Research on Intervention Approaches to Assist with Digital Detox

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(千葉大学審査学位論文)

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Abstract

As people's lives increasingly rely on digital products and content, issues such as digital dependency, excessive digital use, digital overuse, and even digital addiction have attracted attention from design practices and academic fields. Correspondingly, research related to digital detox has gained increasing significance. In an effort to assist users with varying degrees of digital dependency in practicing digital detox and enhancing their digital well-being, we conducted a study on intervention approaches to promote digital detox.

The concept of digital addiction, despite widespread concern, remained poorly defined. Previous studies have suggested that self-perceived addiction can assist users in changing their addictive behaviors. Existing research often categorizes individuals as addicted based on an objective phenomenon of that an individual unable to stop the behavior. The study of Chapter 2 introduced the subjective perspectives and hypothesizes two subjective cognitions, namely, whether the actor feels regret about their behavior, and whether they want to stop their behavior, also influences individuals' perceptions of addiction. Through a within-subject design experiment, we validated that these two subjective cognitions impact individuals' judgments and revealed how they influence individuals' subjective perceptions of addiction. Furthermore, we found design intervention methods to address digital addiction from individuals' subjective perceptions of addiction. Our findings demonstrated that people tend to define an individual with behavior-cognitive inconsistency (regret or want to stop the behavior) as addicted, while those with behavior-cognitive consistency are not considered addicted. Design interventions that elicit feelings of regret or intentions to quit in users can assist individuals in becoming aware that their behavior is at risk of addiction and further encourage them to make efforts to detox from digital addiction.

Based on the findings of the previous studies, we proposed a theoretical model aimed at assisting individuals in reducing digital usage in Chapter 3. Drawing upon the Expectation Confirmation Theory, which posits that perceived performance (PP) and expectation (EX) contribute to the continuous use of information systems, we introduced the concept of cognitive consistency (CC) representing behavior-cognitive consistency, as identified in the previous chapter, into this model. Therefore, the model we proposed comprises three quadrants: PP, EX, and CC. We hypothesized that reducing individuals' perceptions of these three quadrants can diminish their intentions of continuing a behavior. An empirical study demonstrated the effectiveness of the proposed model in eliciting users' intentions to discontinue continuous digital behaviors. Our findings contribute to the design of interventions for encouraging individuals to make digital detox efforts. In the final chapter, we presented the theoretical contributions and practical implications of this study, summarized its limitations, and outlined avenues for future research.

This study addresses the gap in people's subjective definition of addiction and contributes by proposing intervention methods for digital detox efforts to promote the development of digital well-being.
Keywords: *Digital Detox, Digital Addiction, Intervention Approaches*

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Chapter 1

Introduction

1. Background

Technological advancements have profoundly enriched various aspects of people's lives, serving as pivotal tools through which individuals connect with the world and fundamentally reshape human interactions. However, the convenience of digital technology has led to overreliance, resulting in specific adverse consequences [1]. Notably, digital dependence, often referred to as digital addiction, emerges as a prominent illustration of these repercussions, directly impacting individuals' digital well-being. It has garnered significant attention from both society and academia, catalyzing dedicated research efforts aimed at mitigating digital addiction. This paper specifically focuses on the discovery of intervention approaches to address the growing issue of digital addiction.

1.1 Digital Addiction

Addiction has been defined as disorders involving psychoactive substance use and behaviors that produce rewards, resulting in persistent behavior despite negative consequences and reduced control over the behavior. These addictions can be categorized as substance-related and non-substance or behavioral addictions, which encompass behaviors such as gambling, internet use, video game playing, sex, eating, and shopping [2]. Non-substance behavioral addictions share similarities with substance dependence [3]. Volkow (2016) divided addiction into three recurring stages: binge and intoxication, withdrawal and negative effects, and preoccupation and cravings [4]. Addiction typically includes elements like engagement in the behavior to achieve pleasurable effects, preoccupation with the behavior, temporary satiation, loss of control, and negative consequences [5]. Griffiths (2005) clarified that all addictions share six common components: salience, mood modification, tolerance, withdrawal, conflict, and relapse [6]. According to the ICD-11, disorders resulting from substance use or addictive behaviors are categorized as mental and behavioral disorders arising from the use of primarily psychoactive substances, including medications, or specific repetitive, rewarding, and reinforcing behaviors.

Digital addiction is identified as functionally equivalent to all addictions, characterized by compulsive, habitual, and uncontrolled use of digital devices and excessive engagement in specific online behaviors. It is an emerging disorder that has gained widespread attention; however, there are no widely accepted diagnostic criteria. Gaming disorder (GD) is the first digital media-related disorder introduced in the 11th revision of the International Classification of Diseases (ICD-11) by the World Health Organization (WHO). In 2020, the WHO formally recognized technology addiction as a global problem [7, 8]. Standard features for diagnosing digital addiction have not yet been established. Traditional research often adopts criteria for substance use disorder or behavioral disorders, such as gambling. Core symptoms such as compulsive use, negative outcomes, and salience are relevant for diagnosis [9].

Digital addiction is considered a form of technological addiction, which is a nonchemical (behavioral) addiction involving human-machine interaction. It shares some common features with other behavioral addictions, including (1) Salience: The use of digital technology becomes the most crucial activity in a person’s life, dominating their thoughts, feelings, and behaviors. (2) Mood modification: Individuals experience subjective changes in mood as a result of digital technology use. (3) Tolerance: There is a need for increased use of digital technology to achieve the same mood-modifying effect. (4) Withdrawal symptoms: Physical effects and/or unpleasant feelings occur when internet use is suddenly stopped or reduced. (5) Conflict: Various types of conflicts arise due to the extensive time spent online. (6) Relapse: A recurring pattern of excessive internet use follows a period of abstinence or control [10, 11]. However, some studies suggest that the diagnosis of digital addiction is part of the compulsive-impulsive spectrum disorder related to digital media usage, encompassing four components: (1) Excessive use: Often associated with a loss of the sense of time or neglect of basic needs. (2) Withdrawal: Involves feelings of anger, tension, and/or depression when access to digital technology is restricted. (3) Tolerance: Entails a need for better digital equipment, more software, or increased hours of use. (4) Negative repercussions: These include arguments, lying, poor achievement, social isolation, and fatigue, which are characteristics shared with many substance use disorders [12, 13]. Some studies also describe the manifestations of digital addiction, which include psychological dependency on the internet, a constant increase in online time, deriving pleasure and satisfaction from online activities, and feeling discomfort after logging off. Individuals with internet addiction tend to spend minimal time engaging in social activities and interacting with others in real life. They often turn to the internet as an escape from real-life troubles and emotional issues. Additionally, they tend to deny the harm excessive internet use can cause to their studies, work, and daily life [14].

Research on digital addiction has primarily employed methodologies from the fields of social sciences and psychology [15]. Typical studies in this field primarily focus on the correlation between motives for social media usage and social media addiction [16]. Currently, research on the phenomenon of digital addiction primarily revolves around three key aspects: (1) the characteristics of digital product usage behavior and its relationship with digital addiction, (2) the dynamic factors contributing to digital addiction, and (3) the analysis of the root causes of digital addiction. At present, research methods for studying digital addiction predominantly rely on online survey approaches [17]. A review of the literature reveals that the majority of digital addiction studies have primarily centered on the use of measurement scales [18-20].

Research related to digital addiction is prevalent and encompasses estimates of smartphone addiction, social media addiction, internet addiction, and game addiction [21]. Various other terms have been proposed to replace the term 'digital addiction', including problematic digital use, excessive digital use, and compulsive digital use. The concept of digital addiction is the subject of ongoing investigation and debate within the academic community. It is noteworthy that digital addiction is not officially recognized as a mental disorder in diagnostic manuals, such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5). Some experts have suggested that digital and internet-related addiction should be considered for inclusion in DSM-V [22]. However, some researchers have argued that the degree of individuals' dependence on digital products or content varies significantly, making a universal label like 'digital addiction' inappropriate. They suggest that it may be premature to consider digital addiction as a fully-fledged and distinct mental disorder at this time [13, 23].

1.1.1 Causes of Digital Addiction

Some studies argue that excessive internet usage merely represents underlying psychopathology or defense mechanisms that would manifest in some other way if the internet were not available [13]. Several factors predict problematic Internet use, including personality traits, parenting and familial factors, alcohol use, and social anxiety [24]. The satisfaction of innate psychological needs for autonomy, competence, and relatedness can enhance intrinsic motivation and mental well-being, as posited in self-determination theory [25], while the frustration of these three fundamental psychological needs is associated with both substance and behavioral addictions [26]. The research determined that a lack of conscientiousness is a significant predictor of digital game addiction. Conscientiousness is related to a sense of responsibility [27]. It was found that people with lower self-control and high-stress levels were more likely to become addicted to smartphones. Those who used SNS, games, and entertainment content were more likely to develop addiction [28].

Several studies have proposed theoretical models to explain the causes of digital addiction. Young's "ACE" model refers to Anonymity, Convenience, and Escape, which the author believes are three characteristics that lead to user addiction on the internet [29]. Davis introduced a cognitive-behavioral model aimed at explaining the development and maintenance of Pathological Internet Use (PIU) [30]. Grohol presented a stage model, suggesting that so-called digital addiction is simply a phased behavior [31].

Problematic or excessive internet use carries the risk of developing internet addiction. It has been recognized that employing gamification, behavior change mechanisms, and persuasive design can enhance users' engagement and user experience, ultimately increasing their retention [25, 32]. Addictive digital experiences are enabled by product design, advertising, big data dynamics, and the prevalence of 'free' pricing [33]. User interface prosperities such as usability, accessibility, customization and multitasking might also play important roles in facilitating digital addiction [34]. There are four key features that contribute to digital addiction: (1) Achievement: This occurs when software features encourage users to pursue greater accomplishments, such as individuals who continually check and post content to increase their ranking and social capital. (2) Exploration: This feature fosters a high level of curiosity and encourages individuals to stay connected to discover what will happen next. (3) Socializing: Excessive socializing is often facilitated by the wealth of connectivity features and ease of access. This behavior may result from a form of escalating commitments, where individuals remain online not solely for pleasure but to fulfill others' demands and to monitor potential negative comments or reactions. (4) Mental Satisfaction and Stress Relief: This aspect is particularly evident in gaming, where individuals derive mental satisfaction and stress relief from causing virtual harm to others. These features collectively contribute to the phenomenon of digital addiction [26] .

1.1.2 The Harms of Digital Addiction

Negative consequences that excessive digital usage can cause in users are as follows: (1) Prejudice of real social life, such as relationship breakdown. (2) Adverse effects on physical and mental health. (3) Damage to one's public profile. (4) The ease and speed of information spreading without deliberation. (5) Using social networks hastily and thoughtlessly. (6) Consequences on online relationships and contacts. Online activities have the potential to enhance interpersonal communication and alleviate feelings of loneliness and stress. However, social isolation can make people more vulnerable to the detrimental effects of using digital media, such as social comparison, the fear of missing out, or exposure to negative content [35]. Digital media usage can help reduce loneliness when people use it to enhance existing relationships and establish new social connections. Conversely, the feeling of loneliness may increase when social media is used to escape real-world social interactions and withdraw from the challenges of social engagement [36].

Digital addiction has negative impacts on a person's life, including familial disruption, work performance problems, invasion of the privacy of others, dietary-related problems, harm (self-harm, harm to others, and harm from others), emotional problems, personal problems, and social problems [37, 38]. M. Samaha and others found that smartphone addiction risk was negatively correlated with students' academic performance, positively correlated with perceived stress, and indirectly affected life satisfaction [39, 40].

Digital addiction or excessive use of digital technology can lead to an increase in symptoms such as depression, anxiety, loneliness, withdrawal from friends and family, eating disorders, sleep deprivation, and mood disorders. It can also result in difficulties with time management, attention, motivation, and memory. Cross-sectional studies on patient samples have reported a high comorbidity of digital addiction with psychiatric disorders, especially affective disorders (including depression), anxiety disorders (such as generalized anxiety disorder and social anxiety disorder), and attention deficit hyperactivity disorder (ADHD) [24]. Digital addiction can also have various negative impacts on an individual's physical health, including obesity, back pain, neck pain, orthopedic and joint muscle issues, eyesight problems, hearing problems, as well as physical inactivity [41].

1.2 Digital Detox

Researchers have proposed various strategies in response to the issues of digital addiction. These strategies can be categorized into four main groups: psycho-social, software-mediated, pharmacological, and combined approaches. These countermeasures have been effective in reducing addictive digital use [42]. For individuals with digital addiction, cognitive-behavioral approaches have demonstrated efficacy in reducing online time, improving social relationships, increasing engagement in offline activities, and enhancing the ability to avoid problematic internet use [3]. Marital and family therapy may be helpful in selected cases, and online self-help books and tapes are available. Additionally, individuals may need to impose restrictions on their digital usage and internet access in certain situations [24, 43]. The general behaviors in self-management strategies usually involve disconnection, such as physical separation (placing the phone out of reach), turning off (muting notifications or activating airplane mode), or deleting applications [44].

In addition to the extensive range of digital media, A. Meier and L. Reinecke have broadened and refined the scope of digital addiction to encompass abstaining from the use of specific types of digital products, including: Certain categories of applications, such as social media; branded media platforms (e.g., Facebook); particular functionalities (e.g., messaging); interactive features (e.g., active engagement on WhatsApp); messaging elements (e.g., voice messages); behaviors aimed at disconnecting from the internet or digital devices for a specific duration are referred to as digital detox [45]. Nevertheless, given that smartphones are already the most prevalent digital devices for a significant portion of the population, some scholars have directly characterized this practice as a deliberate period of distancing oneself from smartphones [46].

In the effort to address digital addiction, the concept of digital detox has emerged. It has gained increasing interest as a practice for limiting and reducing the time spent on digital technology devices to combat digital or technology addiction. Digital detox involves a defined period during which individuals intentionally abstain from using digital devices or digital content. This period is seen as an opportunity to alleviate stress or engage in real-life social activities. The practice of digital detox extends to encompass the entirety of the internet, social media, or digital devices, such as smartphones or computers. This practice can be summarized as a deliberate effort to restrain or reduce digital usage [47].

The process of digital detox serves as a solution to alleviate excessive usage and addictive behaviors associated with digital technology, helping users build digital well-being [17]. Chinese researchers define detox as follows: users consciously disconnect from digital devices or technology and disconnect with digital services for a certain period [48]. Specifically, the concept of detox can be elucidated as follows: (1) The act of disconnecting from digital devices or creating a deliberate separation from digital technology should be a proactive and conscious choice made by the user. This behavior can be facilitated through external means, such as the use of relevant digital detox applications. (2) The scope of digital detox encompasses both the complete cessation of all internet connections and digital device interfaces, as well as the discontinuation of the use of specific primary internet-enabled devices (e.g., smartphones). (3) The content of digital detox covers all categories of internet information accessible to the user, as well as the avoidance of a specific category of internet information. For instance, this may involve refraining from receiving any messages from chat applications or discontinuing the use of a particular application for a certain period. Additionally, the use of pre-downloaded information that is only accessible in an online state is not considered part of digital detox. (4) The duration of digital detox varies depending on the context and can be measured in hours, days, weeks, months, or specific time periods.

Many researches have shown, through empirical research, that digital detox can have positive effects on users. S. Anrijs and others conducted a controlled experiment in which they monitored users for two weeks and measured their physiological stress levels using skin conductance. The results indicated that digital detox helped reduce physiological stress [49]. C. Hinsch and K. M. Sheldon conducted an assessment of self-control in users after detox and found that disabling or reducing Facebook usage directly alleviated procrastination [50].

Digital detox initiatives illuminate the rise of a self-regulation society, where individuals are expected to take personal responsibility for managing risks and pressures associated with digital technology use. The rationale behind digital detox is driven by a desire to concentrate on one's personal and professional environment while enhancing interpersonal communication [45]. People often employ various intervention methods to assist with digital detox. According to the Fogg behavior model, the ability to perform, along with sufficient motivation and being triggered to perform a behavior, are conditions for a person to engage in a target behavior [51]. Control of behavior performance can be either internally or externally oriented. Enhancing external control of the ability to behave, for example, may improve internal control (i.e., the intention to perform the behavior) [52].

Common digital detox behaviors include deleting applications, muting notifications, and managing sharing habits. Device manufacturers have embedded features like screen time usage right from the factory, while software engineers have developed numerous applications aimed at helping individuals reduce distractions. Digital detox applications have been introduced and gained wide usage, particularly among a substantial proportion of young adults. Research has affirmed the value of digital detox apps as effective tools for mitigating the adverse effects of using social networking sites on the digital well-being of young individuals [46]. Digital detox holidays have emerged as a form of disconnection activity, catering to the needs of travelers seeking respite from digital connectivity [53]. The tourism industry has experimented with strategies to enhance the travel experience by encouraging tourists to reduce their use of digital devices [54].

