Broadening Interventions Strategies for Phone Addiction

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ABSTRACT

This paper explores design interventions to foster mindful and reflective social media engagement along with exploring a potential intervention for social media addiction. Drawing from research on short-form content consumption, we identify emotional triggers and compulsive usage patterns using physiological (heart rate, skin conductance) and self-reported VAD model data. High-arousal content (e.g., sadness, anger) elicits stronger physiological responses, while joy results in moderate engagement. UX interviews highlight emotional fatigue and compulsive scrolling, emphasizing the need for innovative interventions.

We propose emotion-aware strategies such as real-time emotional tracking, adaptive content regulation, context-aware well-being nudges, and potential hardware interventions. By applying insights from affective computing, behavioral science, and HCI, these interventions can inform healthier digital habits that can also be applied to teenagers. This paper underscores the importance of moving beyond traditional app-based interventions to support emotional well-being in digital interactions.

INTRODUCTION & METHODS

Recent studies indicate that teenagers spend an average of 4.8 hours per day on social media platforms such as YouTube, TikTok, Instagram, Facebook, and X (formerly Twitter)(Gallup, 2023).

Additionally, Short-form video platforms, such as TikTok and Instagram Reels, have transformed digital consumption habits, influencing users' emotional and physiological states. While media consumption is known to affect emotions and arousal levels, the specific interplay between short-form content and physiological responses remain underexplored. Our study addressed this gap by investigating how various types of short-form content—characterized by different combinations of valence (positive/negative) and arousal (high/low)—affect users' physiological and affective states using heart rate, skin conductance, and self-reported VAD measures.

Study Design Three participants from the MIT community (ages 18–34) were recruited based on social media usage patterns. Each participant completed a pre-study survey assessing their digital habits. Participants viewed a curated set of 120 TikTok videos, categorized into four emotional quadrants:

- High Arousal/High Valence (HAHV)
- Low Arousal/Low Valence (LALV)
- Low Arousal/High Valence (LAHV)
- High Arousal/Low Valence (HALV)

Each participant engaged in four 5-minute viewing sessions, with physiological data collected via an E4 wearable device. Heart rate variability (HRV) and electrodermal activity (EDA) were recorded to assess autonomic nervous system responses. Following each session, participants completed self-assessment surveys measuring valence, arousal, and dominance.

Post-study UX interviews provided qualitative insights into participants' emotional experiences, engagement behaviors, and strategies for managing social media consumption. The study design ensured content consistency while minimizing exposure to distressing or inappropriate material.

FUTURE WORK AND DESIGN INTERVENTIONS

Future Applications

This study design underscores the value of UX interviews, which provide participants with opportunities to share their current, expected, and ideal social media experiences. These insights enabled collaborative brainstorming and highlighted areas for further investigation (Goodman. et al, 2012).

Integrating these findings with Don Norman's emotional design principles—which address the visceral, behavioral, and reflective dimensions of user interaction—offers a pathway to creating more intentional, engaging, and emotionally supportive digital ecosystems (Norman, 2004). These frameworks are particularly important when designing for emotional regulation, as they guide not only how users interact with social media but also how these interactions shape their emotional experiences.

To address the study's limitations and expand its impact, several future directions are proposed:

Longitudinal Studies on Tech Addiction

The UX interviews revealed that participants often felt emotionally fatigued or overwhelmed after prolonged scrolling, particularly during rapid transitions between emotionally charged content. Future research could explore how users' emotional states shift during these transitions, such as moving from anger to joy or sadness to calmness, within an unpredictable infinite scroll experience.

By measuring delta changes in emotional states and correlating these with physiological data, researchers could uncover patterns driving compulsive behaviors and emotional dysregulation. Studies like Kardefelt-Winther (2017) and Hormes et al. (2014) emphasize how emotional instability reinforces addictive patterns, especially in algorithm-driven environments. These findings could inform reflective design interventions, such as adaptive emotional pauses or user prompts that encourage self-regulation during emotionally intense sessions.

Dynamic Emotionally-Aware Feeds

UX participants expressed a desire for greater control over their content consumption and emotional responses. Emotionally aware feeds could leverage real-time physiological and self-reported data to adapt content delivery based on users' emotional states. For instance:

- Reducing high-arousal content during moments of stress or frustration.
- Introducing calming videos or mindfulness exercises to promote emotional balance.
- Allowing users to set emotional thresholds, such as "promote relaxation" or "minimize stress," to align with their personal goals.

