring capabilities. In particular, DSCTs often require users to identify the causes of
111 their digital wellbeing issues and simultaneously decide on an appropriate strategy to address their unwanted behaviors,
112 such as setting a proper time threshold for a usage timer [16, 19]. Furthermore, these tools do not target the internal
113 mechanisms of an app that contribute to problematic uses, but mainly adopts simple and external interventions like
114 a usage timer that indiscriminately blocks the usage of an app for the rest of the day. Furthermore, these tools often
115 neglect the internal mechanisms within an app that drive problematic app use, but rely primarily on static and external
116 interventions like usage timers that block app access for the entire day [11]. Finally, another concern lies in the fact
117 that these apps might create a dependence on one technology to manage another [11].
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122 2.3 Supporting Digital Wellbeing Through LLMs

123 Unlike traditional methods, LLMs can analyze a user's situation through text input and suggest personalized strategies,
124 potentially offering dynamic support tailored to individual needs [1]. Recent works started to investigate the possibility
125 of adopting LLMs as a personalized intervention strategy, first focusing on domains like academic procrastination
126 and mindfulness practice. For example, Bhattacharjee et al. [1] investigated how LLMs could help address academic
127 procrastination through interviews and focus groups with students and experts. The studies identified both student
128 preferences and challenges in using LLMs. Notably, experts emphasized the importance of fostering emotional validation
129 and critical thinking skills, rather than relying on therapeutic interventions. Kumar et al. [8], instead, explored the
130 potential of LLMs to promote mindfulness exercises, finding that LLMs use increased participants' intention to continue
131 practicing and enhanced their overall experience. Concurrently, some researchers began exploring the use of LLMs in
132 the digital wellbeing domain, particularly to address problematic smartphone use. Wu et al. [22] developed MindShift, a
133 mobile app that implements four different persuasive strategies – understanding, comforting, evoking, and scaffolding
134 habits – to counter problematic smartphone use through LLMs. The app analyzes app usage behaviors, physical contexts,
135 mental states, and user's goals to generate personalized and dynamic persuasive messages like *“try putting down
136 your phone, enjoy the night sky world”* (Table 2, p. 8). Similarly, Li et al. [10] developed StayFocused, a mobile app
137 featuring a chatbot that delivers reflective prompts generated by a LLM whenever the user interrupts a focus session.
138 The success of both apps in the conducted experiments demonstrates that using persuasive messages generated by
139 large language models (LLMs) can effectively increase intervention acceptance rates and help users reduce smartphone
140 usage. Our work leverages these initial findings to explore the role of LLMs in countering problematic smartphone use
141 from a broader perspective. Instead of focusing on single-shot prompts (as in MindShift) or particular use cases like
142 interrupting focus sessions (as in StayFocused), we aim at investigating the possibility for end users to have an *ongoing
143 conversation* with a LLM to support their self-monitoring and regulation capabilities.
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150 3 REPRESENTATIVE PERSONAS OF PROBLEMATIC SMARTPHONE USE