Currently, most of the research on digital detox comes from the fields of behavioral science, computer science, and psychology. Researchers conduct experimental studies with users to investigate the effects of digital detox. However, there are few scholars who address the theoretical intervention approaches to contribute to digital detox from the user's perspective.

1.3 Intervention Approaches

Researchers in the digital addiction intervention field tend to view complete abstinence from the internet as impractical. The primary objectives of prevention and intervention are to modify problematic internet usage patterns, aiming to foster healthy, controlled, and balanced digital usage patterns [55]. Digital technology plays a crucial role in facilitating digital detox. Mobile applications have proven to be effective self-help interventions in assisting individuals in regulating their digital usage [56]. Researchers and practitioners have developed digital detox tools to aid people in achieving digital detox and fostering digital well-being. Some studies have introduced new intervention approaches and conducted empirical research through laboratory experiments or field experiments to evaluate these methods [57]. Research employing nudge and operant conditioning techniques to address smartphone addiction has demonstrated effectiveness in reducing users' digital consumption. However, it's important to note that this reduction was not sustained after the intervention was removed [58, 59]. Both Apple and Google have introduced a set of features and applications aimed at reducing distractions and enhancing users' digital well-being [60]. Examples of these efforts include Digital detox [61] and MyTime [62].

Many studies explored intervention approaches utilized in existing tools through case studies, which analyzed and summarized the functional features and taxonomies based on current products designed to address digital addiction. An intervention app that aims to enhance self-regulation of smartphone use typically consists of three functional components: (1) self-monitoring to visualize objective usage and limiting behaviors, (2) goal-setting and usage limitation, and (3) social learning and competition by sharing limiting practices with others (which helps individuals become more aware of normative behaviors and motivates self-regulation) [44, 57, 63]. Persuasive design techniques have been applied to promote digital behaviors and are also used to combat digital addiction. A study analyzed notable features of applications employing persuasive intervention technology to assist users in reducing their Digital Addiction and identified four main categories of features based on interviews with participants and their feedback: monitoring, feedback, influencing actions, and situational awareness [34]. Researchers and practitioners have tried to improve digital well-being by implementing digital self-control tools (DSCT). Hundreds of DSCTs offer similar interventions, including blocking apps, hiding distracting website elements, tracking and visualizing use, and providing rewards or punishments for device usage. An analysis of 367 digital self-control tools by Lyng identified four common feature clusters: blocking/removal (hiding distracting website elements), self-tracking, goal advancement, and reward/punishment [64, 65]. In a survey of 41 smartphone intervention apps, these apps were categorized into four groups based on their purpose: (1) diagnosing smartphone addiction using smartphone addiction scales, (2) intervening in smartphone overuse, (3) supervising children's smartphone usage, and (4) assisting users in focusing on their current tasks [66]. A study analyzed notable features of applications that employ persuasive intervention technology to aid users to reduce their digital addiction. It concluded four main categories of features by interview participants and informative comments. The four categories are monitoring, feedback, influence actions, and situational awareness [67]. It is important to note that many intervention methods currently measure users' dependency on digital products primarily based on time. However, assessing addiction solely based on time without considering other factors is inaccurate [44, 66].

The design of successful digital well-being applications is expected to be grounded in established theories (especially behavior change theories) [68], for example, the Theory of Planned Behavior [69], the Technology Acceptance Model [70], and the Self-Determination Theory [71]. The Theory of Planned Behavior (TPB) recognizes behavioral beliefs that establish a connection between behavior and the expected outcome. These applications often allow users to set limits and goals as expected outcomes and track their progress. Recent research has applied TPB and revealed its suitability as a theoretical framework for designing and implementing programs aimed at reducing students' dependency on digital games [72]. The Technology Acceptance Model (TAM) suggests that if a user believes in the usefulness and ease of use of a technology, their attitude will be positive, and they are more likely to adopt the technology. All TAM variables in business, academic performance, and personal contexts have been found to positively predict tendencies toward smartphone use disorder [73, 74]. TAM is commonly used in mobile applications to predict digital addiction, such as automated measurement of digital time and time spent on applications [75, 76]. Self-Determination Theory (SDT) is a psychological framework focusing on human motivation and personality development. SDT posits that individuals have intrinsic psychological needs for autonomy (control over their actions), competence (effectiveness in interacting with the environment), and relatedness (connecting with and being valued by others). When these fundamental psychological needs are met, individuals are more likely to be intrinsically motivated, leading to personal growth and well-being. In the context of internet addiction, SDT functions with fundamental psychological needs serving as the primary driving force. Autonomy in controlling one's environment is considered a prerequisite, while external objectives act as accelerators. Ultimately, these factors can lead to negative experiences. Several studies have provided a detailed exploration of the application of SDT in digital addiction interventions and have found that programs based on SDT can be effective interventions [77, 78].

Evidence suggests that many individuals with internet-related issues have undergone various forms of intervention or treatment within psychological or medical institutions, with psychological-behavioral interventions being the most common [79]. Cognitive-Behavioral Therapy (CBT), and Multi-Family Group Therapy (MFGT) are among the prevalent and latest researched approaches. The primary intervention method for digital addiction is CBT, considered one of the most effective treatments for reducing internet usage and enhancing users' self-awareness [80]. CBT is rooted in a cognitive-behavioral model, which posits that cognition determines behavior and changing cognition is instrumental in altering behavior. Accordingly, interventions based on this model are extensively utilized in digital addiction treatment. CBT typically comprises three phases: Behavioral correction: This phase focuses on reducing usage time, with therapists helping patients establish schedules to mitigate pathological usage. Cognitive restructuring: This phase seeks to identify and reverse triggers for overuse and correct cognitive conditions driving individuals to excessive internet usage. Minimizing exposure to problematic content and operations: This phase aims to maintain recovery and prevent relapse [81]. Research has confirmed CBT's effectiveness in assisting with digital detox [82]. MFGT was employed to reduce adolescents' internet usage time, enhance their self-control, and improve parent-child relationships by altering family relations and interactions. The program primarily covers topics related to parent-child communication, parent-child relationships, and the fulfillment of psychological needs. Extensive research conducted by FANG et al. has confirmed its efficacy as an intervention method for digital detox [83].

While the theoretical methods of psychological-behavioral interventions mentioned above have been proven effective in addressing digital-related addiction, several issues persist. First, current treatment methods primarily rely on external medical or program interventions, making them relatively complex and necessitating prolonged guidance and operation by professionals. Second, existing intervention approaches tend to be tailored to individuals with internet addiction, and their intensity can be excessive. Research has demonstrated that the majority of digital users do not reach the level of addiction [23]. Therefore, these psychological and behavioral treatment methods may not be suitable for individuals with varying degrees of digital service dependence.

2. This Study

2.1 Research Scope

The previous literature review revealed that addiction detection using information technology is the most extensively researched area within the field of digital addiction research, with fewer studies dedicated to prevention and intervention efforts [84]. Likewise, existing literature has proposed numerous theoretical models focusing on the mechanisms and causes of digital addiction [12, 29-31]. Moreover, numerous studies have been dedicated to assisting in promoting sustained digital product usage[85-89]. However, there is a scarcity of research concerning the development and validation of theoretical models aimed at mitigating digital addiction or aiding in digital detox. The objective of this study is to propose intervention approaches and a theoretical model for alleviating digital addiction.

Digital media, as a contributing factor to addiction development, can also be harnessed to facilitate digital detox efforts. The software engineering community should actively engage in designing for conscious and informed technology usage, thereby assisting in the establishment of users' digital well-being. This study aims to identify software design methods that can aid users in their digital detox endeavors.

This paper begins by exploring individuals' subjective perceptions of addiction to understand the factors that influence their self-perception. The objective is to identify universal factors that can raise awareness of problematic behavior and help individuals refrain from digital dependence. After identifying the key factors, we will focus on the universal factor that can intervene in excessive behavior and propose a theoretical model that can efficiently support intervention and assist in digital detox.

2.2 Object of Study

An increasing number of studies suggest that it is not suitable to classify individuals demonstrating problematic digital usage as digital addicts. The majority of users may exhibit varying degrees of dependency or excessive use of digital products or content, but it may not reach the level of addiction, given that addiction is a term with clinical diagnostic significance [23]. Certain scholars emphasize the differentiation between digital overuse and digital addiction. M. Büchi and others propose that assessing overuse should be based on the user's subjective experience, defining perceiving digital overuse as the positive discrepancy between actual internet usage and anticipated internet usage [90]. M. Gui, has undertaken a conceptual evolution and empirical analysis of the perception of digital overuse, recognizing it as a prevalent social phenomenon [91]. Wu Meng and collaborators have argued that escalated smartphone usage among college students is predominantly influenced by group culture and identity. They posit that smartphone dependency among college students should not be stigmatized and emphasize the necessity of reevaluating young people's smartphone usage from the perspective of the "digital native" generation [92]. This perspective aligns with the basic premise of this paper. The present study targets the majority of users who exhibit varying degrees of digital dependence or overuse. For most users, perceiving their own excessive use of digital devices and endeavoring to mitigate this excessive usage is a more common situation. The goal of this paper is to assist these users in digital detox.

2.3 Research Framework

Individuals' subjective awareness of their addictive behavior is considered a critical factor in motivating behavior change [80-81]. Changes in individuals' cognition can lead to behavioral modifications. Therefore, this study initially delved into an investigation of factors influencing people's subjective perception of addiction. The aim was to identify elements affecting individuals' recognition of their inappropriate behavior. Subsequently, based on these elements, intervention methods were proposed to help individuals become more aware of their maladaptive behavior and, in turn, modify their actions.

In the results presented in Chapter 2, a universal factor influencing people's subjective perception of addiction, known as cognitive consistency (CC), was identified. The consistency between individuals' cognition of their behavior and their actual behavior plays a significant role in this regard. When these two factors are highly inconsistent, individuals are more likely to perceive their addiction and make behavioral changes, whereas consistency often makes it difficult for them to recognize the issue. In summary, this chapter concluded that cognitive consistency is a universal factor influencing individuals to recognize their problematic digital use.

In Chapter 3, we introduced a theoretical model designed to assist in reducing sustained digital use. Existing research has applied the Expectation Confirmation Theory (ECT) to continuous information system use, emphasizing the importance of perceived performance (PP) and expectation (EX) as two influential factors in determining people's continued use of information technology. This study posits that cognitive consistency (CC) is an essential complementary factor. We integrated CC with ECT's two elements, thus proposing a theoretical model consisting of three elements, PP, EX, and CC, to aid in mitigating excessive digital use. This model was subsequently empirically studied through a within-subject design experiment. In the experiment, PP, EX, and CC were independent variables; the effectiveness of each factor was verified, and a novel approach to digital addiction intervention was explored. Based on the research findings, we further discussed the impact and relationships among these three factors. In summary, this chapter developed a new theoretical model for digital addiction intervention.

Lastly, in Chapter 4, we provided an overview of the entire research study, summarized the theoretical contributions, and derived practical implications from the experimental results. Furthermore, we explored the limitations of this research and suggested future research directions based on the findings and limitations.

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Chapter 2

Digital Addiction Intervention Approaches Based on People's Subjective Perception and Definition of Addiction

Digital addiction received widespread concern but was poorly defined. Self-perceived addiction can aid users in refraining from addiction. People primarily perceive digital addiction subjectively rather than through its objective definitions. The research gap concerning people's subjective perceptions of digital addiction requires further exploration. This study determined how people subjectively perceive and define addiction based on behavioral and cognitive factors. A between-group experiment involving 109 participants from different countries was conducted to classify whether hypothetical individuals described in hypothetical questions were addicted. The findings reveal that thoughts-behavior inconsistency, such as regret, plays a crucial role in self-perception. People perceive digital behavior through its image, content, and impact rather than the medium itself. The study suggests potential interventions, such as presenting information that can trigger regretful emotions, reinforcing negative images of the behavior, indicating harmful content, or demonstrating adverse consequences in application designs, to prevent or abstain users from digital addiction.

1. Introduction

Addiction has been objectively defined in many studies. This term encompasses disorders related to the consumption of psychoactive substances and behaviors that yield rewards. It is a chronic condition characterized by repetitive engagement in rewarding behaviors, despite the persistence of harmful effects [1]. Noteworthy features of addiction include the experience of detrimental effects, continued engagement in specific behaviors, and impaired self-regulation [2, 3]. Addiction entails elements such as engaging in the behavior to achieve appetitive effects, becoming preoccupied with the behavior, experiencing temporary satisfaction, losing control, and enduring adverse consequences [4]. Griffiths (2005) clarified that all addictions have six common components: salience, mood modification, tolerance, withdrawal, conflict, and relapse [5]. Volkow (2016) delineated addiction into three recurring stages: binge and intoxication, withdrawal and negative effects, and preoccupation and cravings [3]. According to the ICD-11, disorders resulting from substance use or addictive behaviors are mental and behavioral disorders that arise from the consumption of psychoactive substances, including medications, or engaging in repetitive rewarding and reinforcing behaviors [6].

Digital addiction, characterized by obsessive and problematic usage of digital media, has received significant research attention. A consensual definition of digital addiction is yet to be established. It has been primarily studied in the context of smartphone addiction, social media addiction, and internet addiction [7]. People generally become addicted to the content rather than the smartphone itself. Users who engage with smartphones for social networking, gaming, and entertainment purposes are more prone to addiction, whereas those using them for study-related content are less susceptible [8, 9]. Design strategies play a crucial role in enhancing the user experience of digital products. However, certain design principles, such as persuasive techniques, can potentially trigger digital addiction [10]. It is crucial to research what design elements can help users avoid smartphone addiction.

Conventional research suggests that individuals who perceive themselves as being addicted are more motivated to overcome their addictive behaviors [11-13]. Individuals often rely on their subjective perception rather than objective definitions of addiction to determine whether they are experiencing addiction. However, addiction is predominantly defined and researched in an objective manner, with little attention paid to human subjective perceptions and affective evaluations for it. People may subjectively perceive spending five hours watching TikTok and five hours reading online news in contrasting ways. It is inappropriate to classify digital behaviors as addictive in general [14].

Conducting fundamental research on how individuals subjectively perceive and define addiction is crucial for understanding what cognitive factors can trigger self-awareness in those at risk of addiction or struggling with addiction, thereby enabling them to recognize their current situation and actively modify their behavior. In other words, gaining insights into people's affective understanding of addiction and translating these perceptual elements into designer suggestions to establish sentimental design elements that can evoke target emotions and perceptions, thereby applying these design elements to the product to encourage those potential users to make positive changes.

The current literature has reached a consensus regarding the presence of negative effects and adverse consequences as typical features of addiction. Health and social consequences (such as interpersonal problem) are negative effects associated with addiction [2-4]. Individuals struggling with addiction often experience intrapsychic conflicts characterized by inconsistency between their intentions and behaviors, and suffer a subjective loss of control in their desire to quit but inability to do so [5]. The intention-behavior inconsistency generally induces feelings of regret [15]. Conflict, and disruptions in decision-making are prominent features of addicts' behavior and experience [2, 3]. Regret is fundamental emotion in decision-making [15, 16]. It is defined as a negative emotion that implies a person acted at fault and experienced negative consequences resulting from the action. Upward counterfactual thoughts that evoke by negative outcomes make addicts regret their past decisions [16, 17]. Guilt feelings or regret can strengthen an individual's intention to discontinue the addictive behavior [11, 17, 18]. The majority of smokers consider a quit attempt as a necessary and sufficient condition for being able to quit [19]. Individuals with quit attempts are more inclined to change their behavior and overcome addiction [20].

Addictive behaviors are generally classified into substance and non-substance or behavioral addiction, both of which are characterized by the presence of negative consequences among addicts[1-4]. Regret and the intention to quit are commonly observed conflicting thoughts addicted people usually possess [5, 12, 15, 17, 18, 20]. Griffith and Larkin have suggested that a successful theory of addiction should account for the varying nature of addiction across cultures [5].

This is a fundamental research aimed at understanding how individuals subjectively perceive and define addiction and digital addiction under the influence of behavioral and mental factors (regret and quit intention). Moreover, it explored whether individuals' perceptions and affective understanding of addiction vary across cultures. This research draws forth a new path for digital addiction intervention approaches from human emotion or affective-cognitive point of view. Translating the results of fundamental research into sentimental design elements and applying them to the digital product design can help users built digital well-being.

2. Methods

2.1 Design

This study concerns how four variables influence people's subjective perception of addiction: behavioral types, thoughts of regrets, quit intention, and the cultural background of people in shaping perceptions and definitions of addiction.

