sInternational Journal of Innovative Research and Scientific Studies, 8(2) 2025, pages: 3332-3339

IJIRSS International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Digital health tools and habit formation: Investigating the role of anti-addiction systems in mitigating social media dependency

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Abstract

The pervasive use of social media has raised global concerns about digital addiction, prompting technology companies to develop anti-addiction systems as part of digital health tools. This mixed-methods empirical study investigates the effectiveness of these systems in mitigating social media dependency, combining quantitative surveys (N=189) and qualitative interviews. Results reveal a significant gap between tool availability and user engagement: only 25% of participants actively used anti-addiction features, while 75% ignored or circumvented them. Despite initial reductions in screen time, long-term efficacy remains limited, particularly among adolescents who exploit technical loopholes (e.g., parental ID binding). Thematic analysis highlights that current systems prioritize short-term restrictions over habit-forming strategies, failing to address intrinsic motivations such as boredom gratification (70%) and social validation (36.67%). Age-specific disparities are evident, with younger users (14–18 years) demonstrating higher resistance to interventions. The study underscores the need to integrate behavioral science principles—such as personalized feedback and gamified rewards—into anti-addiction designs to foster sustainable behavior change. These findings challenge the efficacy of purely technical solutions, advocating for interdisciplinary approaches that bridge digital tools, psychological incentives, and developmental needs.

Keywords: Anti-addiction systems, behavior change, digital health tools, habit formation, and social media dependency.

DOI: 10.53894/ijirss.v8i2.6007
Funding: This study received no specific financial support.
History: Received: 4 March 2025 / **Revised:** 2 April 2025 / **Accepted:** 5 April 2025 / **Published:** 8 April 2025

Competing Interests: The author declares that there are no conflicts of interests regarding the publication of this paper.
Transparency: The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Rapid technological advancements have significantly transformed modern lifestyles, particularly in the realms of communication, social interaction, and entertainment. The explosive growth of social media, coupled with its pervasive presence in daily life, has provided unprecedented convenience [1]. However, it has also raised serious concerns regarding digital addiction. In recent years, social media addiction has emerged as a major global issue, posing a significant threat to mental health. Social media platforms, through mechanisms such as personalized recommendations, push notifications, and real-time feedback, effectively activate the brain's reward system [2]. This constant stimulation drives users to seek social validation and virtual rewards, ultimately leading to excessive use and addictive behaviors. The consequences of social media addiction are far-reaching, impacting not only individuals' mental well-being but also their overall quality of life, with issues such as anxiety, depression, and sleep disorders being commonly observed among addicted users [3].

In response to these concerns, tech giants such as Google and Apple introduced a suite of digital health tools as early as 2019, designed to help alleviate digital addiction [4]. These tools aim to encourage users to more consciously manage their technology usage by limiting screen time, enforcing breaks, and sending reminders to monitor usage. While these measures have been widely adopted and discussed among users, there remains a lack of systematic evaluations regarding their effectiveness. Existing literature has yet to thoroughly explore the actual impact and limitations of these anti-addiction features in real-world settings. As such, assessing the effectiveness of these systems, particularly across different user groups, has become a critical research question in the field of digital health [5].

This study seeks to fill this gap in the literature by systematically analyzing user interactions with anti-addiction system features, evaluating their impact on user behavior, and identifying potential shortcomings in their design. By combining both quantitative and qualitative research methods, this study not only examines the effectiveness of anti-addiction systems but also explores users' personal experiences and feedback during actual use. The goal is to provide both theoretical insights and practical recommendations for optimizing existing digital health tools. Specifically, the study will collect user data through surveys, assessing the effectiveness of anti-addiction systems across various demographic groups, and conduct in-depth interviews to gain further insights into individual user experiences, highlighting challenges and potential issues faced by these features in practice.

The research employs a mixed-methods approach, combining quantitative and qualitative techniques. The quantitative component involves designing a survey to gather data on usage frequency, user satisfaction with the features, and behavioral changes following use, among other factors. The qualitative component will involve interviews, allowing a deeper understanding of users' experiences with anti-addiction tools, exploring their actual impact, sustainability, and the users' needs and expectations regarding system design. Furthermore, this study will examine the acceptance and responses of users across different age groups and social media usage patterns to better understand the diversity of user experiences and the complexities of various usage contexts.