151 To explore how different LLMs can provide tailored support and interventions to counter problematic smartphone
152 use, we first developed four user personas based on existing HCI literature on digital wellbeing. These personas serve
153 as illustrative examples of commonly recognized patterns of problematic smartphone use, each highlighting unique
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157 challenges and behaviors. To develop the personas, we followed the construction process proposed by Jansen et al. [6],
158 which exploits the Self-Determination Theory (SDT) to capture what drives and motivates users to sustainably change
159 their behavior. This process encompasses main steps: gathering and analyzing data, identifying behavioral variables,
160 mapping variables to users, identifying behavior patterns, synthesizing characteristics and goals, and expanding
161 descriptions. Rather than gathering data directly from users, in particular, we performed a literature review on
162 problematic smartphone use. We based our review on three key papers that characterize the triggers and traits of
163 problematic smartphone use: Lukoff et al.'s work on what makes smartphone use meaningful or meaningless [12],
164 Terzimehic et al.'s study on what drives the "mobile phone rabbit hole" [20], and Tran et al.'s research on the engagement-
165 disengagement cycle of compulsive phone use [21]. The following paragraphs describe the resulting personas, from the
166 "time-killer" to the "micro-escaper."
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170 **Time-Killer.** Sonia is a 28-year-old employee who habitually reaches for her smartphone during moments of
171 inactivity, preferring any digital distraction over the perceived monotony of idle time. She likes to have something
172 to do when the alternative is "staring at a wall [21]." Despite her initial intent to occupy herself briefly, Sonia often
173 loses track of time and control, particularly when engaging in activities like checking messages on WhatsApp, playing
174 games like Candy Crush Saga, or consuming short-form content on platforms like TikTok. This habitual behavior leads
175 to feelings of guilt and regret, such as when interrupting a Netflix show to check her phone [21], as she realizes she
176 could have better utilized her time or missed out on meaningful experiences [15]. Sonia's struggle with maintaining
177 mindfulness and temporal awareness underscores the need for strategies to foster more mindful technology usage and
178 enhance present-moment engagement.
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182 **Procrastinator.** Francesco, a 17-year-old high school student, confronts academic pressures and struggles with
183 chronic procrastination. Despite many approaching tests and demanding teachers, he finds it challenging to initiate
184 studying, often deferring tasks with the belief that he will have time later, only to face frantic last-minute rushes to
185 complete assignments. He is also frustrated by the lack of leisure and free time. After lunch, he often gets sucked into
186 his phone for longer than intended, delaying his studies. When he finally starts working on homework, he finds it
187 quite boring. This leads him to take frequent breaks, checking his phone every five to ten minutes [21]. While apps like
188 YouTube can seem like a quick break while studying, they can easily lead to extended phone use. This is true even if
189 the videos he's watching aren't particularly interesting [21]. His procrastination is most pronounced when confronted
190 with subjects or activities he finds unappealing, only to regret the wasted time afterward. Despite recognizing the
191 detrimental impact of his habits, Francesco struggles to break free from this cycle, underscoring the need for strategies
192 to manage his time effectively and cultivate healthier study habits.
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197 **Off-the-Railer.** Riccardo, a 25-year-old university student, navigates a multitude of legitimate smartphone activities
198 but frequently finds himself derailed by distractions. Despite his initial intentions, he often loses track of time while
199 scrolling through notifications or engaging in social media, inadvertently neglecting important tasks. While he relies
200 on his phone for academic resources, email correspondence, and social connectivity, his indulgence in mobile games
201 and YouTube videos often leads to prolonged periods of aimless browsing. For example, he compulsively checks his
202 phone every 15 minutes while waiting for an important email [21], only to get sucked into social media and lose 20
203 minutes to mindless scrolling [20]. In other cases, he turns on the screen to check the time and then goes through
204 all the notifications [15]. Despite recognizing the need to curb his smartphone usage, Riccardo struggles to establish
205 boundaries, vacillating between enjoyment of leisure activities and frustration with his diminished productivity and
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209 disrupted sleep patterns [21], underscoring the challenge of striking a balance between digital engagement and personal
210 well-being.
211

212 **Micro-Escaper.** Giulia is a 22-year-old company employee who has to communicate with customers and perform
213 tasks on her PC. Despite the expectation that she should not use her phone while working, she finds it an escape during
214 moments of stress, such as after arguments with customers [12]. When she feels highly stressed, particularly when
215 trying to assist difficult customers who become angry with her, taking a short break with her smartphone helps her stay
216 calm [12]. Even when experiencing difficulty working on her PC, her smartphone serves as a relief from tension [15].
217 Though she feels less bothered thanks to her smartphone, Giulia becomes concerned when she experiences a “sense
218 of wanting to quit but not doing so just yet [12]” and struggles to return to work. Nonetheless, she does not entirely
219 dislike the time she spends on her phone, as she views it as a form of entertainment [12]. When she uses her phone
220 moderately, she feels a sense of relief and improved mood afterward. Social anxiety also guides some of her smartphone
221 usage, particularly in stressful social situations such as attending parties alone or being in public. In these instances,
222 she instinctively reaches for her phone to alleviate embarrassment and make a good impression on others [21]. Overall,
223 Giulia’s smartphone usage serves as both a source of comfort and a coping mechanism for managing stress and social
224 anxiety, although she acknowledges the need to maintain a balance to prevent it from becoming excessive.
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230 4 LARGE-LANGUAGE MODELS AS DIGITAL WELLBEING ASSISTANTS