A between-group design experiment was conducted with participants from Japan, China, and Western countries. The study manipulated three independent variables: type of behaviors, thoughts of regret, and quit intention. The independent variable of type of behavior consisted of a selection of 19 different behaviors, encompassing both substance and non-substance behaviors. Alongside digital behavior, the chosen behaviors were those in which individuals have the opportunity to indulge in, such as drugs and alcohol[21]. As shown in Table 2-1, the variable of regret was categorized into two levels: an individual regretted or did not regret having the behavior. Similarly, the variable of quit intention had two levels: an individuals wanted or did not want to stop the behavior. These two cognitive factors were combined to form four thought types, as presented in Table 2-1: the hypothetical person regrets and wants to stop the behavior (T1); the person regrets but does not want to stop the behavior (T2); the person does not regret but wants to stop their behavior (T3); and the person does not regret and does not want to stop their behavior (T4).

Table 2-1: The way to construct the 76 HQs

		4 Thought Types			
		Regret		Not Regret	
		Want to Stop	Not Want to Stop	Want to Stop	Not Want to Stop
		T1	T2	T3	T4
19 Behaviors	Behavior 1	B1+T1	B1+T2	B1+T3	B1+T4
	Behavior 2	B2+T1	B2+T2	B2+T3	B2+T4
	……	……	……	……	……
	Behavior 19	B19+T1	B19+T2	B19+T3	B19+T4

The research employed Hypothetical questions (HQ) which offer the advantages of being easy to administer and visualize. HQ replaces the need to find actual subjects in the target situation by inviting random participants to imagine a hypothetical person in that situation. This approach greatly mitigates the limitations associated with finding subjects and helps prevent self-reported bias [22]. We combined the different levels of the three independent variables to form HQ sentence (HQs). Each thought type was paired with each behavioral type once, resulting in the creation of 76 HQs to encompass all levels of independent variables. The structure of an HQs is as follows: a hypothetical person engaging in a specific behavior that led to negative consequences. This person regrets (or does not regret) for the behavior, and wants (or does not want) to stop the behavior. Referring to Figure 2-1, an instance of an HQs considering behavior of smoking and T1 is formulated as follows: A person who is a regular smoker experiences health damage from smoking. This person regrets having this behavior and wants to quit smoking.

Participants were assigned the task of determining whether the hypothetical person in each HQ was addicted or not. They were randomly presented with a set of HQs and asked to classify them into three categories: this person is in addiction (IA), this person is not in addiction (NIA), and not sure (NS). Subsequently, the researcher conducted semi-structured interviews with participants to gain insight into their classification and perceptions. The interviews investigated several key aspects: the basis and rationale for participants' classification, potential differences in their perceptions of digital behaviors (such as TikTok, Instagram, Netflix, or Online News) compared to other behaviors (such as Drugs, Alcohol, Chocolate, or Coffee), the influence of both behaviors and thought types on their perceptions, and the potential impact of cognitive factors (regret and quitting intention) on participants' perception.

To minimize cognitive fatigue and the learning effect resulting from repeatedly reading HQs with similar sentence structures, the 76 HQs were divided into three sets following specific rules, each consisting of approximately 26 sentences. The grouping rules for the HQs were as follows: each set should cover all 19 behaviors to capture participants' comprehensive perceptions of behaviors. Additionally, to examine the influence of cognitive factors (regret and quit intention) on people's perception, different thought types should be tested within the same behavior condition. Due to the limited number of HQs in each set (around 26), certain behaviors (not all) were arranged to be present in at least two thought types conditions within each HQs set. Furthermore, The number of HQs of each thought type should be kept evenly within and among the three sets.

The process of grouping 76 HQs with the aforementioned rules was as follows: all sentences were organized in a table format as displayed in Table 2-1, with 19 behaviors represented as columns and the 4 thought types represented as rows. Initially, the HQs were divided into four sets, with one sentence selected per row in a left-to-right and top-to-bottom order, resulting in 19 HQs per set. Subsequently, the 19 HQs from one set were allocated to the other three sets based on the previously described rules. Therefore, Each sentence set contained all 19 behaviors, with at least 6 behaviors described with more than 2 thought types. Each thought type was represented by approximately 6 HQs within each set. To introduce more randomness, the HQs were regrouped three times by rearranging the order of the rows (19 behaviors). In order to reduce the tediousness of reading sentences and enhance the participants' engagement, the HQs were visualized with illustrations, and a card-sorting game was employed instead of the conventional questionnaire format. Card sorting, as presented in el (c), involves a process similar to dealing cards in a poker game. Participants distribute a set of HQs cards into the aforementioned categories (IA, NIA, and NS) based on their subjective perception of the HQs.

2.2 Participants

A between-group design was employed in this study. The participants were an opportunistic sample of 109 individuals, including 31 Japanese, 45 Chinese, and 33 individuals from Western countries (15 American, 11 Australian, 7 Mexican). Western countries share similar cultural attributes [23]. Participants from multiple Western countries were recruited to form a representative Western group.

Each group of participants was composed of approximately 30% current undergraduate students, 60% postgraduate students, and 10% company employees who had graduated from university within the past two years. The Japanese group consisted of 17 males and 14 females, with 2 participants younger than twenty years old and 29 aged between twenty and thirty. The Chinese group comprised 20 males and 25 females, with 2 participants younger than twenty years old, 40 aged between twenty and thirty, and 3 aged between thirty-one and forty. The Western group included 18 males and 15 females, with 3 participants younger than twenty years old, 28 aged between twenty and thirty, and 2 aged between thirty-one and forty.

All participants volunteered to take part in the study, without pay, and remained naïve to the purpose and hypotheses of the research before completing the task and interview. As our research data neither included the personal information of participants nor any invasive research methods, the experiment did not require any certifications by the ethical committee of our institutions.

2.3 Materials

The materials comprised 79 cards and 1 interview sheet and were prepared in three languages: Japanese, Chinese, and English. Figure 2-1 provides a graphical representation of the materials employed for HQs card sorting. One set of cards consisted of 76 poker-sized HQs cards and 3 strip-shaped category title cards. The former featured a descriptive illustration printed above the corresponding sentence,

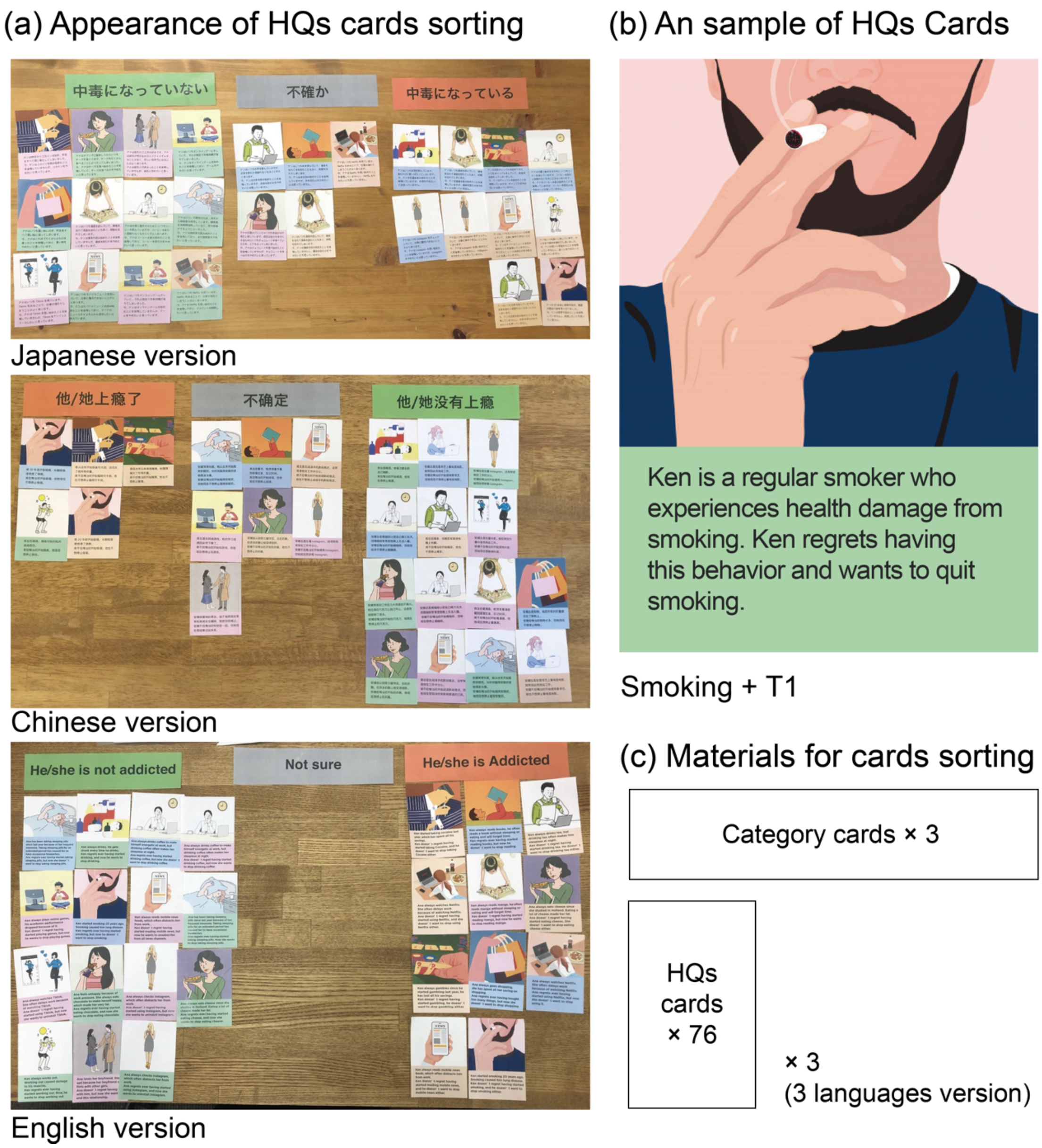

Figure 2-1: Material for HQs cards sorting

while the latter presented three categories (IA, NIA, and NS) separately. The translation of the materials was conducted while maintaining the semantic meaning unchanged. The translations were reviewed by native speakers of each of the three languages who were proficient in at least two of the three languages. Furthermore, the researcher, a native Chinese speaker, conducted interviews with the assistance of two translation assistants who were native speakers of Japanese and English and proficient in the other two languages.

2.4 Procedures

Participants completed the task individually in a quiet and undisturbed room. The survey commenced by providing participants with general information about the study. We introduced their assignment and interview arrangement and obtained their consent to record the interviews. Participants were informed that the general purpose of the study was to understand people's subjective perception of addiction. There were instructed that their task was to determine whether the person described in the HQs was in addiction, and that they needed to classify the HQs cards into three categories based on their subjective ideas. To ensure the reading sequence of the cards was randomized, the cards were shuffled before being assigned to participants. After completing the task individually, a semi-structured interview was conducted with each participant in the same room. All data were fully collected after the interview.

2.5 Measures

The dependent variable in the experiment was the frequency of the HQs being classified into each category. The number of participants differed in the three groups, and the frequencies of classifications for each HQs were also different. Therefore, we calculated the proportion of frequencies that each thought type’s HQs were classified into each category relative to the total frequencies that this thought type’s HQs were classified. Similarly, we calculated the proportion of frequencies that each behavior’s HQs were classified into each category relative to the total frequencies that this behavior’s HQs were classified.

The measurement encompassed quantitative and qualitative data. The SPSS Statistics (version 26) was used for the statistical analysis. All quantitative measures were treated as categorical variables. Chi-Square Tests were utilized to examine the effects of the 4 thought types and 19 behaviors on participants' perceptions of addiction. Pairwise comparisons were performed to assess significant differences among the three groups. Bonferroni-adjusted significance tests for pairwise comparisons were calculated, with alpha set at .05. For three comparisons, the LSD p-value required for significance would be .0167 [24].

3. Results

Quantitative data of participants' classifications for HQs cards were analyzed to examine the effects from two perspectives: thought types and behavioral types.

3.1 The Effect of Thought Types on People's Subjective Perception and Definition of Addiction

To compare the influence of thought types on subjective cognition of addiction, we analyzed and compared participants' classifications of HQs cards based on the four thought types. Additionally, we conducted interviews to explore the effects of thought types on their cognition and classification. The total number of HQs cards was 76, including sentences illustrated in the four thought types. Each thought type had 19 descriptions paired with 19 corresponding behaviors, respectively.

Sorting a card once was counted as one response. Among the 31 Japanese participants, a total of 1040 sorting responses were recorded, with the number of responses for the four thought types (from T1 to T4) being 267, 258, 250, and 265, respectively. For the 45 Chinese participants, a total of 1306 sorting responses were recorded, with the number of responses for the four thought types being 316, 323, 324, and 343, respectively. The Western group, consisting of 33 participants, yielded a total of 906 card sorting responses. The four thought types received 236, 220, 222, and 228 responses, respectively.

Table 2-2 presents the following information: the total number of classifications for each thought type's HQs in each group, the frequency of each thought type's HQs being categorized into each category, the proportion of each category's frequency within a thought type to the total number of classifications for that thought type's HQs, and the between-group differences. As shown in Figure 2-2 and Table 2-2, significant differences were observed between the Japanese group and the other two groups in the classifications for HQs of T2 and T4. No significant difference was found between the Chinese and Western groups.

The Japanese group sorted T2 cards 258 times, with 61.6% of the total classifications categorized as IA, which was significantly lower than the percentages of 76.2% and 77.7% in the Chinese and Western groups, respectively. Additionally, the Japanese group classified T4 cards 265 times, with 35.5% of the total classifications falling into the IA category. This proportion was significantly lower compared to the Chinese group's 75.5% and the Western group's 69.3% in the same category. Among the four thought types, T2 had the highest proportion of categorizations into the IA category in the Japanese group, while T4 had the lowest proportion in IA category.

Table 2-2: Chi-square results, count and % within thought types

Type of Thought	Category	Japanese Group (N=31)	Chinese Group (N=45)	Western Group (N=33)
		Count (% within the thought type)		
T1	IA	122 (45.7)^{a}	126 (39.9)^{a}	97 (41.1)^{a}
	NIA	107 (40.1)^{a}	131 (41.5)^{a}	110 (46.6)^{a}
	NS	38 (14.2)^{a}	59 (18.7)^{a}	29 (12.3)^{a}
	Total	267 (100.0)	316 (100.0)	236 (100.0)
T2	IA	159 (61.6)^{a}	246 (76.2)^{b}	171 (77.7)^{b}
	NIA	50 (19.4)^{a}	41 (12.7)^{b}	35 (15.9)^{ab}
	NS	49 (19.0)^{a}	36 (11.1)^{b}	14 (6.4)^{b}
	Total	258 (100.0)	323 (100.0)	220 (100.0)
T3	IA	90 (36.0)^{a}	107 (33.0)^{a}	85 (38.3)^{a}
	NIA	100 (40.0)^{a}	157 (48.5)^{b}	98 (44.1)^{ab}
	NS	60 (24.0)^{a}	60 (18.5)^{a}	39 (17.6)^{a}
	Total	250 (100.0)	324 (100.0)	222 (100.0)
T4	IA	94 (35.5)^{a}	259 (75.5)^{b}	158 (69.3)^{b}
	NIA	115 (43.4)^{a}	55 (16.0)^{b}	51 (22.4)^{b}
	NS	56 (21.1)^{a}	29 (8.5)^{b}	19 (8.3)^{b}
	Total	265 (100.0)	343 (100.0)	228 (100.0)

Note: superscripts ^{a,b} means scores with different superscripts were significantly different in the pairwise comparisons ($P < 0.0167$). The total number of card sorting times was 1040 in the Japanese group, 1306 in the Chinese group, and 906 in the Western group.

The interview results regarding participants' perceptions and affective ideas of regrets, quit intention, and thought types are summarized in Table 2-3. The table elucidates the disparate classification tendencies observed between the Japanese group and the other two groups. A primary concern for Japanese participants was the consistency between thoughts and behaviors. They tended to interpret inconsistencies as indicative of addiction, which subsequently caused cognitive dissonance that could drive individuals to modify their behavior in order to achieve thought-behavior consistency.

