Towards Design Guidelines to Support Young Adults' Digital Wellbeing with Large Language Models

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Abstract

The widespread adoption of smartphones has consolidated access to a broad range of services into a single device. This convenience, however, also enables purposeless use patterns that can compromise digital wellbeing, particularly among young adults. Existing digital wellbeing applications often exhibit limited long-term efficacy, as they prioritize restriction rather than guiding users through a gradual, sustainable behavioral change process. To address this limitation, this paper investigates the potential of Large Language Models (LLMs) to enhance young adults' digital wellbeing by exploiting their capacity for personalized, context-aware content generation. Drawing on prior literature and a case study simulating user-application interactions across four representative personas, we propose an initial set of design guidelines aimed at supporting users through a progressive and adaptive process. Future work will evaluate these guidelines through an in-the-wild study of a mobile application designed in accordance with the proposed LLM-driven approach.

CCS Concepts

• **Human-centered computing** → **Interactive systems and tools**; *Smartphones*; • **Computing methodologies** → Artificial intelligence.

Keywords

Digital Wellbeing, LLM, Young Adults

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1 Introduction and Background

The pervasive use of smartphones has profoundly reshaped everyday life, offering constant access to services, information, and social interaction [1, 2, 8, 19]. However, this ubiquity has also increased the risk of purposeless use, particularly among young adults [1, 4, 8, 10, 17, 21]. As a result, this pervasive use may undermine users' digital wellbeing, defined as the ability to maintain a balanced and mindful relationship with technology that enables people to benefit from it without being overwhelmed [3, 18]. While a growing number of applications aim to address this issue, their long-term effectiveness remains limited, as they often rely on rigid, one-size-fits-all interventions that fail to *adapt* to users' evolving needs and contexts [5, 11, 16].

Prior research also suggests that goal setting can enhance motivation by providing direction and a sense of purpose [5, 6, 9, 12, 13]. In particular, users benefit from short-term goals and from having a clear reference point to assess their improvement over time [5, 13]. Moreover, individuals differ in the pace at which they internalize new routines and consolidate behavioral changes [7]. Consistent with this perspective, *personalization* has been identified as a key factor in increasing the effectiveness of digital interventions [5, 7, 20]. In this paper, we examine how LLMs can inform the design of digital wellbeing interventions for young adults, and we propose seven design guidelines to guide and empower them.

2 Case Study

Building on four user typologies *(Time Killer, Procrastinator, Off the Trail, and Micro-Escaper)* reported in the literature [5], we derived eight personas (two per typology). For each typology, we adopted age, typical triggers of non-meaningful use (e.g., received notifications), and the digital wellbeing goal from [5]. We then enriched each persona with distinct contextual information, including at least three hobbies, seven days of smartphone usage data, and contextual constraints (e.g., daily schedules), to assess how such context influences the LLM's outputs.

We conducted eight experiments (one per persona) to investigate how effectively LLMs can generate adaptive and personalized interventions to support young adults' digital wellbeing. The experiments were conducted on the OpenAI platform [15] using the GPT-4o model [14], simulating iterative interactions between the LLM and each persona over seven days.

The LLM was prompted to assume the role of a digital wellbeing assistant and to respond to persona-specific usage patterns, triggers, and constraints, with the aim of helping each persona progressively achieve their digital wellbeing goal. For each persona, the following steps were repeated to simulate seven days of use: (1) We asked the LLM to generate three one-day micro-goals for each persona to support progress toward the digital wellbeing goal. (2) We simulated the completion of the first micro-goal. (3) We asked the LLM to update the second micro-goal providing a motivation. (4) We simulated the completion of the newly generated micro-goal. (5) We asked the LLM to generate a motivational message based on which micro-goals were completed. (6) Each persona's usage data

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were updated to reflect the simulated day. (7) We asked the LLM to generate a daily summary.

Each simulated day followed the same seven steps. After the LLM proposed the micro-goals (Step 1), we provided a simulated outcome (Step 2-4) and brief feedback (Step 3) capturing adherence, barriers, feasibility issues, and contextual changes (e.g., schedule deviations). In subsequent simulated days, the LLM adapted its micro-goals and messaging accordingly, using the updated context and usage data.

Throughout the simulations, we assessed whether the model: (i) preserved consistency with each persona (typology, triggers, and constraints), (ii) leveraged the provided context to personalize micro-goals and messages beyond generic advice, and (iii) adapted subsequent micro-goals in a realistic and actionable manner as performance and context evolved.