Through the comprehensive analysis of both quantitative and qualitative data, this study will provide a thorough evaluation of the effectiveness of current digital health tools and offer empirical insights to inform future research in this area. The findings are expected to provide valuable recommendations for technology developers, guiding them to design more efficient and user-centered anti-addiction features. Moreover, the study will offer decision-making insights for policymakers, helping to advance the digital health field and address the growing issue of digital addiction.

In summary, this research, through systematic quantitative and qualitative analysis, aims to provide crucial academic support for the improvement of digital health tools and the optimization of anti-addiction systems. It also seeks to offer practical solutions to mitigate social media addiction, contributing to the development of both theoretical knowledge and practical solutions in this field.

2. Literature Review

2.1. The Role of Digital Health Tools and the Context of Social Media Dependency

In recent years, with the rapid development of information technology and the widespread use of social media, the time spent by global users on these platforms has shown a significant upward trend. Experts generally recommend that daily social media usage should be limited to no more than 30 minutes to ensure both psychological and physiological well-being [6]. However, statistics from 2020 revealed that the average time spent by regular users on social media platforms was as high as 2 hours and 24 minutes, with approximately 50.1% of mobile device usage time allocated to social media applications. This usage far exceeds the recommended healthy limits and has become a major factor contributing to negative health effects, such as anxiety, depression, and sleep disorders [7].

Against this backdrop, digital health tools have emerged, with the primary goal of utilizing information technology to assist users in self-monitoring and regulating their digital device usage behaviors. Tools such as Google's "Digital Wellbeing" and Apple's "Screen Time" provide users with a self-regulation mechanism through real-time monitoring, data feedback, and usage time limitations [8]. These tools not only allow users to quantify their device usage but also encourage reflection on their usage habits through visualized data and behavioral reminders, thereby reducing over-reliance on technology. The application of digital health tools has been viewed as a potential intervention for addressing social media addiction, and the effectiveness and mechanisms of these tools are gradually gaining attention in academic research [9].

2.2. Mechanisms of Habit Formation and Behavior Change

Behavioral science and psychology research indicate that habit formation relies on the repeated execution of a specific behavior under consistent situational cues, eventually turning it into an automatic response [10]. In the context of social media usage, the repetitive actions of users and the real-time feedback systems are key factors driving the formation of unhealthy usage habits. Meanwhile, digital health tools, if designed to integrate core principles of habit formation theory, such as goal-setting, reward mechanisms, and continuous feedback, have the potential to intervene in user behavior and help users gradually establish healthier digital usage patterns [11].

Existing research has shown that the sustainability of behavior change is not only dependent on external constraints but, more crucially, on the stimulation of intrinsic motivation and the enhancement of self-regulation abilities. Therefore, when designing anti-addiction systems, integrating self-determination theory and habit formation mechanisms could not only limit excessive social media usage in the short term but also facilitate long-term behavior change by strengthening users' sense of self-efficacy and intrinsic motivation [12]. The role of digital health tools in this process lies in promoting users' self-awareness and behavioral reflection, guiding them from passive dependence to active self-regulation. This provides both the theoretical foundation and practical pathway for building a healthy and sustainable digital lifestyle [13].

2.3. Effectiveness of Anti-Addiction Systems and Influencing Factors

Since 2019, in response to the growing issue of digital addiction, tech giants such as Google and Apple have rolled out anti-addiction systems. These systems attempt to provide users with self-regulation tools by monitoring app usage time, setting usage limits, and issuing mandatory break reminders [14]. However, despite their well-intentioned design, the actual effectiveness of these tools has shown significant variability across various studies. On the one hand, some users exhibit noticeable behavioral adjustments during the initial stages of using these systems, reacting sensitively to usage restrictions. On the other hand, as users become more familiar with the system and their usage time increases, many users learn to circumvent or ignore these restrictions, a phenomenon particularly pronounced among adolescent users [15].