Regret and quitting intention were considered typical cases of thought-behavior inconsistency, indicating that individuals held a mental opposition to the behavior but still engaged in it. Therefore, Japanese participants tended to perceive individuals experiencing regretful emotion and expressing a desire to quit (T1) as being addicted. Those who classified individuals with T1 as NIA believed that they might eventually quit the behavior in order to achieve thought-behavior consistency. In contrast, most Japanese participants considered individuals with thoughts of T4 to be satisfied with their behavior, viewing the behavior merely as a hobby or interest. They emphasized the importance of respecting personal choices and refrained from making judgement about whether these individuals was addicted or not. T2 was predominantly categorized as addiction, with the highest percentage at 61.6%. The main explanation provided was that individuals with T2 thoughts experienced a dual conflict: conflict between thought

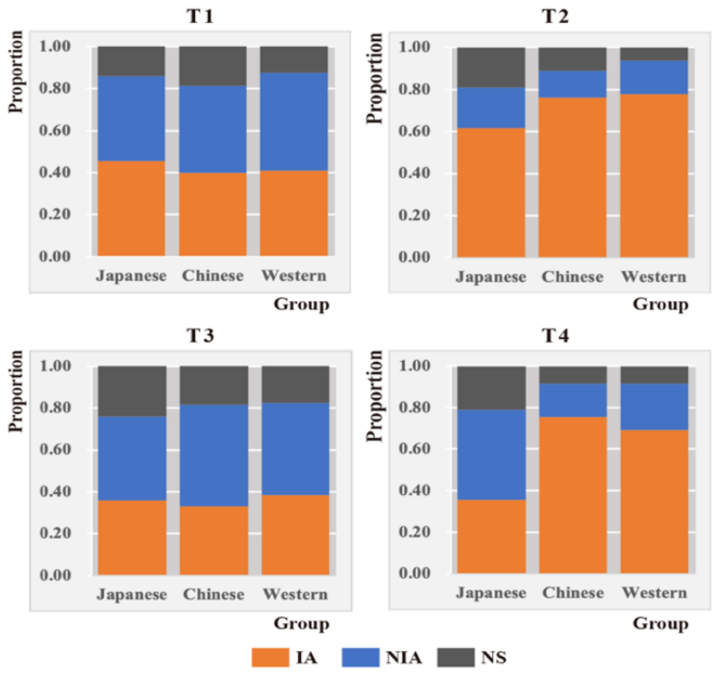

Figure 2-2: The proportion of categories within a group in each thought type

Table 2-3: Participants' responses on the impact of thoughts on their perception of addiction: number of participants who mentioned the item and the proportion of these people in the total number of participants within the group

Thoughts	Perceptions	Main explanations	Japanese (n=31)	Chinese (n=45)	Western (n=33)
			Count & % within group		
R	IA	• The person's thoughts and behavior are inconsistent. The inconsistent will cause cognitive • The person subjective disapproves of having the behavior. • A negative emotion. • People regret when the behavior causes irreversible adverse consequences.	24 (77.4)	5 (11.1)	4 (12.1)
NR	NIA	• The person's thoughts and behavior are consistent. • The person subjective approves of having the behavior. • The negative effect is so light that the person feels no regret.			
NR	IA	• The person lacks self-awareness and the ability to judge good from bad.	4 (12.9)	20 (44.4)	14 (42.4)
R	NIA	• The person is self-awareness and realizes the harm of the behavior. • A precondition and positive signal of recovery.			
WTS	IA	• The person's thoughts and behavior are inconsistent. • The person disapproves of his or her behavior.	19 (61.3)	2 (4.4)	2 (6.1)
NWTS	NIA	• The person's thoughts and behavior are consistent. • The person approves of his or her behavior. • It remains the possibility to stop the behavior if the person wants to.			
NWTS	IA	• The person does not want to stop the behavior because he or she cannot stop. • The person violates knowingly. He/she clings to the mistake instead of correcting it. • The adverse effects continue if the person unwills to stop.	6 (19.4)	34 (75.6)	23 (69.7)
WTS	NIA	• A precondition and positive signal of recovery. • The person has self-awareness and the ability to self-control.			
T1	IA	• The person's thoughts and behavior are inconsistent. • The person disapproves of having the behavior. • Regret means that the harm of the behavior is severe and irreversible; Want To Stop indicates that the harm is continuing.	19 (61.3)	6 (13.3)	7 (21.2)
	NIA	• Both thoughts are preconditions and positive signals for recovery. • Regret means that the person is self-reflective; Want To Stop indicates that the person is preparing to stop the behavior.	9 (29.0)	23 (51.1)	18 (54.5)
T2	IA	• The person faces double conflicts: the conflict between two thoughts (Regret, but Not Want To Stop), the conflict between thought and behavior (Regret, ongoing Behavior). • The person clings to the wrong behavior with awareness of adverse consequences. • The person is unable to stop.	24 (77.4)	33 (73.3)	23 (69.7)
T3	IA	• A part of the person's thoughts (Want To Stop) is inconsistent with the ongoing behavior, which means the person disapproves of having the behavior.	11 (35.5)	3 (6.7)	2 (6.1)
	NIA	• The person is self-awareness and wants to quit before the adverse effect gets severe. • The person wants to stop the behavior even if the adverse effects of the behavior are not severe (because he/she feels no regret).	9 (29.0)	25 (55.6)	16 (48.5)
T4	IA	• The person is too mentally numb, incurable, and impenitent to reflect themself. • The behavior and the adverse effects of the behavior will continue.	9 (29.0)	33 (73.3)	21 (63.6)
	NIA	• The person's thoughts are consistent with the ongoing behavior. • The behavior is the person's choice and interest.	18 (58.1)	6 (13.3)	3 (9.1)
Considered and assessed the thought of whether the person regrets their behavior.			29 (93.5)	25 (55.6)	18(54.5)
Considered and assessed the thought of whether the person wants to stop the behavior.			25 (80.6)	36 (80.0)	23 (69.7)
Considered and assessed the person's type of thoughts concerning the behavior.			30 (93.5)	36 (80.0)	25 (75.8)

Note: R: regret having the behavior; NR: not regret having the behavior; WTS: want to stop the behavior; NWTS: not want to stop the behavior.

and behavior (i.e., regretting the behavior but continuing to engage in it) and conflict between the two thoughts (i.e., regretting the behavior but not wanting to stop it). Conversely, T3 was classified as addiction due to the inconsistency between the desire to quit and the ongoing behavior. However, those who held the opposite classification argued that the intention to quit would ultimately lead to discontinuation in reality.

The Chinese and Western participants held similar views, with little emphasis on thought-behavior consistency. 20 (44.4%) of Chinese participants and 14 (42.4%) of Western participants believed that regret serve as the premise and sign of behavior correction. Likewise, most of them believed that having a desire to quit is a positive indication that an addict can stop the behavior, while not having a desire to quit is a negative sign suggested that individuals unwilling or unable to do so. T2 had the highest rate of addiction classification among the four thought types in both the Chinese and Western groups. The main explanation for this tendency was that individuals with T2 refused to correct their behavior despite being aware of its irreversible adverse effects. T4 was also frequently classified as IA, with rates of 75.5% and 69.3% in the Chinese and Western groups, respectively, ranking second to T2. This tendency stemmed from the belief that individuals with T4 were mentally numb, incurable, and unrepentant. The majority of Chinese and Western participants did not consider individuals with T1 thoughts as being addicted because the presence of regret and the desire to quit indicated the possibility of actually stopping the behavior. T3 had the lowest rate of addiction classification in both groups, at 33.0% and 38.3%, respectively. Participants assumed that individuals with T3 could stop the behavior if they were willing to do so.

3.2 The Effect of Behavioral Types on People's Subjective Perception and Definition of Addiction

Participants generally took into account both behavioral types and thoughts, but 1 Japanese, 9 Chinese, and 8 Western participants reported considering only the behavioral aspect and barely noticing the person's thoughts. To compare the influence of behavioral types on subjective cognition of addiction, we analyzed and compared participants' classifications for HQs cards based on 19 behaviors, as shown in Table 2-4. The interview results explaining the classification tendencies are summarized in Table 2-5. Table 2-4 provides the following information: the total number of times HQs of each behavior were sorted in each group, the frequency of each behavior's HQs being

Table 2-4: Chi-square results, count and % of behaviors

Behavior	Categories	Japanese (N=31)	Chinese (N=45)	Western (N=33)
		Count (% within a behavior)		
Sleeping pills	IA	26 (50.0)^{a}	42 (63.6)^{a}	27(57.4)^{a}
	NIA	16 (30.8)^{a}	14 (21.2)^{a}	16 (34.0)^{a}
	NS	10 (19.2)^{a}	10 (15.2)^{a}	4 (8.5)^{a}
	Total	52 (100.0)	66 (100.0)	47 (100.0)
Cocaine	IA	42 (77.8)^{a}	67 (89.3)^{a}	35 (79.5)^{a}
	NIA	6 (11.1)^{a}	3 (4.0)^{a}	5 (11.4)^{a}
	NS	6 (11.1)^{a}	5 (6.7)^{a}	4 (9.1)^{a}
	Total	54 (100.0)	71 (100.0)	44 (100.0)
Alcohol	IA	36 (69.2)^{a}	43 (66.2)^{a}	38 (77.6)^{a}
	NIA	11 (21.2)^{a}	15 (23.1)^{a}	6 (12.2)^{a}
	NS	5 (9.6)^{a}	7 (10.8)^{a}	5 (10.2)^{a}
	Total	52 (100.0)	65 (100.0)	49 (100.0)
Smoking	**IA**	**33 (63.5)^{a}**	**58 (85.3)^{b}**	**39 (83.0)^{b}**
	NIA	**11 (21.2)^{a}**	**4 (5.9)^{b}**	**2 (4.3)^{b}**
	NS	**8 (15.4)^{a}**	**6 (8.8)^{a}**	**6 (12.8)^{a}**
	Total	**52 (100.0)**	**68 (100.0)**	**47 (100.0)**
Online Game	**IA**	**23 (43.4)^{a}**	**56 (78. 9)^{b}**	**25 (56.8)^{a}**
	NIA	**16 (30.2)^{a}**	**10 (14.1)^{b}**	**12 (27.3)$^{a, b}$**
	NS	**14 (26.4)^{a}**	**5 (7.0)^{b}**	**7 (15.9)$^{a, b}$**
	Total	**53 (100.0)**	**71 (100.0)**	**44 (100.0)**
Online Newsfeed	IA	22 (39.3)^{a}	20 (29.0)^{a}	17 (36.2)^{a}
	NIA	24 (42.9)^{a}	38 (55.1)^{a}	24 (51.1)^{a}
	NS	10 (17.9)^{a}	11 (15.9)^{a}	6 (12.8)^{a}
	Total	56 (100.0)	69 (100.0)	47 (100.0)
Chocolate	IA	24 (42.9)^{a}	32 (48.5)^{a}	28 (57.1)^{a}
	NIA	18 (32.1)^{a}	26 (39.4)^{a}	19 (38.8)^{a}
	NS	14 (25.0)^{a}	8 (12.1)$^{a, b}$	4 (8.2)^{b}
	Total	56 (100.0)	66 (100.0)	49 (100.0)
Cheese	IA	16 (30.2)^{a}	31 (47.0)^{a}	16 (34.0)^{a}
	NIA	28 (52.8)^{a}	22 (33.3)^{b}	21 (44.7)$^{a, b}$
	NS	9 (17.0)^{a}	13 (19.7)^{a}	9 (19.1)^{a}
	Total	53 (100.0)	66 (100.0)	47 (100.0)
Coffee	**IA**	**20 (33.9)^{a}**	**38 (56.7)^{b}**	**30 (63.8)^{b}**
	NIA	**26 (44.1)^{a}**	**23 (34.3)^{a}**	**15 (31.9)^{a}**
	NS	**13 (22.0)^{a}**	**6 (9.0)^{b}**	**2 (4.3)^{b}**
	Total	**59 (100.0)**	**67 (100.0)**	**47 (100.0)**
	NIA	**16 (26.8)^{a}**	**28 (33.3)^{a}**	**16 (29.6)^{a}**
	NS	**15 (26.8)^{a}**	**13 (15.5)^{a}**	**9 (16.7)^{a}**
	Total	**56 (100.0)**	**84 (100.0)**	**54 (100.0)**

Behavior	Categories	Japanese (N=31)	Chinese (N=45)	Western (N=33)
		Count (% within a behavior)		
Tea	IA	21 (34.4)a	31 (50.8)a, b	26 (53.1)b
	NIA	26 (42.6)a	24 (39.3)a	17 (34.7)a
	NS	14 (23.0)a	6 (9.8)a	6 (12.2)a
	Total	61 (100.0)	61 (100.0)	49 (100.0)
Book	IA	13 (27.1)a	29 (40.3)a, b	24 (53.3)b
	NIA	25 (52.1)a	27 (37.5)a, b	14 (31.1)b
	NS	10 (20.8)a	16 (22.2)a	7 (15.6)a
	Total	48 (100.0)	72 (100.0)	45 (100.0)
Manga	IA	24 (43.6)a	42 (56.8)a, b	29 (67.4)b
	NIA	17 (30.9)a	23 (31.1)a	10 (23.3)a
	NS	14 (25.5)a	8 (10.8)b	4 (9.3)b
	Total	55 (100.0)	74 (100.0)	43 (100.0)
Working out	**IA**	**9 (16.7)a**	**17 (28.3)a**	**23 (47.9)b**
	NIA	**35 (64.8)a**	**30 (50.0)a**	**23 (47.9)a**
	NS	**10 (18.5)a**	**13 (21.7)a**	**22 (4.2)b**
	Total	**54 (100.0)**	**60 (100.0)**	**48 (100.0)**
Gambling	IA	33 (64.7)a	57 (81.4)b	33 (73.3)a, b
	NIA	9 (17.6)a	6 (8.6)a	8 (17.8)a
	NS	9 (17.6)a	7 (10.0)a	4 (8.9)a
	Total	51 (100.0)	70 (100.0)	45 (100.0)
Shopping	IA	26 (48.1)a	34 (53.1)a	25 (52.1)a
	NIA	16 (29.6)a	15 (23.4)a	15 (31.3)a
	NS	12 (22.2)a	15 (23.4)a	8 (16.7)a
	Total	54 (100.0)	64 (100.0)	48 (100.0)
Relationship	**IA**	**14 (24.1)a**	**22 (34.9)a**	**9 (18.4)a**
	NIA	**33 (56.9)a**	**25 (39.7)a**	**38 (77.6)b**
	NS	**11 (19.0)a**	**16 (25.4)a**	**2 (4.1)b**
	Total	**58 (100.0)**	**63 (100.0)**	**49 (100.0)**
Instagram	IA	30 (53.6)a	33 (47.8)a	23 (48.9)a
	NIA	18 (32.1)a	27 (39.1)a	18 (38.3)a
	NS	8 (14.3)a	9 (13.0)a	6 (12.8)a
	Total	56 (100.0)	69 (100.0)	47 (100.0)
TikTok	IA	28 (46.7)a	43 (55.8)a	35 (62.5)a
	NIA	21 (35.0)a	24 (31.2)a	15 (26.8)a
	NS	11 (18.3)a	10 (13.0)a	6 (10.7)a
	Total	60 (100.0)	77 (100.0)	56 (100.0)
Netflix	IA	25 (44.6)a	43 (51.2)a	29 (53.7)a
	NIA	16 (26.8)a	28 (33.3)a	16 (29.6)a
	NS	15 (26.8)a	13 (15.5)a	9 (16.7)a
	Total	56 (100.0)	84 (100.0)	54 (100.0)

Note: superscripts a,b means scores with different superscripts were significantly different in the pairwise comparisons (P < 0.0167).

categorized into each category, the proportion of each category's frequency to the total number of times each behavior's sentences were classified within each group, and the between-group differences.

Participants do not have different criteria for perceiving digital behavior compared to other behaviors. However, digital behaviors were less to be perceived as addiction compared to behaviors that are commonly associated with addiction, such as substance use. Significant differences between groups were observed in the behaviors of Smoking, Online Games, Coffee, Working Out, and Relationships, as depicted in Figure 2-3. The proportion of IA in behaviors of Smoking and Coffee was significantly lower in the Japanese group compared to the other two groups. Additionally, the proportion of Chinese participants categorizing HQs of Online Games as IA was significantly higher than that of the Japanese and Western groups. Similarly, the proportion of IA in behaviors of Working Out in the western group was significantly higher than that in the Chinese and Japanese groups. However, Romantic Relationships had a lower proportion in the IA category in the Western group compared to the Chinese and Japanese groups. The main explanations for these classification trends can be found in Table 2-5.