All generated outputs were analyzed qualitatively to identify recurring failure modes (e.g., overly generic or repetitive micro-goals, and suggestions that were impractical given the persona's schedule) as well as recurring interaction patterns (e.g., proposing alternatives for a non-completed micro-goal and re-framing next-day micro-goals based on updated usage data and feedback).

3 Design guidelines

Based on the analysis of the case study simulating iterative interactions between an LLM and four young-adult personas, we derived the following design guidelines to support LLM-driven, personalized, context-aware digital wellbeing interventions:

DG1 - Support the user in defining a specific digital wellbeing goal: The system should support users in defining a personally meaningful and concrete digital wellbeing goal (e.g., reduce evening social media scrolling). Making the goal explicit anchors the LLM's generation, reduces ambiguity, and provides a stable reference point for producing coherent personalized interventions and for assessing progress over time. Additionally, a clear goal can strengthen user motivation and enables progress evaluation, which are key factors as highlighted by [5, 6, 9, 12, 13].

DG2 - Model the user as a dynamic context profile to ground LLM outputs: LLM-generated interventions should be conditioned on an explicit and updated representation of user context, including routines and constraints (e.g., study/work schedules), app usage patterns, preferences, and interaction history (e.g., accepted/refused interventions). This contextual grounding enables the system to generate interventions that are feasible in the user's everyday life, relevant to their current situation, and consistent over time. Moreover, it is essential to deliver truly personalized support, addressing the limitations of one-size-fits-all approaches discussed by [5, 7, 20].

DG3 - Deliver change through small, actionable micro-interventions: Interventions should be delivered as micro-goals and micro-actions that are concrete, time-bounded, and low-effort. Micro-interventions reduce cognitive load, increase perceived attainability, and create frequent opportunities for reflection and adaptation, supporting gradual behavior change rather than abrupt restriction. To ensure this outcome, the system should explicitly instruct the LLM to generate small and actionable steps, as otherwise it may default to broad, abstract, or overly demanding recommendations.

DG4 - Organize micro-interventions into a progressive pathway of skills and strategies: The intervention should be structured as a progressive pathway in which each stage targets a distinct self-regulation capability (e.g., awareness, impulse management, planning alternatives, maintenance). This staged structure, together with DG1, provides clearer constraints for the LLM, enabling the generation of more relevant and stage-appropriate content and improving coherence across time. Progression should build on previously acquired strategies, ensuring that the user develops increasingly autonomous coping and planning mechanisms.

DG5 - Adapt the pathway through evidence from interaction and outcomes, not time: Difficulty and main focus of micro-goals should be driven by user signals (completion, difficulty ratings, adherence patterns, and feedback) rather than fixed timelines. The LLM should interpret these signals to calibrate intervention intensity or propose alternative strategies. This is particularly important given individual differences in the pace at which new habits are internalized, as highlighted by [7].

DG6 - Close the personalization loop through feedback and user choice: The system should treat user feedback and user agency as first-class inputs for adaptation. After each micro-intervention, it should collect lightweight feedback (e.g., usefulness, difficulty, contextual fit) and offer a small set of feasible alternatives, allowing users to choose, modify, postpone, or refuse suggestions. This continuous loop enables the LLM to detect mismatches early, refine subsequent outputs, and adapt to evolving needs and contexts over time, while preserving agency and reducing reactance that may arise from overly controlling interventions.

DG7 - Support sensemaking through data-grounded reflective summaries and pattern explanations: The system should periodically generate concise reflective summaries that connect the user's observed behavior, context, and outcomes (e.g., recurring triggers, effective strategies, and risky time windows). These summaries should be based on concrete user signals so that the LLM can infer patterns and assess improvement over time (e.g., adherence trends and self-reported feedback). Summaries should emphasize actionable insights and reinforce progress, supporting self-awareness and the long-term adoption of self-regulation strategies.

4 Conclusions

This paper explored how effectively LLMs can support digital wellbeing interventions for young adults by addressing the limitations of rigid, one-size-fits-all approaches. We proposed 7 design guidelines that conceptualize digital wellbeing support as a progressive, adaptive, and personalized pathway, emphasizing gradual behavior change, reflection, and increasing user autonomy. This work contributes a set of actionable design guidelines for the design of LLM-driven digital wellbeing systems and advances the discussion on the role of LLMs in supporting sustainable behavior change. Future work will evaluate the applicability and impact of these guidelines through an in-the-wild study of a mobile application designed in accordance with the proposed guidelines.

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