Moreover, many anti-addiction systems primarily focus on providing real-time monitoring and short-term behavioral interventions but lack long-term motivational incentives based on habit formation mechanisms [11]. This design limitation has led to the failure of anti-addiction systems to effectively encourage the development of healthy usage habits over the long term [3]. Scholars generally agree that the effectiveness of anti-addiction systems should be evaluated from two perspectives: first, the immediate regulatory effect on user behavior; and second, the ability to achieve long-term behavioral transformation through the stimulation of intrinsic motivation and the formation of new habits [16].

In light of this, this study will further explore the role of anti-addiction systems in enhancing user self-control, reducing impulsive social media usage, and promoting the formation of healthy habits. The research will integrate both quantitative and qualitative data to analyze behavioral changes in different user groups under the intervention of anti-addiction systems, evaluate their actual effectiveness, and identify the key factors influencing their outcomes.

2.4. Research Hypotheses

To examine the role of digital health tools and anti-addiction systems in promoting habit formation and reducing social media dependency, this study proposes the following four hypotheses in Table 1.

Table 1.
Hypothesis.

Hypothesis			
H1	H2	H3	H4
Digital health tools, particularly anti-addiction systems, can significantly reduce users' daily time spent on social media	Habit formation strategies embedded in anti-addiction systems contribute to sustained behavior change and healthier usage patterns	The impact of anti-addiction systems varies across different age groups, with younger users showing more significant behavior change compared to older users	User engagement with anti-addiction systems correlates with perceived effectiveness in reducing social media dependency

3. **Methodology**

3.1. Research Design

This study adopts a mixed-methods approach, combining both quantitative and qualitative data collection techniques to assess the effectiveness of anti-addiction systems in mitigating social media dependency. By utilizing a questionnaire survey, the study aims to understand the interaction between users and the anti-addiction features embedded in digital health tools, particularly those designed to limit social media usage. The research seeks to comprehensively evaluate how these tools influence user behavior, focusing on their role in shaping healthier digital habits.

3.2. Participants

The research sample comprised 200 participants drawn from a diverse demographic. To ensure a broad perspective on the effectiveness of anti-addiction systems, participants were stratified into three distinct age groups: minors aged 14 to 18 years, adults aged 19 to 35 years, and adults aged 36 to 50 years. All participants were users of mobile devices running on iOS, Android, or Huawei operating systems, each equipped with integrated anti-addiction features such as usage time monitoring, app limits, and break reminders. These age groups were specifically selected to provide insights into the effectiveness of anti-addiction tools across different stages of life, from adolescence to adulthood.

3.3. Data Collection

Data for this study was collected via an online questionnaire, designed to capture both quantitative and qualitative information regarding user experiences with anti-addiction systems. The questionnaire was structured to explore several dimensions: (1) participants' social media usage patterns, (2) their motivations for using social media platforms, (3) their experiences with anti-addiction features on their devices, and (4) the perceived effectiveness of these tools in modifying user behavior.

The survey sought to understand the types of social media platforms participants engage with, the average duration of their daily usage, and the specific features they utilize within anti-addiction systems. Further, participants were asked to reflect on their motivations for using social media, including factors such as entertainment gratification, boredom relief, social interaction, and self-expression. These questions were intended to identify the underlying psychological drivers of social media usage, which may impact the effectiveness of anti-addiction features.

Additionally, the questionnaire included questions aimed at determining the perceived usefulness of anti-addiction tools. Participants were prompted to reflect on their engagement with the built-in anti-addiction features on their devices and to evaluate their experiences with specific applications designed to prevent smartphone addiction. The study also sought feedback on potential improvements to these systems, exploring whether offline integration and user preferences could enhance their effectiveness.

3.4. Questionnaire Structure

The questionnaire comprised a series of open-ended and closed-ended questions, ensuring a balance between numerical data and participant narratives. The primary categories of questions included:

Demographic Information: Participants were asked to provide basic demographic data, including their age and device type (iOS, Android, Huawei).

Social Media Usage Patterns: Questions assessed the frequency and duration of social media usage, the types of platforms used (e.g., Instagram, TikTok, Facebook), and the typical daily interaction times spent on each platform.