231 4.1 Methodology

232 4.1.1 *Tested LLMs.* We considered several widely known chatbots powered by large language models (LLMs), as these
233 chatbots may be the target of individuals seeking assistance with digital well-being concerns in real-world scenarios.
234 Specifically, we selected four chatbots: Claude (based on the Claude 3 model), Gemini (based on the Gemini 1.5 model),
235 ChatGPT (based on the GPT 4o model), and Bing Copilot (based on the GPT-4 model). All of these chatbots offer at
236 least a free version accessible online for users in Italy, with the exception of Claude, for which we utilized a virtual
237 private network (VPN) connection. All interactions with these large language models were conducted in English.
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242 4.1.2 *Procedure and Questions.* We conducted a semi-structured interaction for each persona defined in Section 3 with
243 the selected chatbots, leading to a total of 16 interactions. Each interaction was conducted by one of the author of
244 this paper by following a 4-step procedure (Figure 1). First, an *initial prompt* was given to the evaluated chatbot to
245 provide the necessary context. This introductory message contained all the defined information about the respective
246 persona, structured as a personal profile card divided into three sections for personal information, usage data, and
247 textual description. LLMs were instructed to retain and utilize the provided information in subsequent interactions
248 with the persona to offer more personalized assistance. Then, the author impersonated the user persona based on three
249 predefined messages. The messages for the different personas followed the same overall structure. The persona greeted
250 the LLM and presented their perspective (*Message 1*). To enhance the authenticity of these messages, we derived them
251 from actual user quotes from other research papers (e.g., [12, 15, 20, 21]). The second and third messages were the
252 same across all four personas. In the former, the persona inquired whether the LLMs perceived any issues with their
253 smartphone usage patterns and why they considered it problematic. In the latter, LLMs were prompted to suggest
254 potential solutions tailored to each persona’s specific needs, enabling the personas to attempt implementing those
255 solutions and improve their digital well-being. The interaction was semi-structured because some LLMs’ responses
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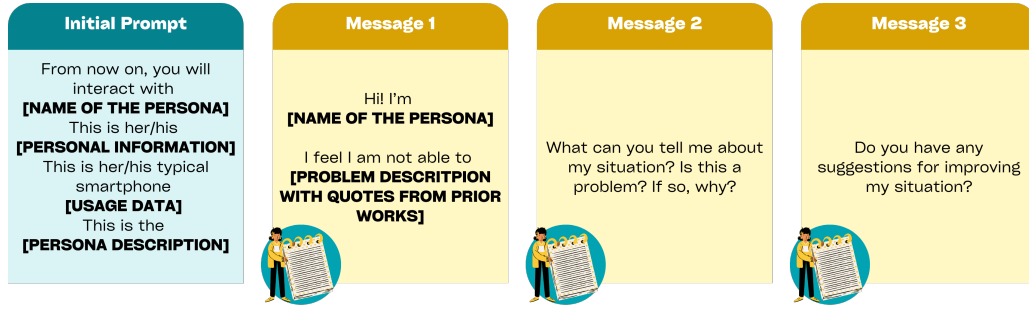


Fig. 1. The steps – composed of one initial prompt and three messages – through which one of the authors impersonated the four user personas defined in Section 3 to interact with LLMs.

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.