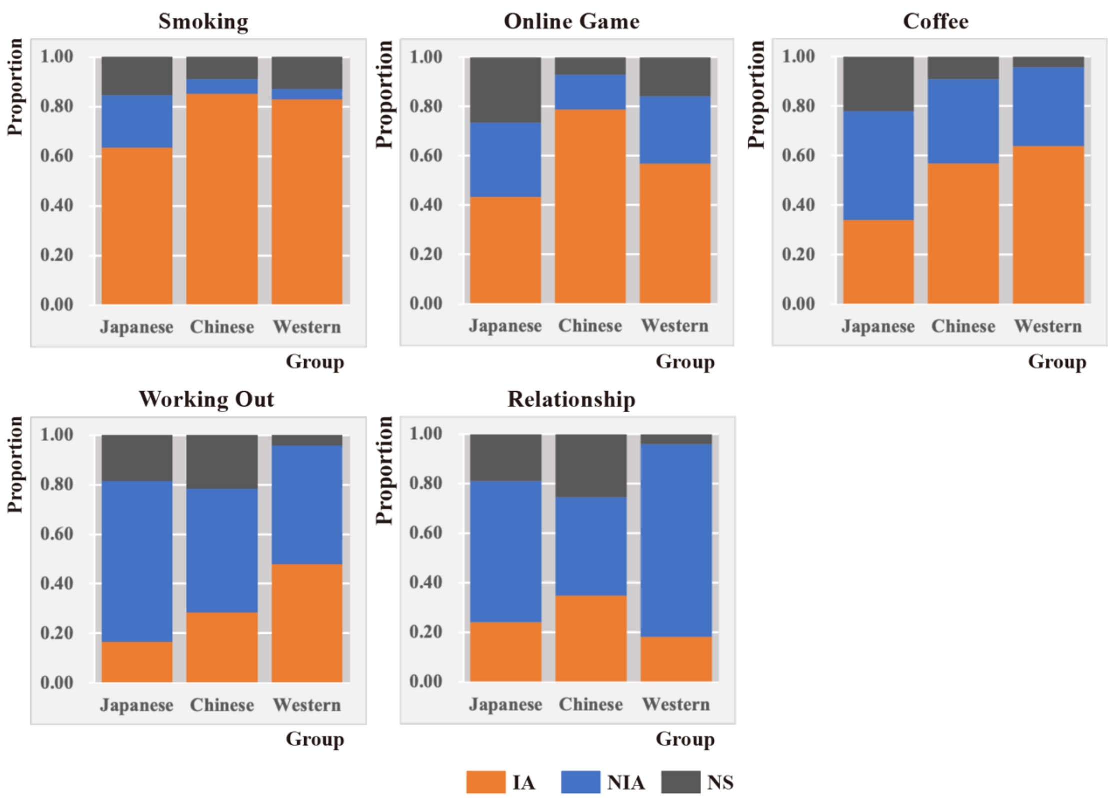

Figure 2-3: Proportion of significant group differences in behavior categories

Table 2-5: Participants' responses on the impact of behavioral types on their perception of addiction: number of participants who mentioned the item and the proportion of these people in the total number of participants within the group

View on behaviors	Perceptions	Main explanations	Japanese (n=31)	Chinese (n=45)	Western (n=33)
			Count & % within the group		
Social image	IA	The behavior has a negative social image: illegal, with high social warning and social attention.	2 (6.5)	18 (40.0)	0
	NIA	The behavior has a Positive social image: advocated behavior, Prevalent and conventional behavior.			
Subjective Impressions	IA	The individual has an inherent impression that the behavior is addictive.	9 (29.0)	14 (31.1)	23 (69.7)
	NIA	The individual has an inherent impression that the behavior is positive or unrelated to addiction.			
Content	IA	Physiological Dependence: The content of the behavior contains addictive components leading to uncontrollable physical dependence (eg. substance use).	16 (51.6)	34 (75.6)	28 (84.8)
		Psychological Dependence: The content of the behavior leading to uncontrollable psychological dependence (eg. gambling producing dopamine).	9 (29.0)	16 (35.6)	10 (30.3)
	NIA	The behavior is self-controllable, and the content of the behavior is positive.	12 (32.3)	25 (55.6)	19 (57.6)
Negative impact on oneself	IA	The behavior caused physical harm.	15 (48.4)	27 (60.0)	23 (69.7)
		The behavior caused psychological harm.	4 (12.9)	11 (24.4)	12 (36.4)
		The behavior resulted in improper monetary loss.	7 (22.6)	17 (37.8)	19 (57.6)
		The behavior negatively affects the person's studies or work.	8 (25.8)	15 (33.3)	4 (12.1)
	NIA	The impact of behavior on oneself is positive or the positive outweighs the negative, or the negative impact is innocuous.	15 (48.4)	27 (60.0)	23 (69.7)
Negative impact on others	IA	The behavior or the harm caused by the behavior negatively affects others or causes trouble to others.	12 (38.7)	0	0
	NIA	The behavior does not cause distress to others and only slightly affects oneself.			

Note: R: regret having the behavior; NR: not regret having the behavior; WTS: want to stop the behavior; NWTS: not want to stop the behavior.

The social image of the behavior had the most significant influence on the perception of Chinese participants compared to the other two groups. Chinese participants tended to perceive illegal behaviors or behavior with a high degree of social warning or attention as addiction. In contrast, the Japanese group had fewer participants mentioning the social image of behaviors, and Western participants made little comment on it. Chinese participants who took the social image into account generally viewed Drugs, Gambling, Smoking, or Online Game as illegal or socially unacceptable behavior. They believe that behaviors with a negative social image needed to be corrected. HQs of Online Games were frequently classified as IA because Chinese participants considered Online Games as a severe and widely discussed social issue in China. Conversely, Japanese participants held the opposite viewpoint and classification for Online Games, perceiving it as a common behavior or cultural phenomenon. This led to the Japanese group categorizing HQs related to this behavior as IA in the lowest proportion among the three groups. A similar explanation can be applied to the high proportion of IA classification for Smoking in the Chinese group. Although there were no statistical differences among the three groups in categorizing Cocaine use and Gambling, the Chinese group had a higher proportion of categorizing them as addiction compared to the other two groups.

Western participants tended to assess someone's behavior and thoughts based on their subjective impressions and views. 29.0% of Japanese and 31.1% of Chinese participants mentioned that they referred to their subjective impression of the behavior. In comparison, the Western group had 69.7% of participants mentioning that their subjective impression of the behavior heavily influenced their perception. This explains why few Western participants categorized Romantic Relationships as addiction since most of them believed this behavior was unrelated to addiction.

We found that 51.6%, 75.6%, and 84.8% of Japanese, Chinese, and Western participants, respectively, believed that a person is considered addicted if their behavior leads to uncontrollable physiological dependence. They often associated behaviors such as Cocaine use, Smoking, Alcohol consumption, and Sleeping Pill use with physical dependence. Additionally, 29.0%, 35.6%, and 30.3% of participants in each group, respectively, considered behaviors that result in uncontrollable psychological dependence as addictions, with Gambling being frequently mentioned. Consequently, behaviors such as Sleeping Pill use, Cocaine use, Alcohol consumption, Smoking, and Gambling had proportions of IA classification exceeding 50% in all three groups.

Participants generally held a positive impression of self-controllable behaviors or behaviors with positive content and effects. This indirectly explained why the proportions of IA classification for behaviors such as Online Newsfeed use, Cheese consumption, Working Out, and Romantic Relationships were below 50% in all groups.

Participants generally expressed objections to behaviors that caused adverse effects on the individual engaging in the behavior. Japanese participants particularly emphasized the consideration of whether a behavior caused trouble for others. In fact, 38.7% of Japanese participants highlighted the importance of valuing the feelings of others and strongly opposed causing trouble for them. They tended to believe that individuals whose behaviors did not cause trouble for others and only minimally affected themselves were not addicted.

4. Discussion

Digital Addiction is an emerging widespread concern that denotes obsessive or problematic digital media usage. The definition of determining a digital behavior as addictive is unclear. Conventional studies found that self-perceived addiction helps addicts abstain from addiction [11-13]. People generally perceive addiction based on their subjective views rather than relying on objective definitions of addiction. Understanding people's subjective perceptions and affective definitions of digital addiction is crucial for helping digital users to be self-aware and keep away from addiction. Previous research has predominantly focused on studying addiction from objective viewpoints, which remains a research gap regarding people's subjective views of addiction and digital addiction that needs to be addressed by researchers.

The present study investigated how people perceive and define addiction (and digital addiction) under the effect of behavioral and thoughts types. The research explored whether people perceive digital addiction differently from addiction in general, and whether the perceptions and definitions vary across cultures. A between-group experiment was conducted with participants from Japan, China, and Western countries. Participants were presented with HQs in which the independent variables of behavioral and thought types were manipulated. They were asked to classify HQs cards into one of three categories (IA, NIA, and NS).

This study reveals that the behavior's image, content, and impact, along with an individual's thoughts about their behavior, influenced people's subjective perceptions.

The influence of these factors varies across cultures. The behavioral aspects primarily influenced participants who had a clear impression of the behavior, while the engaged person's thoughts more influenced those with a neutral or ambiguous impression of the behavior. People barely had different criteria for perceiving digital behaviors. However, digital behaviors were perceived as less addictive than behaviors with higher susceptibility to addiction, such as substance use or gambling.

The Japanese participants in this study placed significant emphasis on thoughts-behavior consistency. They believed that consistency indicated personal approval of the behavior, while inconsistency indicated the presence of addiction-related risks. They also noted that thought-behavior inconsistency can lead to cognitive dissonances, which motivate individuals to change their behavior to achieve consistency. This idea aligns with suggestions that individuals experiencing cognitive dissonance due to addiction are inclined to discontinue the behavior to alleviate unpleasant feelings [18]. Regret and intentions to quit demonstrate thoughts-behavior inconsistency in their perspective. Meanwhile, Chinese and Western participants tended to believe that regret triggers the intention to quit. They thought individuals who experienced regret or had intentions to quit were likelier to cease or modify their behavior. Conventional studies also supported that regrets serve as an emotional motivation for individuals to develop intentions to quit and ultimately discontinue the behavior [11, 17, 19, 20]. Although there were variations in the categorized tendencies among different cultures, participants shared the common belief that experiencing regretful emotions and having the intention to quit are conducive to overcoming addiction.

The design solutions for eliciting thought-behavior inconsistencies or cognitive dissonance by evoking the conflict thought of regret in users can enhance self-awareness and deter indulgence. Various emerging digital products have been developed to help users reduce excessive digital usage in response to the advocacy of digital well-being. Examples include self-control applications created by Apple and Google, which functioned in periods of planned abstinence and post-review of phone-use data. The findings suggest the need to reconsider information presentation. One feasible approach is to visualize time in a manner that can induce feelings of regret or personal reflection rather than ordinary time representations.

The image, content, and impact of behavior were found to have influences on people's subjective perceptions. However, the importance placed on these factors of behaviors may vary across cultures. People perceive behaviors with content that makes users unable to self-control or is detrimental to their status quo or personal growth as addiction. Reading digital news or books was considered a self-improvement activity, while spending time on watching short videos or social media was seen as time-consuming behavior. By incorporating design traits that address the fear of being controlled by digital products, users can be aware of the potential risks of the behavior and maintain a healthy digital usage.

Chinese stressed the social image and public acceptance of the behavior. Addressing negative social images associated with specific online behaviors can be beneficial in preventing excessive digital use among Chinese individuals.

People generally care about the negative impact of the behavior on the users. Japanese participants pay extra attention to the impact on other people. This inclination aligns with their preference in considering thought types. It gives us a glance at a trait that Japanese people are averse to causing trouble to others, and they value the thoughts and experiences of other people. An example of utilizing negative consequences to promote self-awareness is using graphic images depicting smokers' physical injuries on cigarette packaging. Time management or self-control applications are commonly employed to help individuals reduce their digital media usage. Demonstrating the adverse consequences of excessive digital use places a practical approach to awaken users to modify their inappropriate online behavior. Noting the negative impact on others is particularly effective for Japanese users. Giving prominence to the potential side effects of online behaviors on others can encourage Japanese users to adopt more responsible and mindful digital practices.

Japanese individuals value subjective thoughts and experiences of others. Chinese individuals not only consult their subjective views but also pay close attention to social regulations and public acceptance of the behavior. Western individuals tend to prioritize their subjective views. The findings imply the distinction between individualistic and collectivist cultures. Asian countries are generally categorized as collectivist societies, while Western countries are characterized as individualistic. Collectivist cultures prioritize collective interests over individual interests and place importance on the opinions of others. In contrast, individualistic cultures promote independent thinking and value individual perspectives [23]. Therefore, a one-size-fits-all definition to explain how people subjectively perceive addiction does not exist. Tailored approaches to addiction intervention are necessary for individuals from different cultural backgrounds.

To develop a user-assistance system, incorporating functions and designs to visualize negative aspects (image, content, and impact) of problematic smartphone usage and identifying inconsistencies between users' thoughts and behaviors can evoke users' subjective perceptions of excessive smartphone use or addiction. Negative images can be represented by negatively portraying smartphone overuse through elements like alarming colors (e.g., red), icons, or sounds. The system tailored to Chinese users can showcase the adverse social evaluations and official endorsements associated with excessive smartphone usage, such as employing visual patterns (e.g., pyramid-shaped) symbolizing the position of the behavior at the bottom of social acceptance or presenting positive role models who adhere to social consensus. To help users become aware that the content of smartphone use is causing a loss of self-control, a strategy such as renaming "screen time" as "the time I let my phone control me" can evoke emotional responses. It helps users perceive that during this period, the device controls them rather than the other way around. To illustrate the negative impact of overuse, the system can visualize physical harm, such as the degree of deterioration in visual acuity, damage to posture, or harm to beauty and appearance, caused by accumulated mobile phone usage time. For systems designed for Japanese users, the adverse consequences brought to others can raise their awareness. For instance, using interactions between virtual characters to depict issues (e.g., delays) arising from the user's excessive smartphone usage in collaborative teamwork. Furthermore, building upon these applications, the system design can illuminate users' thought-behavior inconsistencies, eliciting feelings of regret. This may involve visualizing the incongruity or gap between their initial intentions and subsequent actions or highlighting the disparity between behavioral attributes (e.g., purely entertainment-oriented) and their cognitive aspirations (e.g., self-improvement). In summary, these strategies collectively empower users to subjectively recognize their smartphone addiction and subsequently initiate corrective actions.

The findings of this research extend the current knowledge on people’s perceptual and affective comprehension of addiction. To apply the fundamental research results, we can translate the affective factors of people’s perceptions of addiction into physical traits or design elements that can be applied to the product. By applying these elements to the digital product design, the user experience can evoke the intended emotions in users, leading to increased self-awareness and reduced excessive digital media usage, thereby contributing to the development of digital well-being.

The study has some limitations that need to be addressed. Firstly, considering the constraints of the research conditions, the external validity of the research findings is limited because the participants predominantly included students aged between 20 and 30, and the relatively small sample size. The limited sample size and specific participant features restrict the generalization of the findings to broader populations. To enhance the external validity of future research, it is necessary to increase the sample size and incorporate participants with diverse attributes. Secondly, during the pandemic period, conducting face-to-face experiments and interviews presented challenges in recruiting an adequate number of participants from the same Western country. Considering the similar culture shared among Western countries, participants from multiple Western countries were formed a representative group. However, cultural differences exist among countries, and further distinction and comparison among people from different Western countries should be pursued. Furthermore, the study employed the third-person perspective in constructing hypothetical scenarios. This approach was adopted to overcome the difficulty of finding individuals fitting the specific situation described in the HQs and to mitigate self-report bias associated with using the first-person perspective. However, People may subconsciously perceive and portray themselves differently compared to how they do for others. Therefore, conducting additional experiments from a first-person perspective can provide a more comprehensive understanding of how individuals subjectively perceive addiction. Additionally, the research utilized chi-square to analyze data, with the independent variable levels were qualitatively assigned as categorical variables (IA, NIA, and NS). Categorical variables with three levels offer less detailed compared to using a scale. To obtain elaborate data and information, the design of variables will be optimized in future experiments. Overall, these limitations highlight areas for improvement in future research.

5. Conclusion

Regret is a widely recognized thought that can prompt behavioral modification. Design solutions that arouse self-reflection and regret emotions in users who are indulged in digital behaviors can help them become self-aware and develop the will to quit. Negative images, harmful content, and adverse consequences of the behavior offer various paths for awakening individuals' self-awareness of problematic digital use. Social consensus greatly influences Chinese individuals' awareness. Bringing trouble for others makes Japanese individuals being caution about their behavior. Subjective perceptions dominate Westerners' ideas. The effectiveness of utilizing the factors of the findings might be expected to vary across cultures. Harnessing the aforementioned factors lives conceivable footpaths for our follow-up research. In our future research, we will address the remaining issues from this study. On the other hand, we will develop theoretical hypotheses and design methods that can assist digital users in overcoming addiction based on the findings of this research.