Motivations for Social Media Use: This section aimed to probe the psychological and social reasons behind social media engagement. Respondents were asked to identify their primary motivations (e.g., boredom, entertainment, seeking friendship) and whether they preferred online or offline interactions.

Engagement with Anti-Addiction Systems: Participants were asked whether they use digital health tools like Screen Time or Digital Wellbeing, and if so, how often they engage with these features. Questions also explored the perceived effectiveness of these tools in reducing social media use.

Perceived Effectiveness and Preferences: This section gauged participants' attitudes toward the design of anti-addiction systems, asking which features they found most useful and which improvements they would recommend.

3.5. Data Analysis

The data collected from the questionnaires were analyzed using a combination of descriptive and inferential statistical techniques. Descriptive statistics were employed to summarize the demographic profiles of the respondents, their social media usage habits, and their engagement with anti-addiction tools. Frequency distributions, means, and percentages were calculated to better understand general patterns in the data.

In addition to descriptive statistics, the study utilized correlation analysis to examine relationships between demographic factors and the effectiveness of anti-addiction systems. This analysis allowed for the identification of any significant differences in the usage patterns or perceived effectiveness across age groups. The qualitative data, gathered through open-ended responses, were subjected to thematic analysis to identify recurring themes and patterns related to user motivations, system features, and effectiveness. Thematic coding was used to categorize participant feedback, providing deeper insights into user experiences and preferences regarding anti-addiction systems.

3.6. Ethical Considerations

The study adhered to ethical research standards throughout its design and implementation. Informed consent was obtained from all participants prior to their involvement in the survey. Participants were assured of their confidentiality, and all personal data were anonymized to prevent any potential identification. Additionally, the study complied with ethical guidelines concerning data storage and protection, ensuring that all responses were securely stored and used exclusively for the purposes of this research.

4. Results

This chapter presents the findings derived from the survey conducted to evaluate the effectiveness of anti-addiction systems and understand social media usage behavior and its motivations. The analysis consists of both quantitative and qualitative insights based on the responses from the survey and interviews.

4.1. Demographic Distribution of Participants

A total of 189 valid responses were collected from participants across three different age groups: Group 1 (14-18 years), Group 2 (19-35 years), and Group 3 (36-50 years). Group 2, consisting of participants aged 19-35, represented the largest group, accounting for 70% of the total respondents. Group 3, participants aged 36-50, accounted for 20%, while Group 1, the minor group, comprised 10%. This distribution ensures that the results provide a broad perspective of social media usage across various age groups and life stages.

4.2. Social Media Usage Patterns

Survey results revealed significant variations in daily social media usage patterns. The most frequently used platforms were TikTok (46.47%), Xiaohongshu (33.33%), and a combination of Instagram and Facebook (11.67%). All these platforms integrate built-in anti-addiction features. On average, respondents reported spending 4.3 hours per day on social media, with the highest reported usage reaching 22 hours per day and the lowest at 1 hour. This wide range of social media usage reflects varying patterns of engagement, with some users demonstrating excessive usage while others engage more moderately.

To ensure clarity, this data has been presented in the following Figure 1:

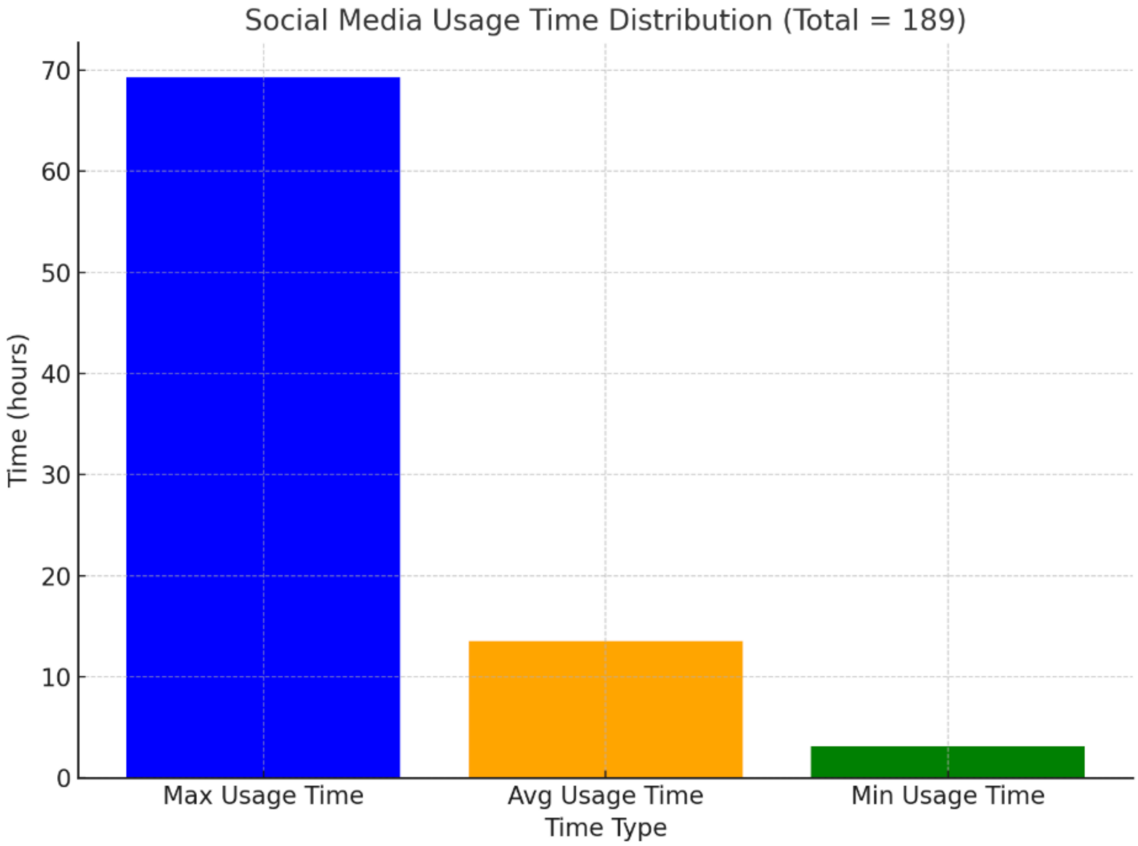

Figure 1.
Daily Social Media Usage Duration.

A histogram, created in Python's Matplotlib library, presents the distribution of usage hours across different participants, highlighting the significant variance in usage patterns.

4.3. Motivations for Social Media Usage

The survey also aimed to explore the primary motivations behind social media usage. According to the responses, the major motivators were boredom gratification (70%), entertainment gratification (51.67%), and seeking friendship (36.67%). These findings align with existing literature that suggests social media usage is often driven by emotional and social needs, particularly during periods of boredom or loneliness. Other motivations, including relationship maintenance, self-expression, and escapism, were cited less frequently but still contributed to the overall pattern of usage motivations (see Table 2).

Table 2.
Motivational Factors for Social Media Usage.

Motivation	Percentage of Respondents
Boredom Gratification	70%
Entertainment	51.67%
Seeking Friendship	36.67%
Relationship Maintenance	21%
Self-expression	15%
Escapism	10%

These findings are consistent with prior studies that view social media as a tool for emotional relief and social interaction, particularly for users experiencing boredom or loneliness.

4.4. Anti-Addiction System Engagement

While the survey revealed that anti-addiction systems are integrated into mobile operating systems such as iOS, Android, and Huawei, user engagement with these features was significantly low. Only 25% of respondents (15 participants) actively used the anti-addiction features on their devices. The remaining 75% either did not check or ignored these features, indicating a considerable gap between the availability of these tools and their practical use.