- 313 • **Alternative activities.** In almost all cases, LLMs have suggested that the personas may entertain themselves
314 with something other than their smartphone to avoid picking it up during breaks or in their free time. An
315 extremely wide range of alternative activities are proposed, from stretching or having a healthy break to
316 writing poetry on a block notes. When possible, the LLMs tried to tailor the proposed activities to the specific
317 persona they were talking to. For example, to the micro-escaper, a worker, Gemini has suggested chatting with
318 a coworker during a break or when she needs to.
319
- 320 • **DSCTS.** The LLMs often suggested using apps, browser extensions, or features that allow one to self-control
321 their smartphone usage. Frequently, there is at least a small reference to the built-in digital well-being features,
322 present in all smartphones nowadays. In some cases, there are also some suggestions for downloadable apps.
323 The aim of using these apps and features varies based on the needs of the specific persona.
324
- 325 • **Free phone zones/times.** In many cases, the user is suggested to avoid using the phone on some occasions. This
326 may be reached, for example, by activating airplane or do not disturb mode to stop distracting notifications and
327 so avoid picking up the phone or by putting it in another room or a drawer.
328
- 329 • **Good sleep habits.** The off-the-railer persona, reporting problems of excessive smartphone usage at night, is
330 encouraged to preserve his sleep by using blue-light filters or avoid using the phone at least half an hour before
331 sleep.
332
- 333 • **Time management.** Stressing the empowerment that comes with effective time management, in almost all
334 cases, users are advised to take control of their work or study time. By using timers, alarms, or other reminders,
335 and by maintaining a precise schedule for work times and small breaks, they can feel more in control of their
336 time and tasks. The suggestion to try the Pomodoro technique further empowers them to manage their time
337 effectively.
338
- 339 • **Awareness.** Users are highly encouraged to reflect before, during, and after usage, considering their intentions.
340 They are told to keep track of their usage in various ways to identify the triggers that make them start using
341 their phone and set goals they would like to reach. It is important to adjust their goals with respect to their
342 progress. Concerning the emotional aspects, some personas are told to celebrate every small success and to
343 practice self-compassion if they fail.
344
- 345 • **Coping with social anxiety.** Since the micro-escaper reported using her phone to escape social situations,
346 she often receives suggestions for overcoming this. These regard simple actions like smiling at people, making
347 eye contact, and starting conversations thanks to previously prepared conversation-starters. In one case, the
348 time-killer also received a similar suggestion.
349
- 350 • **Work environment and organization.** Sometimes, LLMs provide suggestions about how to organize work.
351 They talk about the environment, suggesting, for example, to work in a clean and tidy space, having all that
352 is needed at hand, and scheduling work, prioritizing some tasks or alternating them to prevent boredom,
353 encouraging good routines and mindsets.
354
- 355 • **Seek help or cooperation.** Personas are encouraged to seek assistance or cooperation with others since this
356 can help them obtain better control over their phone usage. Family and friends can help pursue the fixed
357 goal; a study group can also help put down the phone for the students. Only Gemini proposes to maintain a
358 collaboration with it to help users stick to their goals. Sometimes, seeking professional support is advised.
359
- 360 • **Minimize distractions.** Various different suggestions regarded the limitation of possible distractions. Users
361 are encouraged to disable some notifications or use some email filters. Also, uninstalling apps or unfollowing
362
363
364

365 some social accounts can be helpful. However, there is also some advice regarding using alternative tools that
366 do not involve social media or smartphones.
367

368 5 DISCUSSION

369 The results obtained in this study indicate that LLMs demonstrate considerable potential to serve as facilitators for
370 promoting digital well-being among users. When provided with pertinent background information about an individual's
371 circumstances, the LLMs generally exhibited the capacity to comprehend the situation and propose a range of tailored
372 solution strategies. However, notable variability was observed across different LLM architectures and distinct personas
373 conversations with a given model. This variability manifested in terms of the recommended solutions but also extended
374 to the language and expressed empathy employed by the LLMs. Since different users may exhibit distinct preferences
375 for the interactive style and advice-giving approach adopted by particular LLM models based on their individual needs,
376 communication preferences, and situational contexts, they can possibly prefer to interact with one model or another.
377 For example, some users seeking direct problem resolution may favor LLMs like Bing, which does not provide any
378 follow-up. Conversely, others may appreciate a more guided, step-wise approach akin to supportive counseling when
379 dealing with digital well-being challenges.
380

381 Overall, our results may inform the development of novel DSCTs [13] that exploit LLMs to assist users in their “race
382 towards digital well-being [14].” Such applications hold promise, as they could be tailored to the user's needs before
383 interactions commence. For example, users could complete a form detailing their current situation and preferences,
384 indicating the extent to which they wish to lead or be guided by the chatbot. Providing explicit prompting or instructions
385 to LLMs could allow customization of their interactive modalities, taking into account preferences and potentially
386 enhancing the user experience of the guidance.
387

388 To enhance the reproducibility and reuse of our results, we are sharing all the interactions with LLMs that we
389 analyzed in this work in the following repository: <https://osf.io/q7rn5/>.
390