Expansion of Design Fields Based on The Trends in Design Award

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Chapter 3

A Theoretical Model for Addressing Excessive Smartphone Use: The Interventions Concerning Perceived Performance, Expectation, and Cognitive Consistency

Drawing upon the findings from Chapter 3, cognitive consistency emerges as an essential factor influencing individuals' subjective identification of addiction. Individuals experiencing cognitive inconsistency are more inclined to self-perceive addiction, subsequently facilitating their detoxification process. The excessive use of smartphones has become a pervasive concern in contemporary society, with escalating implications for individuals' well-being. Despite ongoing exploration of interventions to address this issue, a comprehensive theoretical framework is still needed to guide these efforts. This study endeavors to address this gap by introducing a theoretical model that centers on the interplay of Perceived Performance (PP), Expectation (EX), and Cognitive Consistency (CC) and their influence on users' discontinuance of excessive smartphone use. A within-subject design experiment was conducted, involving 72 participants, to examine the efficacy of different interventions proposed within the model. The study explored how the adjustment of the three quadrants formed by PP, EX, and CC influences users' likelihood of discontinuing smartphone use. The findings confirm the model's effectiveness in addressing continuous smartphone use under controlled experimental conditions. The results indicate that applying PP should involve extending the intervention duration beyond the threshold that prompts users to shift their behavioral intentions toward discontinuation. The study revealed a disparity in the relation between EX and behavior discontinuation compared to the hypothetical model. This suggests that strategies for regulating EX are intricate and cannot be simplified as a unidirectional axis. Regulating EX can be accomplished through methods such as elevating or erasing expectations, or setting goals. When adjusting CC, it is essential to provide users with adequate cognitive space and response time. In addition to verifying the static relationship between PP and EX, this study confirmed their dynamic interactions. PP, EX, and CC operate within a framework of mutual influence and support. These findings unveil potential pathways for more in-depth research into the interrelationships and path analyses among these factors. In essence, this study provides a theoretical foundation and novel perspectives for product design aimed at assisting users in reducing excessive smartphone usage, thereby addressing a pressing issue in our digital age.

1. Introduction

Smartphones are now considered an indispensable part of contemporary life. Given their relevance to various aspects of people's lives, smartphones have become one of the most crucial mediums connecting individuals to the external world. The smartphone has made people's lives more convenient but has also brought about some social issues. People's dependence on smartphones has made excessive smartphone usage gradually become a common social issue. It is regarded as a potentially addictive behavior and has garnered attention from various practical and fundamental research fields. This study focuses on methods to mitigate the problem of excessive smartphone usage among individuals.

Internet or smartphone addiction shares similar behavioral patterns with substance addiction, including tolerance, withdrawal, repeated unsuccessful attempts to quit, and impairments in daily functioning [1, 2]. However, addiction to information technology bears a closer resemblance to behavioral addictions than substance addictions, demonstrating a stronger correlation with problematic gambling than with alcohol use disorder [3]. The study suggests that describing excessive smartphone usage as 'problematic smartphone use' is more appropriate than 'smartphone addiction.' This distinction is made because addiction is a disorder with severe adverse effects on both physical and psychological health. It is posited that 'problematic' or 'maladaptive' smartphone use is a more fitting term, as the consequences of such behavior do not reach the same level of severity as those associated with addiction [4].

Research suggests that smartphone addiction is more about being addicted to the content accessed on smartphones rather than the smartphones themselves [5, 6]. Smartphone content leads to people's smartphone dependency through numerous approaches. Some persuasive design principles such as reduction, reward, social comparison, personalization, and liking may trigger digital and smartphone addiction [7]. Continuing to use an information system over time is predicted by both intention and habit. Habit is a more influential predictor of information system continuance than intention alone [8]. The Hook Model, a customer habit-forming framework, consists of a four-phase process (trigger, action, variable reward, and investment) that businesses utilize to create products or services habitually used by customers. The primary goal of applying this model is to encourage voluntary, high-frequency engagement [9]. Gamification designs are widely employed in the development of smartphone products to engage users and encourage them to continuously invest time and effort in the product [10]. Algorithm-based personalization enables products to gain a better understanding of users, thereby immersing them further in the experience. Entertainment use for social media might lead to social media addiction. Personalization and entertainment content cause site attachment, and interpersonal and site attachment make people addicted to the social media platform and short video platform [11, 12]. Positive or negative reinforcement compels users to repeatedly interact with applications to maintain positive emotions or reduce negative ones [13].

The smartphone itself can induce smartphone dependency, but factors outside the smartphone also contribute to this issue. The phenomenon of one addiction being substituted for another has been observed [14]. Internet addiction may serve as a compensatory mechanism for abstaining from another addiction, such as nicotine dependence [15]. The satisfaction of innate psychological needs for autonomy, competence, and relatedness can enhance intrinsic motivation and mental well-being, as posited in self-determination theory [16-18]. A higher degree of Fear of Missing Out (FOMO), a mental disorder caused by social media use, correlates with lower satisfaction levels with these three innate psychological needs [19]. Internet addiction shows positive correlations with interpersonal difficulties [20-22]. The fulfillment of social and tactile needs can elucidate problematic smartphone usage [23]. Factors such as relationship maintenance and giving or receiving online social support may predict whether an individual becomes addicted to social media [24]. Several risk factors for Internet addiction have been identified, including high exploratory excitability, low self-esteem, disclosure, low family functioning, and loneliness [25]. The usage of short video applications by family members can intensify adolescents' addiction tendencies [26]. Psychological needs satisfaction partially mediates the association between stressful life events and Internet addiction [27]. Individuals experiencing negative emotions such as anxiety, depression, and distress tend to seek mental solace through excessive internet use [22]. Emotion suppression has a positive correlation with short-form video addiction [28]. Low perceptions of life meaning, states of boredom, and sensation-seeking tendencies contribute to increased addiction to livestreaming and short videos [26, 29].

The problematic use of mobile phones can lead to numerous issues in individuals' lives, such as negative impacts on users' subjective well-being [12, 30]. The ways to resist problematic smartphone use include but are not limited to three main aspects: external monitoring, offline support, and self-assistance. Parental guidance on social media platforms plays a pivotal role in preventing addiction among adolescents [22]. Offline social support, along with the fulfillment of relatedness needs, can contribute to the prevention of online addiction [28]. Mobile applications have the potential to serve as effective self-help interventions aimed at assisting individuals in self-regulating their smartphone usage [31].

2. Theoretical Framework of EPC Model

Excessive smartphone use manifests in both excessive frequency (use count) and excessive duration (continuous time spent) [25, 32]. This study focuses on the issue of excessive duration of smartphone use, aiming at the challenge of discontinuing smartphone usage during prolonged usage periods among users. The research objective is to propose a theoretical approach that effectively increases the likelihood of users discontinuing excessive smartphone use. A theoretical model was hypothesized and subsequently verified through empirical study. This foundational research can serve as a theoretical basis for self-help intervention practices in addressing problematic smartphone use.

2.1 Perceived Performance

Perceived performance refers to an individual's subjective assessment and evaluation of how well a product, service, or system performs during actual use. It emphasizes the importance of an individual's subjective experience and perception of performance rather than relying solely on objective performance metrics. Perceived performance can encompass various aspects, such as the speed, usability, availability, stability, and overall user experience of a product or system. PP is often employed to gauge user satisfaction and acceptance of a particular product or system. Satisfaction, attitude, hedonic value, and flow are among the factors that can predict the intention of IS continuance [33]. Perceived enjoyment (PE) positively affects satisfaction [34]. Fred Davis initially introduced the Technology Acceptance Model (TAM), which examines the positive influence of perceived ease of use (PEOU) and perceived usefulness (PU) on users' attitudes toward IS usage. These factors are crucial in increasing the likelihood of technology system usage [35]. Short-form video features lead users to become addicted by triggering their perceived enjoyment (associated with perceived positive performance) and feelings of withdrawal (experienced after stopping use). These features positively or negatively reinforce users' interactions, compelling them to engage repeatedly to sustain positive emotions or alleviate negative ones [13]. Enjoyment and usefulness have been identified as key determinants in leisure information systems, such as gaming [36]. Web or information quality positively influences perceived value and user satisfaction, subsequently determining users' intentions to continue using e-learning or IS systems [37, 38]. Software feature updates have a positive impact on users' intentions to continue using IS [39].

2.2 Expectation

Expectation denotes an individual's anticipations, beliefs, or predictions about future events, outcomes, or experiences. These expectations are based on a combination of previous experiences, information, knowledge, and personal beliefs. Expectations can influence a wide range of human behaviors, decisions, and perceptions [40]. Expectancy theory explains that an individual's behavior or actions are motivated by their expectations regarding the outcomes of the chosen behavior[41]. Expectancy is a predictor of internet addiction, as positive expectations about internet use exacerbate addiction development. Interventions addressing internet-related expectations can aid in addiction treatment [42]. The Expectation-Confirmation Theory (ECT), which describes and evaluates consumer satisfaction with products or services and post-purchase behavior, has been widely studied and referenced in the consumer behavior literature. It elucidates how perceived performance and expectations influence user satisfaction with products or services and their repurchase intentions. ECT explains how consumers generate repurchase intentions based on the confirmation of the expectation-performance discrepancy. Consumers typically have specific expectations for a product or service before making a purchase. After using the product or service, they form perceptions of its performance. Subsequently, consumers confirm the expectation-performance gap. Positive confirmation indicates that consumer expectations were lower than the actual perceived performance of the product or service, resulting in user satisfaction and an enhanced repurchase intention. Apart from its significant research in product repurchase and service continuity, this theory has found valuable application in studying information systems (IS) continuance. ECT is effectively employed to examine the factors and their structural connections that encourage users' sustained use of IS. It aims to foster and maintain users' ongoing usage. Users' intention determines IS continuous usage. Bhattacherjee extended ECT to investigate IS continuance, where user satisfaction with prior IS usage predicts their intention to continue using the system. This satisfaction is influenced by users' confirmation of their prior expectations and perceived performance and usefulness [8, 43, 44]. Satisfaction and attitude strongly predict IS continuance intentions. The Multi-Motive Information Systems Continuance Model (MISC) expands expectations by incorporating design-expectations fit, perceived ease of use, and design aesthetics, all of which have a positive impact on users' attitudes and satisfaction with their IS usage [45].

2.3 Cognitive consistency

The degree of users' cognitive consistency also influences their intention to continue using smartphones. Cognitive consistency refers to the psychological state in which an individual's beliefs, attitudes, and behaviors are in alignment or congruence with each other. It signifies a state of harmony within one's cognitive framework, where thoughts, beliefs, and actions are in agreement, resulting in a sense of psychological comfort. This concept is rooted in cognitive psychology and social psychology and is often explored to understand how individuals strive to maintain a coherent and consistent mental state. The term "consistency" is also referred to as consonance, coherence, congruence, balance, or compatibility in various psychological research disciplines. When cognitive inconsistencies arise, individuals may experience cognitive dissonance, prompting them to seek ways to restore cognitive consistency through changing beliefs or justifying actions. Cognitive consistency theory is fundamental in studying how humans manage cognitive conflicts and maintain psychological equilibrium [46]. It is important to note that addicted individuals often experience intrapsychic conflicts characterized by intention-behavior inconsistency, where they have the intention to stop but are unable to do so [47, 48]. People in Information technology addiction experience cognitive dissonance [49]. Leon Festinger first explained cognitive dissonance as the perception of inconsistency between one's beliefs and behaviors in his work, "A Theory of Cognitive Dissonance" . Festinger introduced the term "cognitive consonance" to describe the state of having beliefs, attitudes, and behaviors that are in agreement with each other. When individuals undergo cognitive dissonance, they are motivated to enact changes aimed at alleviating the psychologically uncomfortable sensations [50]. Cognitive consistency is proposed to enhance self-awareness among users who engage in excessive smartphone usage. The introduction of cognitive consistency aims to assist users in recognizing and attending to the inconsistency between their cognitions and behaviors, thereby fostering self-awareness. Multiple studies suggested that self-awareness can contribute to a reduction in excessive smartphone usage or smartphone addiction[51, 52]. A moderate to notable shift in intention typically results in a commensurate but modest adjustment in behavior [53]. The incorporation of cognitive consistency is intended to help users become more self-aware and further reduce their excessive smartphone usage.

2.4 Comprehensive explanation of the PEC Model

This study focuses on the problem of excessive smartphone use, which involves users struggling to discontinue their continuous engagement with their smartphones. A theoretical model is introduced to assist users in discontinuing smartphone use during extended periods of engagement. The model can be applied to adjust user behavior within the spectrum between cessation and continuation.

Perceived Performance (PP) represents users' current experiential perceptions of the experience, while Expectation (EX) pertains to their anticipations of future experiences. Both dimensions encapsulate users' subjective feelings regarding the temporal aspects of the behavior itself. The third quadrant of the model, Cognitive Consistency (CC), reflects the degree of alignment between users' behavior and their beliefs, attitudes, and cognitions regarding that behavior. It illustrates users' perceptions and reflections regarding their behaviors. A higher level of behavior-cognitive consistency is linked to an enhanced sense of psychological comfort, suggesting a close alignment between the user's actions and their mental perceptions and attitudes toward the behavior.

Adjusting the three dimensions within the quadrants, PP, EX, and CC, can facilitate shifts in user behavior between cessation and continuation. Higher levels of PP, EX, and CC are positively correlated with behavior continuity and negatively correlated with the likelihood of cessation. Elevated PP signifies a positive present experience, high EX reflects heightened future expectations, and increased CC indicates a closer alignment between behavior and cognitive perceptions, signifying a narrower gap between behavior and cognition. Higher levels of PP, EX, and CC are associated with a tendency toward continued behavior, whereas lower levels of PP, EX, and CC indicate a greater likelihood of behavior cessation. Therefore, the volume formed by three dimensions can predict the likelihood of users ceasing their behavior. Adjusting users' perceptions across these three dimensions toward lower levels increases the likelihood of behavior cessation.

Empirical research is employed to validate the effectiveness of the model's assumptions. The experimental objectives of the study are threefold: firstly, to confirm the efficacy of the model in regulating users' continuous smartphone use (CSU) behavior; secondly, to substantiate the assumptions regarding the direction of regulation by these three dimensions on continuous behavior; thirdly, given the hypothesis of varying degrees of influence by the three dimensions on continuous behavior, another experimental goal is to explore the differences in their impact.

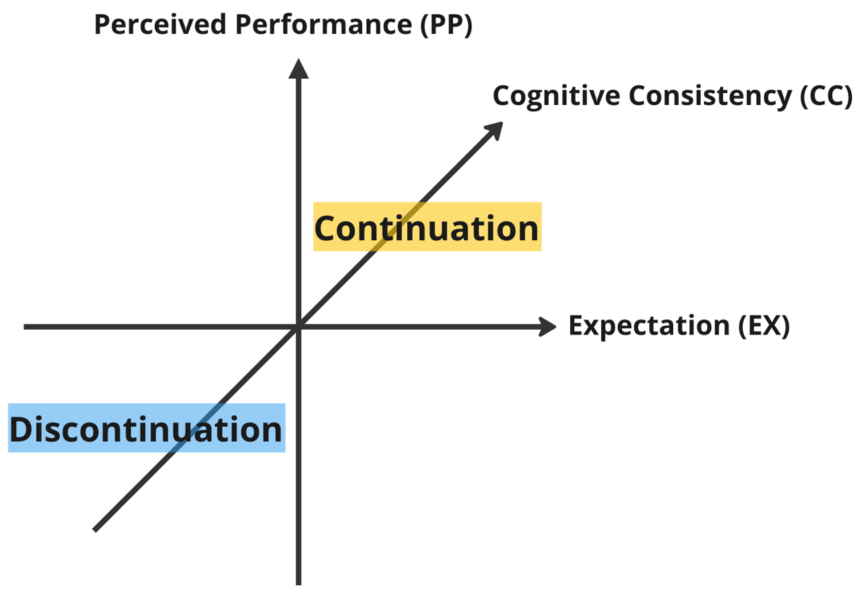


Figure 3-1: PEC Model

3. Method

3.1 participants

Seventy-two university students (37 males and 35 females) were recruited as participants. 41 were aged 18 to 24, 20 were aged 25 to 30, and 11 were aged 31 to 35. The participants included 24 Japanese students, 25 Chinese students, and 23 students from other countries. As the experimental task was presented in the form of short video consumption, all participants were regular users of smartphones and short video platforms. Self-reported data on participants' daily smartphone usage revealed that more than half of the participants (49 individuals) used their smartphones for more than 3 hours a day, and almost half of participants (37 individuals) reported frequent use of short video content. All participants voluntarily participated in the study without receiving compensation and were unaware of the objectives and hypotheses of the research before they completed the task and interview. This study received approval from the ethical committee of our institutions, and informed consent was obtained from each participant.

3.2 Research Design

3.2.1 Experimental task

Short video consumption can be a common contributing factor to problematic smartphone use. Short videos, often designed for quick and frequent consumption, tend to engage users for extended periods. This high engagement can result in increased screen time and the development of habitual smartphone usage patterns [54]. This study addresses the issue of CSU, with the experimental objective of validating the utility of a theoretical model aimed at addressing this problem. Given that, short video consumption represents a specific manifestation of the target behavior in this research. In addition, compared to other forms of social media, short videos allow participants to engage and immerse themselves in experimental tasks quickly. Therefore, short video consumption was selected as the representative behavior of CSU for the experimental task.