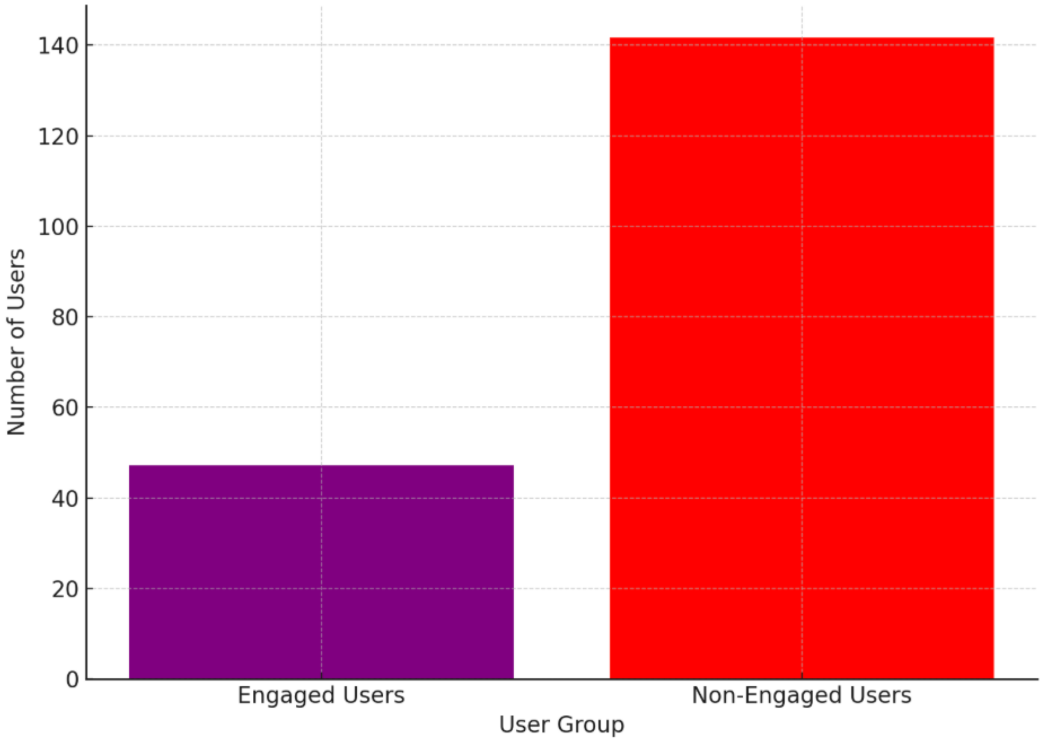

Figure 2.
Engagement with Anti-Addiction Features.

This bar chart, created in SPSS, highlights the stark contrast between the availability of anti-addiction tools and actual user engagement, supporting the hypothesis that these systems do not effectively address social media addiction.

Many respondents expressed skepticism about the effectiveness of anti-addiction features. For instance, a 16-year-old participant noted:

"Although I need to bind my ID, I can choose to bind my parents, and they don’t play games, so it doesn’t really matter. The system is still normal; I can play several apps at once, and that doesn’t add up."

For adults, many described the anti-addiction system as a mere reminder function that did not effectively curb excessive social media usage. One respondent shared:

"As long as the system is in place, I feel like I am doing my part to reduce addiction, but in reality, it doesn't change how much time I spend on social media."

4.5. Qualitative Insights: User Behavior and System Effectiveness

Additional insights from open-ended questions and interviews shed light on users' perceptions of anti-addiction systems. A significant number of participants, especially teenagers, reported bypassing these systems or finding ways to work around the limitations. Many expressed that these tools were seen more as moral safeguards rather than practical solutions to addiction.

For example, one participant explained:

"I know it's not effective, but as long as I have it activated, I can tell myself that I'm doing something to control my screen time."

These findings support the hypothesis that anti-addiction systems, while available, often fail to address the underlying psychological drivers of social media addiction, such as the need for social validation and instant gratification.

5. Discussion

5.1. Interpretation of Key Findings

This study reveals a critical paradox in the implementation of anti-addiction systems: while these tools are widely available on mainstream digital platforms, their actual engagement rate remains strikingly low (25%), and their effectiveness in reducing social media dependency is limited, particularly among younger users. The quantitative data indicate that participants spend an average of 4.3 hours daily on social media, significantly exceeding the recommended healthy threshold, despite the presence of usage-limiting features. Qualitative insights further emphasize that users, especially adolescents, frequently bypass these systems through technical loopholes, such as binding parental IDs, or perceive them as symbolic rather than functional interventions. These findings align with previous research that highlights the gap between technological design and behavioral psychology.