391 5.1 Limitations

392 This study utilized constructed user personas to simulate interaction with LLMs. While efforts were made to model these
393 personas on realistic user behaviors, they inevitably simplified actual individuals' diverse experiences and dispositions.
394 For instance, some users may exhibit greater reluctance to share personal data with conversational agents than portrayed
395 in the personas. Additionally, real users may engage LLMs without providing essential contextual information about
396 their situation, hindering the model's ability to accurately diagnose problems and offer tailored solutions. It is also
397 noteworthy that LLM outputs can exhibit variance across conversational instances. Consequently, the specific responses
398 elicited during the interactions analyzed in this study may differ from the outputs a given LLM would generate in future
399 exchanges with the same prompts.
400

401 6 CONCLUSIONS AND FUTURE WORKS

402 In this study, we explored how effectively different LLMs can support users' digital wellbeing by understanding and
403 addressing problematic smartphone use patterns across four user personas. The analyzed LLMs have demonstrated
404 proficiency in understanding users' problems and needs, offering various solutions that may be possibly tailored to
405 different users with different situations and triggers. Our results may contribute to shed light on the role of LLMs in
406 countering problematic smartphone use and guide the development of personalized DSCTs that utilize LLMs to offer
407 customized advice.
408

REFERENCES

- [1] Ananya Bhattacharjee, Yuchen Zeng, Sarah Yi Xu, Dana Kulzhabayeva, Minyi Ma, Rachel Kornfield, Syed Ishtiaque Ahmed, Alex Mariakakis, Mary P Czerwinski, Anastasia Kuzminykh, Michael Liut, and Joseph Jay Williams. 2024. Understanding the Role of Large Language Models in Personalizing and Scaffolding Strategies to Combat Academic Procrastination. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 15, 18 pages. <https://doi.org/10.1145/3613904.3642081>
- [2] Christopher Burr, Mariarosaria Taddeo, and Luciano Floridi. 2020. The Ethics of Digital Well-Being: A Thematic Review. *Science and Engineering Ethics* (2020), 2313–2343. <https://doi.org/10.1007/s11948-020-00175-8>
- [3] Hyunsung Cho, DaEun Choi, Donghwi Kim, Wan Ju Kang, Eun Kyoung Choe, and Sung-Ju Lee. 2021. Reflect, not Regret: Understanding Regretful Smartphone Use with App Feature-Level Analysis. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 456 (oct 2021), 36 pages. <https://doi.org/10.1145/3479600>
- [4] Google. 2024. Digital Wellbeing - Find a balance with technology that feels right for you. <https://wellbeing.google/> Accessed: 2024-05-21.
- [5] Alexis Hiniker, Sungsoo (Ray) Hong, Tadayoshi Kohno, and Julie A. Kientz. 2016. MyTime: Designing and Evaluating an Intervention for Smartphone Non-Use. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) (*CHI '16*). Association for Computing Machinery, New York, NY, USA, 4746–4757. <https://doi.org/10.1145/2858036.2858403>
- [6] Arne Jansen, Maarten Van Mechelen, and Karin Slegers. 2017. Personas and Behavioral Theories: A Case Study Using Self-Determination Theory to Construct Overweight Personas. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) (*CHI '17*). Association for Computing Machinery, New York, NY, USA, 2127–2136. <https://doi.org/10.1145/3025453.3026003>
- [7] Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko, and Uichin Lee. 2019. LocknType: Lockout Task Intervention for Discouraging Smartphone App Use. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) (*CHI '19*). Association for Computing Machinery, New York, NY, USA, 1–12. <https://doi.org/10.1145/3290605.3300927>
- [8] Harsh Kumar, Yiyi Wang, Jiakai Shi, Ilya Musabirov, Norman A. S. Farb, and Joseph Jay Williams. 2023. Exploring the Use of Large Language Models for Improving the Awareness of Mindfulness. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, Article 129, 7 pages. <https://doi.org/10.1145/3544549.3585614>