3.2.2 Independent variables

In this study, the independent variable was interferences in short video consumption, including three types of experimental levels and one control level. These levels are as follows: the first experimental level, representing PP, involved manipulating the present experience to influence users' experience during video consumption. The second experimental level, EX, entailed manipulating future content to influence users' expectations regarding upcoming experiences. The third experimental level, CC, focused on altering users' self-awareness concerning their behavior, thereby impacting their cognitive understanding and self-perception of their actions. Additionally, the control condition (CTRL) served as the baseline condition with no interventions applied to the content or viewing process.

To provide a comprehensive interpretation of the three experimental conditions and avoid potential bias resulting from interpreting each condition with a single intervention, this experiment employed three different levels for each experimental condition. This approach allowed for a more complete understanding of the implications of the experimental conditions.

1. For the PP condition, three levels were implemented: Desaturation (PP-D), which involved transforming videos into black and white. Mute (PP-M) entailed removing audio from the videos. Buffer (PP-B) meant that videos could not be loaded.
2. In the EX condition, three levels were introduced: Repetition (EX-R) involved repeating the videos. Advertisement (EX-A) featured videos as ads. Language (EX-L) presented video content in an unintelligible language.
3. Three levels were implemented in the CC condition: Risk (CC-R): A 2-minute animated short film named "Life Smartphone" was played before the short video task. Time (CC-T), Participants were presented with a material named "life grid" before the task, which visualized and imbued time with meaning. Harm (CC-H), Participants needed to answer a self-review questionnaire regarding the harm caused by smartphone overuse to themselves before the task.

3.2.3 Design

A within-subject design was employed, with the independent variable consisting of ten levels. These levels comprised three for each of the three experimental conditions, resulting in nine levels, along with an additional controlled level. To mitigate potential fatigue and adaptation effects stemming from participants encountering a relatively high number of treatment levels, this study adopted a partial repeated measures design approach. Each participant underwent testing for only four levels, encompassing one level from each experimental condition and the control level. This approach ensured that every participant experienced testing across all experimental condition levels while minimizing cognitive burden and facilitating participants in maintaining cognitive focus and attention.

Considering that the sequence of multiple treatment conditions could impact the results, we employed Latin Square Design to control for potential order effects and minimize confounding factors. The sorting process proceeded as follows: Initially, we allocated the four conditions (PP, EX, CC, and CTRL) into a Latin square. Subsequently, we assigned the levels of each experimental condition into separate Latin squares, resulting in three Latin squares. From each of these three experimental condition Latin squares, we selected one level. Finally, these selected levels were arranged in the sequence of the Latin square design for the four conditions. This process was repeated six times, yielding a total of 72 ordered sequences (randomly assigned to 72 participants). This arrangement ensured that each participant received tests for four conditions (PP, EX, CC, and CTRL), with each condition presented an equal number of times in different sequences. Additionally, it guaranteed that the various levels within each experimental condition were presented at least once and were equally represented in different sequences.

3.2.4 Counterbalancing

To control for the influence of confounding factors, the study manipulated videos used in the experiment, including the type of videos, video duration, and presentation order of videos. A baseline stabilization task (BST) was also implemented to ensure uniformity in each participant's initial state.

The study ensured homogeneity in video types across all experimental conditions to reduce the potential impact of video content. Initially, 30 diverse and broadly representative search keywords (e.g., Food, Animal, Song, Dance) were listed to respond to participants' varying interests. These keywords were then used to search for videos on prominent short video platforms. The top-liked videos under each keyword were downloaded to ensure that the videos possessed attractiveness and could engage participants successfully. Given the diverse linguistic backgrounds of the participants, the selected videos were non-verbal, requiring no language comprehension for understanding. After video selection, the various videos stemming from the 30 keywords were evenly distributed to the four conditions according to the video type, with 80 videos in each condition.

The total duration of continuous watching short videos was the objective measurement of participants' performance. The study also controlled for the impact of single video duration on experimental outcomes. All videos played in the experiment were standardized to approximately 20 seconds in length, with variations limited to within 3 seconds. Furthermore, the maximum duration for each testing session was capped at 5 minutes. Participants had the autonomy to end a session, and if they did not stop voluntarily, the experimenter would conclude the current round of testing when the duration reached 5 minutes.

The sequence of video presentations in each experimental condition was uniformly controlled. Each test condition included untreated videos (normal) (N) and treated videos (stimuli) (S). Initially, N and S videos were randomly arranged within each condition. Subsequently, N and S videos were interleaved according to a predefined pattern shown in the Figure 2. The quantity of N videos progressively decreased with each iteration until it reached one, at which point the decrease ceased. In contrast, the number of S videos increased with each iteration without restriction. The presentation order followed this pattern: 5 N videos followed by 1 S video, then 4 N videos, followed by 2 S videos, and so on. To ensure that the outcome variable measured participants' responses to stimuli, participants were required to view a minimum of 6 videos before they could request to terminate the current test round.

Figure 3-2. The presentation order of untreated videos and stimulus

The experiment introduced a Baseline Stabilization Task (BST) to ensure that participants began each test session in a consistent state. This was done to reduce potential sequence effects, where the outcomes of prior test sessions might influence subsequent ones. Moreover, the BST was intentionally designed as a low-interest task, deliberately contrasting the engaging nature of short videos characterized by higher levels of engagement and richness. The aim was to facilitate participants' swift engagement and immersion in the short video-watching testing phase. The BST was a 3-minute task that required participants to accurately transcribe gibberish text from paper documents into digital files on a computer. This task was administered before each test session to reset and standardize participants to the same initial condition. The sequence in which participants began the testing phase after completing the BST was repeated over four sessions for each participant. Completing the four test sessions marked the conclusion of the experimental phase.

3.2.5 Materials

The videos were uploaded to the TikTok platform to create an authentic experience. They were arranged in strict accordance with the experimental design. The materials used in this experiment included an iPhone 13 Pro Max with the TikTok app installed, printed gibberish text on paper, a computer for conducting the BST, an iPad for playing videos in the CC-R condition, a printed life grid for the CC-T condition, a questionnaire page for the CC-H condition, a subjective measurement scale (SMS) for subjective assessments, and a semi-structured interview script.

3.3 Experimental procedure

The experiment took place in a quiet, empty room at the university. Before commencing the tests, the experimenter provided participants with an overview of the experimental procedures and requirements. Participants were informed that they could initiate termination of the current test session at any time after viewing six videos (Participant-Initiated Termination). In cases where participants did not wish to stop, the experimenter would instruct them to conclude the session when the maximum duration was reached (Experimenter-Initiated Termination).

Each participant underwent four stages: the experimental phase, the ranking phase, the questionnaire phase, and the semi-structured interview phase. The experimental phase comprised four testing sessions, each following the same procedure. After completing a 3-minute gibberish text input task, participants proceeded to the short video-watching test. Following the test, participants were required to respond to an SMS scale containing three questions. During the experimental phase, experimenters recorded the actual duration participants spent on each session, the number of videos viewed, and participants' reactions and performance.

In the subsequent ranking phase, participants were asked to rank the four sessions based on their desire to stop. The questionnaire phase involved participants responding to a brief survey regarding smartphone usage habits, including demographic information questions. In the final semi-structured interview, the experimenter conducted interviews with each participant, guided by a predefined framework of questions and ad hoc questions tailored to each participant's experimental performance. Throughout the entire experiment, participants had the option to withdraw at any point.

3.4 Dependent variables

This study employed a combination of both quantitative and qualitative research methods. The quantitative approach involved the objective measurement of participants' responses and performance, as well as the subjective assessment of their ideas. The qualitative component incorporated data gathered through observations and interviews, providing a deeper and more comprehensive understanding of participants' perceptions and offering explanations for quantitative statistical results. The rationale for integrating both methods was to maximize the opportunity to capture the underlying meaning within the data.

3.4.1 Objective Measures

The dependent variables in the experiment encompass both objective measurements and subjective assessments. Objective measurements include the task duration (TD), which measures the time participants spent on each session of the short video-watching task, the number of viewed videos (NVV) within that duration, and the average time spent on each video (ATSEV), calculated by dividing TD by NVV.

3.4.2 Subjective Measures

Subjective measurements consist of three 7-point Likert scale questions designed to evaluate participants' perceptions of their current testing session. These questions assess their PP, EX, and CC as follows:

1. Measurement of Perceived Performance (MPP): How would you rate your experience of watching short videos in this session?
2. Measurement of Expectation (MEX): To what extent do you desire to continue watching the next short video in this session?
3. Measurement of Cognitive Consistency (MCC): How much do you agree with your behavior of continuously watching short videos in this session?

After completing the four testing sessions, participants are required to rank the sessions based on their degree of desire to stop. A ranking of first indicates the strongest desire to discontinue watching short videos, while a ranking of fourth indicates the least desire to stop.

The questionnaire on smartphone usage habits includes single-choice and multiple-choice questions. For multiple-choice questions, participants are instructed to select no more than three or five options, as indicated in Table 1 for the responses.

3.4.3 Qualitative Measures

The semi-structured interviews serve four main objectives:

1. Explanation of quantitative data (objective and subjective measurements, rankings, questionnaires), such as the reasons behind their ranking results.
2. Interpretation of qualitative data to understand the reasons for participants' performance and specific behaviors observed by the interviewer, such as why you started scrolling quickly during the third testing session but slowed down towards the end.
3. Understanding how the model influences participants' CSU behavior, for instance, the impact of reading the life grid on your subsequent behavior or which approach proved most effective in helping you stop using your smartphone.
4. Exploring potential methods for assisting users in reducing excessive smartphone use, for example, how do you usually control or reduce the frequency and duration of smartphone usage in daily life?

These interviews aim to gain deeper insights into participants' experiences and behaviors throughout the experiment.

3.5 Statistical analysis

Statistical analysis in this study was performed using SPSS V26.0. Repeated Measures Analyses of Variance (RMANOVA) were conducted for six dependent variables, including performance metrics (TD, NVV, ATSEV) and subjective measures (MPP, MEX, MCC). Additionally, a Friedman test was used for ranking measures. Post-hoc pairwise comparisons were performed using Bonferroni tests to identify significant differences among the four conditions. Parametric statistical tests, which rely on means, were not used for ranking measures because ranking sequences for two items may not accurately represent the distance between them. The level of statistical significance for all these analyses was set at 0.05. Effect sizes were assessed using partial ETA Squared in the context of RMANOVA.

4. Results

4.1 Self-Reported Smartphone Usage Habits

Participants self-reported that their primary motives for CSU predominantly included killing time, seeking entertainment, and maintaining social connections. The smartphone functions most likely to result in continuous use were social media, entertainment videos, and maintaining social contacts. Social interaction and entertainment constitute the primary content of continuous smartphone engagement. The primary reasons leading to CSU were enjoyable experiences, feelings of boredom when not using their devices, expectations of encountering new content, and the inertia of sustaining browsing. The selection of emotions that prompted smartphone use included positive and negative feelings, each comprising seven options. Participants tended to report negative emotions as the primary drivers of CSU, such as tiredness, loneliness, and anxiety.

The key factors responsible for participants voluntarily discontinuing CSU typically included having more important matters to attend to, engaging in self-reflection and experiencing feelings of guilt, reduced attraction and enjoyment, excessive time consumption, interruptions during continuous use, and being influenced by positive role models.

With the exception of 15 participants who expressed uncertainty, a total of 53 participants indicated a desire to reduce their daily smartphone usage. While the majority of participants (42 individuals) recognized the need for product assistance, most reported only occasionally or rarely seeking help from the current products (56 individuals). One explanation for this trend was the belief among participants that existing products offered limited utility in helping users achieve their goal of reducing smartphone usage, a perspective shared by 48 participants.

Table 3-1: Demographic information and results of self-reported smartphone usage habit

	N(%) (n=72)
Frequency of Daily Short Video Viewing	
Never	2 (2.8)
Occasionally	15 (20.8)
Sometimes	18 (25.0)
Often	28 (38.9)
Always	9 (12.5)
Frequency of Daily Mobile Phone Usage	
30 minutes-1 hour	3 (4.2)
1-2 hours	6 (8.3)
2-3 hours	14 (19.4)
3-4 hours	21 (29.1)
4-6 hours	18 (25.0)
>6 hours	10 (11.6)
Most Common Purposes for Continuous Smartphone Usage (MCQ)	
Killing time	47 (65.3)
Entertainment	43 (59.7)
Social contact	20 (27.8)
Searching	18 (25.0)
Study	17 (23.6)
Mobile Apps Causing You Continuous Smartphone Usage (MCQ)	
Social media (Instagram, Facebook…)	64 (88.9)
Entertainment Video (Tiktok, Youtube)	57 (79.1)
Social contact/SNS (Line, Wechat, Whatsapp)	53 (73.6)
Game	35 (48.6)
Website browsing	25 (34.7)
Primary Reasons for Continuous Phone Usage (MCQ)	
Enjoyable experience	50 (69.4)
Boring/idleness	41 (56.9)
Expecting new content	34 (47.2)
Inertia of sustained browsing	28 (38.9)
Connection, relief from Lonliness	17 (23.6)
Primary Emotions Leading to Continuous Phone Usage (MCQ)	
Bored	31 (43.1)
Tired	29 (40.2)
Curious	28 (38.9)
Stress	22 (30.6)
Lonliness	19 (26.4)
Anxious	18 (25.0)
Primary Reasons for Stopping Continuous Phone Usage (MCQ)	
Have more important things to do	47 (65.3)
Sense of guilty, self-reflection	46 (63.9)
Less attraction and enjoyment	40 (55.6)

Spent too much time	38 (52.8)
Being interrupted	26 (36.1)
Influence by a positive model	19 (26.4)
Whether Want to Reduce Daily Mobile Phone Usage	
Want to reduce	53 (73.6)
Do not want to reduce	4 (5.6)
Not sure	15 (20.8)
Whether Need Product Assistance to Reduce Usage	
Need	42 (58.3)
Do not need	8 (11.1)
Not sure	22 (30.6)
Frequency of Using Product Assistance to Reduce Usage	
Never	32 (44.4)
Occasionally	24 (33.3)
Sometimes	8 (11.1)
Often	5 (6.9)
Always	3 (4.2)
The Effectiveness of Existing Products Assistance	
Effect	9 (12.5)
Ineffective	48 (66.7)
Not sure	15 (20.8)

4.2 Performance and subjective measures

Each of the three experimental conditions consisted of three levels of stimuli to represent it. In the PP condition, there were three types of stimuli: Desaturation, mute, and Buffer. The EX condition featured three stimuli: repetition, advertisement, and unknown language. The CC condition included three stimuli: videos indicating the risks of CSU, a life grid visualizing the value of time, and questionnaires reminding responders of the harm to them caused by CSU.

Before comparing the four conditions, separate one-way ANOVAs were conducted for the three levels within each experimental condition to determine if there were statistically significant differences in participant performance and evaluation under each experimental condition. If the results showed no statistically significant differences, RMANOVA analysis would be implemented by comparing four conditions. Conversely, the analysis would be conducted by ten levels, representing the combinations of four conditions. The results of the RMANOVA are presented in the Table 2 below. Post hoc tests revealed no statistically significant differences in participant performance and evaluation metrics among the different stimulus levels within each experimental condition ($P > 0.05$). Therefore, we proceeded with the comparison of the four conditions.