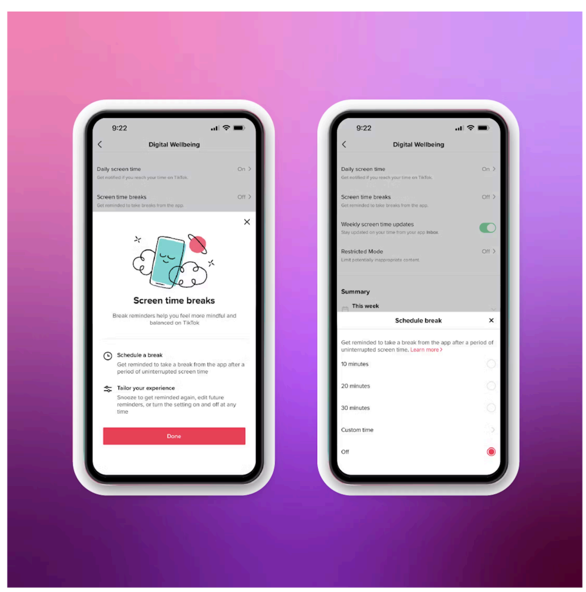

Figure 3:
TikTok settings include "Digital Wellbeing" that includes features to control daily screen time and reminder texts.

The integration of such adaptive systems in social media may show promise in enhancing user well-being; however the engagement performance is unknown on these social media sites.

Future designs could include interactive elements that allow users to rate their emotional responses to videos, improving emotion detection models and fostering self-awareness.

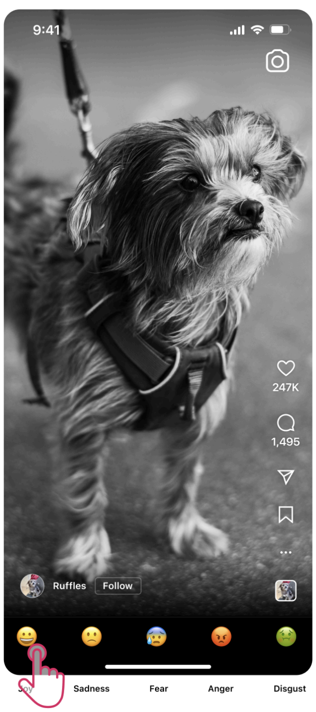

Figure 4:
Example Instagram Reel interface that enables users to emotional rate the viewed content.

Real-time adjustments to the user interface, such as changes in background colors, font sizes, or motion effects, could reflect users' emotional states and subtly guide healthier engagement behaviors. Such adaptive feedback mechanisms are supported by evidence from multimodal emotion studies with visual, auditory, or interactive elements to create an environment that reinforce positive states (Calvo & D'Mello, 2010).

Digital Wellness Reports

Reflecting on insights from UX interviews, participants showed interest in tools that provide visibility and self-awareness into their emotional patterns during social media use. Digital wellness reports could address this need by summarizing emotional highs, calming moments, and stress spikes, paired with actionable recommendations to promote balance. For example:

- A weekly report visualizing emotional peaks and troughs tied to specific content types.
- Personalized insights to help users set and track emotional goals, fostering resilience and intentional habits.

These tools would enable users to track their emotional patterns over time and set personalized goals, fostering emotional resilience and intentional digital habits proactively.

Figure 5:
Example wellness report UI using Freud UI Kit. Displays weekly emotional insights, including highs, calming moments, and stress trends, with actionable recommendations for balance and self-awareness.

Longitudinal tracking of emotional patterns could further enable users to set and monitor emotional goals, supporting a more intentional approach to social media usage. Similar approaches in other applications of emotional feedback have demonstrated the value of reflective tools in promoting user well-being (Norman, D.A, 2004).

Hardware Intervention for Social Media Addiction

Our team is exploring innovative interventions to mitigate compulsive social media use, particularly through smartwatch-based solutions designed to disrupt behavior patterns associated with continuous scrolling.

One promising approach is leveraging temperature-based feedback, specifically applying a cooling effect to the wrist via a smartwatch, as a method to break habitual engagement with digital content. This hypothesis is supported by research in both biology and psychology, which suggests that exposure to cold can enhance cognitive control and interrupt repetitive behaviors.

Cold exposure activates the sympathetic nervous system, triggering the release of norepinephrine, a neurotransmitter linked to increased alertness and improved self-regulation. This physiological response may help users regain focus and resist the urge to continue scrolling. For instance, a study found that participants felt more active, alert, and attentive after cold-water immersion, with positive emotional changes associated with increased connectivity between brain regions involved in attention control and self-regulation (Yankouskaya & Williamson, 2023).

Additionally, regular cold exposure has been shown to build mental resilience, training the body to tolerate discomfort and enhancing stress management capabilities (Esperland & de Weerd, 2022). While research on localized cooling interventions via wearable devices is limited, existing findings suggest that integrating cold-based stimuli into smartwatch technology could be a novel and effective strategy for disrupting maladaptive digital consumption habits.

Moving forward, we aim to design and conduct a study to evaluate the effectiveness of this approach, further exploring its potential as a hardware-based intervention for social media addiction.

Conclusion: Well-Being as a Design Principle

Future research and product development should prioritize well-being as a core design principle, shifting focus from short-term engagement metrics to fostering emotionally healthy digital environments.

Social media platforms must balance ethical responsibility with business sustainability by promoting healthier usage patterns. Positioning mental health resources as proactive tools rather than reactive solutions can enhance user support. Informed by research and user insights, these strategies offer a roadmap for implementing emotion-aware systems that encourage mindful social media engagement.

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