The low engagement rate can be attributed to two primary factors. First, there is a lack of intrinsic motivation. As posited by Self-Determination Theory, external constraints, such as forced breaks, are unlikely to sustain behavior change unless users internalize the value of reduced usage. Second, design limitations in current systems may also contribute to the low engagement. These systems prioritize short-term restrictions, such as screen time alerts, over habit-forming strategies, such as personalized feedback or incremental rewards. These limitations suggest that while anti-addiction tools are effective at providing immediate interventions, they lack mechanisms to foster long-term behavior change by promoting deeper engagement and internal motivation.

5.2. Theoretical and Practical Implications

5.2.1. Theoretical Contributions

This study makes a significant contribution to the literature on digital health tools and habit formation by demonstrating that anti-addiction systems must integrate behavioral science principles more thoroughly. Habit formation, as supported by existing literature, relies on contextual cues and repetition. However, current digital health tools lack the necessary mechanisms to reinforce these processes, limiting their effectiveness in promoting lasting behavior change.

The study's finding of age-specific variability in system effectiveness (H3) underscores the need for developmental psychology to inform the design of digital interventions. Adolescents, in particular, exhibit a higher tendency to circumvent restrictions, suggesting that factors such as peer influence and identity exploration may override technical controls. This highlights the importance of considering developmental stages and social factors when designing anti-addiction tools.

5.2.2. Practical Recommendations

From a practical perspective, the study offers several recommendations for improving the effectiveness of anti-addiction systems. First, personalization is essential. Developers should incorporate adaptive features that align with users' motivations, such as offering alternatives to social media use that cater to individual needs (e.g., boredom vs. social connection). For instance, systems could suggest offline activities tailored to user preferences, fostering healthier engagement with digital technologies.

Second, gamification could enhance intrinsic motivation. Introducing rewards for meeting usage goals, such as unlocking premium content after reducing screen time, might encourage users to engage more actively with the system and reinforce positive behavior patterns.

Lastly, multi-stakeholder collaboration is crucial. Parents and educators should be integrated into the design of anti-addiction systems, particularly for minors, to provide external accountability and ensure that usage limits are respected outside of the digital realm.

5.3. Limitations and Future Research

While this study provides valuable insights, several limitations must be acknowledged. Firstly, sample bias is a concern, as the majority of participants (70%) were aged between 19 and 35. This demographic skew limits the generalizability of the findings to other age groups, particularly younger adolescents or older adults. Future studies should aim to achieve a more balanced demographic sample to ensure that the results are representative of a wider range of users. Additionally, self-reporting bias is another limitation. Since the study relied on self-reported usage data, it is possible that participants underreported their actual screen time. To address this, future research could incorporate objective metrics, such as device usage logs, to enhance the validity of the data.

Future research should also explore several avenues. Longitudinal studies would be valuable to assess long-term behavior change and the sustainability of anti-addiction interventions. Additionally, neuropsychological methods, such as fMRI, could be used to investigate how anti-addiction tools impact reward circuitry in the brain, providing deeper insights into the mechanisms behind behavior change. Finally, cross-cultural comparisons should be conducted to evaluate whether the findings of this study hold true in different cultural contexts and to assess the universality of these results.

6. Conclusion

In conclusion, this study critically examines the role of anti-addiction systems in mitigating social media dependency through a mixed-methods approach that captures both behavioral patterns and user perceptions. The findings highlight three key conclusions. First, while anti-addiction tools can temporarily reduce screen time, their effectiveness diminishes over time due to low user engagement and circumvention strategies. This suggests that current systems fail to sustain long-term behavior change. Second, the effectiveness of these systems is age-dependent, with younger users (14–18 years) exhibiting higher resistance. This underscores the need for age-specific interventions that account for developmental motivations, such as peer validation. Finally, the study proposes that to achieve sustained behavior change, digital health tools must evolve beyond restrictive features and integrate habit-forming mechanisms, such as personalized feedback loops and context-aware nudges. These conclusions challenge the current paradigm of anti-addiction system design, advocating for a shift from passive monitoring to active engagement. By aligning technological solutions with behavioral theories, developers and policymakers can foster healthier digital ecosystems. Future efforts should prioritize interdisciplinary collaboration, merging computer science, psychology, and public health to address the multifaceted nature of digital addiction.

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