- [9] Simone Lanette, Phoebe K. Chua, Gillian Hayes, and Melissa Mazmanian. 2018. How Much is 'Too Much'? The Role of a Smartphone Addiction Narrative in Individuals' Experience of Use. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 101 (nov 2018), 22 pages. <https://doi.org/10.1145/3274370>
- [10] Zhuoyang Li, Minhui Liang, Ray Lc, and Yuhan Luo. 2024. StayFocused: Examining the Effects of Reflective Prompts and Chatbot Support on Compulsive Smartphone Use. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 247, 19 pages. <https://doi.org/10.1145/3613904.3642479>
- [11] Kai Lukoff, Ulrik Lyngs, Karina Shirokova, Raveena Rao, Larry Tian, Himanshu Zade, Sean A. Munson, and Alexis Hiniker. 2023. SwitchTube: A Proof-of-Concept System Introducing "Adaptable Commitment Interfaces" as a Tool for Digital Wellbeing. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 197, 22 pages. <https://doi.org/10.1145/3544548.3580703>
- [12] Kai Lukoff, Cissy Yu, Julie Kientz, and Alexis Hiniker. 2018. What Makes Smartphone Use Meaningful or Meaningless? *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 1, Article 22 (mar 2018), 26 pages. <https://doi.org/10.1145/3191754>
- [13] Ulrik Lyngs, Kai Lukoff, Petr Slovak, Reuben Binns, Adam Slack, Michael Inzlicht, Max Van Kleek, and Nigel Shadbolt. 2019. Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) (*CHI '19*). Association for Computing Machinery, New York, NY, USA, 1–18. <https://doi.org/10.1145/3290605.3300361>
- [14] Alberto Monge Roffarello and Luigi De Russis. 2019. The Race Towards Digital Wellbeing: Issues and Opportunities. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. <https://doi.org/10.1145/3290605.3300616>
- [15] Alberto Monge Roffarello and Luigi De Russis. 2021. Coping with Digital Wellbeing in a Multi-Device World. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 538, 14 pages. <https://doi.org/10.1145/3411764.3445076>
- [16] Alberto Monge Roffarello and Luigi De Russis. 2023. Nudging Users Towards Conscious Social Media Use. In *Proceedings of the 25th International Conference on Mobile Human-Computer Interaction* (Athens, Greece) (*MobileHCI '23 Companion*). Association for Computing Machinery, New York, NY, USA, Article 14, 7 pages. <https://doi.org/10.1145/3565066.3608703>
- [17] Alberto Monge Roffarello, Kai Lukoff, and Luigi De Russis. 2023. Defining and Identifying Attention Capture Deceptive Designs in Digital Interfaces. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 194, 19 pages. <https://doi.org/10.1145/3544548.3580729>
- [18] Felix Richter. 2023. Charted: There are more mobile phones than people in the world. <https://www.weforum.org/agenda/2023/04/charted-there-are-more-phones-than-people-in-the-world/> Accessed: 2024-05-21.
- [19] Alberto Monge Roffarello and Luigi De Russis. 2023. Achieving Digital Wellbeing Through Digital Self-control Tools: A Systematic Review and Meta-analysis. *ACM Trans. Comput.-Hum. Interact.* 30, 4, Article 53 (sep 2023), 66 pages. <https://doi.org/10.1145/3571810>

- 469 [20] Nada Terzimehic, Florian Bemann, Miriam Halsner, and Sven Mayer. 2023. A Mixed-Method Exploration into the Mobile Phone Rabbit Hole. *Proc.*
470 *ACM Hum.-Comput. Interact.* 7, MHCI, Article 194 (sep 2023), 29 pages. <https://doi.org/10.1145/3604241>
- 471 [21] Jonathan A. Tran, Katie S. Yang, Katie Davis, and Alexis Hiniker. 2019. Modeling the Engagement-Disengagement Cycle of Compulsive Phone Use.
472 In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) (*CHI '19*). Association for Computing
473 Machinery, New York, NY, USA, 1–14. <https://doi.org/10.1145/3290605.3300542>
- 474 [22] Ruolan Wu, Chun Yu, Xiaole Pan, Yujia Liu, Ningning Zhang, Yue Fu, Yuhan Wang, Zhi Zheng, Li Chen, Qiaolei Jiang, Xuhai Xu, and Yuanchun Shi.
475 2024. MindShift: Leveraging Large Language Models for Mental-States-Based Problematic Smartphone Use Intervention. In *Proceedings of the CHI*
476 *Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 248, 24 pages.
477 <https://doi.org/10.1145/3613904.3642790>
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