Table 3-2. Statistical results of one-way ANOVAs for levels within each experimental condition

Conditions	Levels	TD (S) M (SD)	TD (S) P Value	NVV M (SD)	NVV P Value	ATSEV (S) M (SD)	ATSEV (S) P Value
PP	PP-D	210.91 (72.06)	0.684	30.65 (13.43)	0.689	7.92 (3.65)	0.407
	PP-M	224.83 (78.51)		30.00 (12.91)		9.17 (5.76)	
	PP-B	209.40 (72.70)		33.02 (15.86)		7.67 (3.99)	
EX	EX-R	185.48(65.89)	0.378	31.9(13.52)	0.613	6.66(3.54)	0.417
	EX-A	208.97(74.66)		34.83(11.87)		6.53(2.75)	
	EX-L	208.53(74.73)		32.17(12.22)		7.83(5.4)	
CC	CC-R	168.81(79.77)	0.224	30.77(14.85)	0.099	6.42(3.85)	0.970
	CC-T	147.88(73.3)		27.53(13.82)		6.32(3.87)	
	CC-H	186.16(87.06)		36.36(15.9)		6.61(5.02)	

(a) Performance

Conditions	Levels	MPP M (SD)	MPP P Value	MEX M (SD)	MEX P Value	MCC M (SD)	MCC P Value
PP	PP-D	4.10 (1.47)	0.639	3.72 (1.67)	0.300	3.62 (1.57)	0.888
	PP-M	4.00 (1.28)		3.14 (1.30)		3.45 (1.33)	
	PP-B	3.77 (1.43)		3.33 (1.37)		3.57 (1.22)	
EX	EX-R	3.39(1.4)	0.850	2.96(1.58)	0.570	3.43(1.53)	0.801
	EX-A	3.42(1.63)		3.35(1.58)		3.26(1.69)	
	EX-L	3.62(1.65)		3(1.52)		3.54(1.58)	
CC	CC-R	3.23(1.36)	0.551	2.58(1.48)	0.819	2.48(1.44)	0.184
	CC-T	2.89(1.42)		2.43(1.23)		2.32(1.57)	
	CC-H	3.28(1.49)		2.68(1.68)		3.08(1.68)	

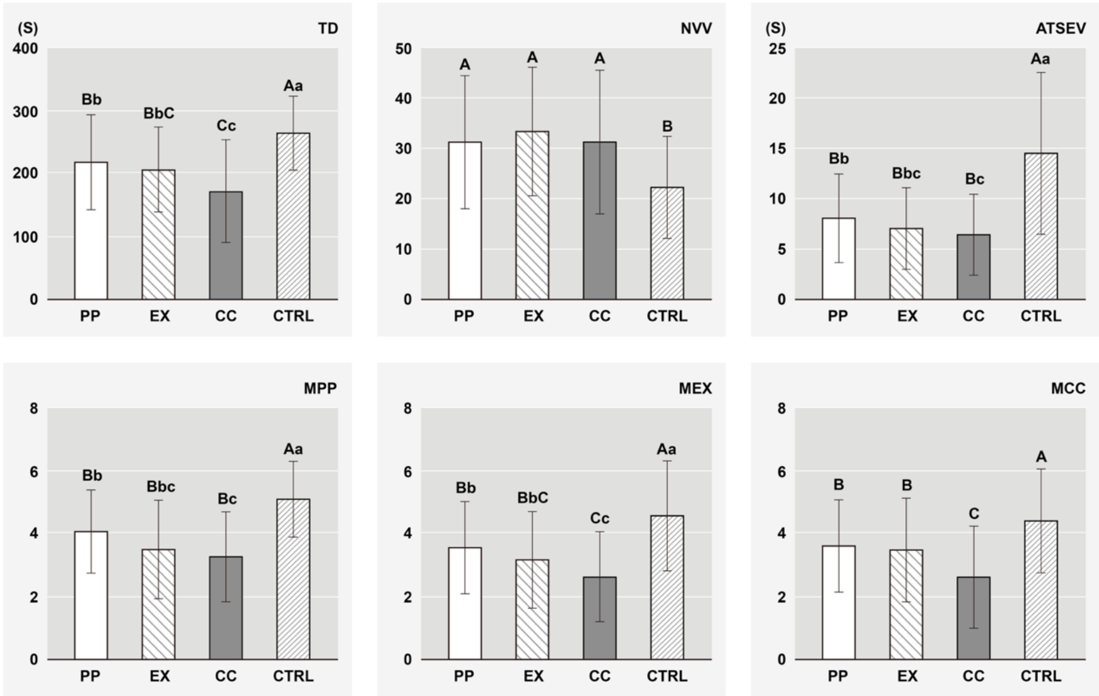
(b) Subjective measures

Table 3 presents the statistical summaries of objective and subjective measures. The RMANOVA conducted for the conditions of interest revealed significant effects for both performance and subjective measurements. Significant effects of performance were observed for TD [$F(3, 213)=39.468$, $P<0.001$, $\eta^2=0.357$], NVV [$F(3, 213)=26.671$, $P<0.001$, $\eta^2=0.273$], and ATSEV [$F(3, 213)=43.966$, $P<0.001$, $\eta^2=0.382$]. As depicted in the Figure 3, post hoc tests showed that the CTRL condition had significantly higher values than the three experimental conditions in terms of TD ($P<0.01$), while CC had significantly lower values than the other three conditions ($P<0.05$). This indicates that participants in the CTRL group had longer viewing durations compared to the three experimental groups, and CC had significantly shorter viewing durations than the other three groups. Regarding NVV, the CTRL condition had significantly lower values than the three experimental conditions ($P<0.01$), indicating that participants in the CTRL condition viewed significantly fewer videos. ATSEV, calculated by dividing TD by NVV, revealed that participants in the CTRL condition spent significantly more time on each video compared to the other three groups ($P<0.01$).

Subjective measurements exhibited significant differences in MPP [$F(3, 213)=39.691$, $P<0.001$, $\eta^2=0.359$], MEX [$F(2.656, 188.557)=34.429$, $P<0.001$, $\eta^2=0.327$], and MCC [$F(2.65, 188.148)=31.062$, $P<0.001$, $\eta^2=0.304$]. Post hoc tests revealed that participants showed similar assessment trends across these three measurements. As seen in the Figure 3, participants' subjective evaluations of the CTRL condition were significantly higher than those of the other three experimental conditions in terms of MPP, MEX, and MCC ($P<0.01$). This indicates that participants perceived the experience as better, had higher expectations for continuing to watch the next video, and felt a higher level of consistency between their behavior and their self-perception in the CTRL condition. For the CC condition, participants' subjective evaluations were significantly lower than the other three conditions in measuring MCC ($P<0.01$) and MEX ($P<0.05$), suggesting that participants experienced the highest level of inconsistency between their behavior and self-perception and had lower expectations of continuing to watch videos. Additionally, participants' subjective evaluations of the PP and EX conditions showed no significant differences across all three measurements, indicating that the intervention approaches in PP and EX had similar effects on participants' assessment of the three measurements.

Table 3-3. Statistical results of RMANOVA

Conditions	Performance			Subjective Measurement (7-likert point)		
	TD (S)	NVV	ATSEV (S)	MPP	MEX	MCC
	M(SD) (n=72)	M(SD) (n=72)	M(SD) (n=72)	M(SD) (n=72)	M(SD) (n=72)	M(SD) (n=72)
PP	217.38(74.11)	31.03(13.39)	8.23(4.26)	4.03(1.36)	3.58(1.44)	3.63(1.41)
EX	205.31(69.19)	33.31(12.49)	7.03(3.98)	3.52(1.53)	3.19(1.54)	3.51(1.58)
CC	171.90(81.58)	31.21(14.21)	6.44(3.98)	3.28(1.40)	2.63(1.43)	2.67(1.58)
X	264.61(58.78)	22.24(9.96)	14.68(8.04)	5.10(1.19)	4.58(1.74)	4.44(1.60)



Note: Uperscripts ^{A,B,C} means scores with different superscripts were significantly different in the pairwise comparisons (P < 0.01)， Uperscripts ^{a,b,c} means scores with different superscripts were significantly different in the pairwise comparisons (P < 0.05).

Figure 3-3. The difference in the performance and subjective measurements among four conditions

4.3 Ranking of desire to stop

Table 4 presents the following results: the number of participants for each ranking, the percentage of participants in each rank relative to the total number of participants in that ranking, the median (P25, P75) ranking for each condition, and the rankings of the four conditions determined by the Friedman test.

A Friedman test was conducted to assess variations in stopping preferences among the four conditions. The results revealed a significant main effect of conditions (Chi-squared = 114.797, df = 3, p < 0.05, Kendall's W = 0.531). Post-hoc pairwise comparisons were performed using the Nemenyi test, and the significance values were adjusted using the Bonferroni correction for multiple tests.

As depicted in the Figure 4, the results showed significant differences in pairwise comparisons for all conditions except between PP and EX (P < 0.05). This led to rankings for stopping preferences from first to third place: CC condition, PP and EX conditions, and CTRL condition.

Table 3-4. Statistical results of ranking of desire to stop

Conditions	1st Desire to Stop N(%)	2^{nd} Desire to Stop N(%)	3^{rd} Desire to Stop N(%)	4^{th} Desire to Stop N(%)	M (P_{25},P_{75})	Ranking of Desire to Stop
CC	40 (55.6)	23 (31.9)	8 (11.1)	1 (1.4)	1 (1,2)	1^{st}
EX	24 (33.3)	26 (36.1)	19 (26.4)	3 (4.2)	2 (1,3)	2^{nd}
PP	8 (11.1)	19 (26.4)	35 (48.6)	10 (13.9)	3 (2,3)	3^{rd}
Ctrl	0 (0)	4 (5.6)	10 (13.9)	58 (80.6)	4 (4,4)	4^{th}

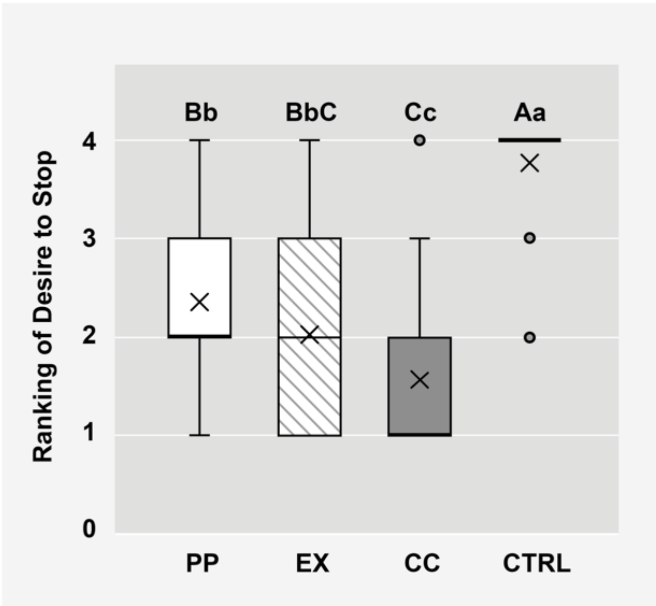


Figure 3-4. The difference in ranking of desire to stop among four conditions

4.4 Qualitative measures

The main observations from the experiment were mainly three points outlined in the Table 5. Under experimental conditions, the appearance of a few stimuli in the initial stages did not cause the participants to stop video scrolling but did accelerate the frequency of scrolling. However, as stimuli continue to appear for longer durations, participants' responses fall into two categories. The first involves participants requesting to stop the behavior after quick video scrolling. Participants who did not request to stop exhibited a transition from fast to slow video scrolling. Those who requested to stop explained that they initially scrolled quickly in search of more interesting videos to compensate for their unpleasant experience. They eventually stopped due to an overload of uninteresting content. On the other hand, participants who transitioned from fast to slow scrolling realized that they could not find interesting videos, resulting in them lowering their expectations and trying to appreciate the unsatisfactory videos. This demonstrated that extended periods of low-quality experiences or distractions can lead users to either stop the behavior or lower their expectations to continue the behavior.

In terms of the willingness to stop, the experimental groups had more participants who actively requested to stop compared to the control group. The number of participants voluntarily requested to stop in the CC and EX conditions was similar, with 63 and 62 participants, respectively. The PP condition had 55 participants, while the CTRL condition had 23 participants. These participants generally had a higher scrolling frequency than others, resulting in less time spent on each video. They explained that distractions gradually pulled them out of their immersive state, making it difficult for them to re-engage and causing them to consider stopping their viewing. This observation explains the implication of ATSEV. Less time spent on each video suggests greater detachment and a higher likelihood of voluntary cessation. Conversely, more time spent on each video indicates deeper immersion and a lower likelihood of stopping voluntarily. In the observation, participants showed a noticeably higher video scrolling frequency under experimental conditions than in the control condition.

Table 3-5. The results of observation and its implication, including number of participants who mentioned the item

Observation	Explanations	Implications
• Participants' responses to continuously appearing stimuli shifted from quickly scrolling to stopping.	43: I scroll very fast because I was looking for enjoyable video to make up for previous unpleasant experience. I finally stopped watching because of too much undesirable content.	• Low-quality experience initially **increases** the intention to continue the behavior. After reaching a **threshold**, the intention begins to **decrease** until behavior cessation, forming an **inverted U-shaped curve.** The threshold varies among individuals.
• Participants' responses to continuously appearing stimuli shifted from quickly scrolling through	28: I scrolled from fast to slow because I realized there were barely any interesting	• Users may develop **learned helplessness** to deal with continuous dissatisfaction. (lowering expectations and increasing

all videos to patiently watching all videos.	videos, and I had to accept it and try to enjoy those videos.	tolerance).
• Participants who scrolled faster were more likely to stop voluntarily (N: 55(PP), 62(EX), 63(CC), 23(Ctrl)).	32: I was unable to focus or immerse myself.	• Detached or disengaged states make stopping easier. • Less time spent on per video suggests greater detachment and a higher likelihood of voluntary cessation.
• Participants scrolled faster in experimental conditions than in the control condition.		

The interviews not only provided explanations for the observed results but also offered insights and supplementary explanations related to other aspects of the model, as presented in the Table 6. Participants believed that the variability and unpredictability of smartphone content were among the reasons people continued scrolling their phones. Individuals lost interest and expectations when the content became monotonous and lacked diversity, eventually leading to behavior cessation. They suggested introducing variety and uncertainty into one's life could reduce smartphone addiction. When users used their phones with a specific goal, their expectations aligned with the goal. If the goal was achieved, they tended to stop scrolling. Conversely, in the absence of specific goals, the satisfaction of met expectations led to continued scrolling.

Participants addressed that PP and EX shared a dynamic relationship. When participants enjoyed their current experience, they expected more attractive content. They lowered their expectations for the upcoming experience when they did not enjoy it. In turn, when participants had high expectations for the content, they found it hard to be satisfied with the current experience, thereby leading to behavior cessation. However, when they had no expectations, they were more likely to be satisfied with the experience and would continue their behavior.

Participants perceived that CC easily caused negative emotions of self-blame and self-doubt, which led them to self-attribution. CC affected them to reflect on their behavior, which led to changes in their smartphone use behavior. In contrast, PP and EX let participants blame the product, which may result in discontinuing the use of that particular product but not ending continued phone scrolling behavior. Those with low PP and EX may stop using the unsatisfactory platform but continue smartphone use by using other digital products. CC is employed for promoting self-awareness. However, participants realized that a reminder to arouse self-awareness would cause aversion if it appeared in their immersed states. Instead, self-awareness naturally emerged when they perceived a low-quality experience. Participants reported that they did not perceive any benefits from short video scrolling, which made them regret wasting time, resulting in an immediate cessation of the behavior.

Regardless of the methods employed, participants emphasized that the behavior discontinuation should result from their choice rather than being compulsory or forced. A sense of coercion could lead to resistance and sustained unwanted behavior. Additionally, participants suggested that the current self-help methods primarily evoked negative emotions in users. They wished for assistance methods to employ approaches that triggered positive emotions and attitudes in users.

Participants mentioned that despite setting reminders, they often bypassed the restrictions when reminders appeared and continued scrolling. They highlighted that limitations of existing products could often be skipped at very low costs, rendering the restrictions ineffective. Participants noted that the effectiveness of reminders diminished with increased frequency; the more times they received reminders, the easier it was for them to ignore them. The complexity of product usage and settings often discouraged users from even starting. Many participants believed that current product designs often failed to resonate with them, as they did not perceive the relevance of the information to their own lives. They also felt that the reward and punishment methods were not directly related to their personal interests, failing to evoke their reaction of stopping scrolling.

Table 3-6. The results of Interview and its implications: including number of participants who mentioned the item

Interview	Implications
16: More curiosity and exploration in life leads to less immersion in phone use. 37: Repeated content made me stop. Varied content kept me engaged (variable rewards).	• People anticipate and are curious about **controllable unknowns and variations.** • Life enrichment can reduce excessive smartphone use.
14: When I have a goal, I will stop once I achieve it. Without goal, I tend to keep scrolling.	• **With a goal,** when expectations are met, behavior tends to stop. **Without a goal**, when expectations are met, behavior tends to continue. • An attainable purpose brings a destination(ends) to continuous behavior.
22: If I like the content, I expect more enjoyable content. If I don't like it, I will stop. 27: I initially enjoyed videos. As the content became less attractive, I tried to continue	• **PP can adjust EX.** A high-quality experience can maintain high EX or even increase them, while a low-quality experience will lower EX. • **EX can adjust PP.** High EX, low tolerance

appreciating it. When it was constantly uninteresting, I could only stop. 16: I couldn't tolerate those videos because I expected good content. Thus, I could stop easily. 24: I didn't have much expectation for it, so I could continue watching for a while even though the content was unattractive.	for experience, decrease PP; low EX, high tolerance for experience, increase PP. • People stop behavior when EX is high and PP is low. **Raising expectations** can be a solution.
29: CC led to self-awareness and self-blame, which made me stop the behavior. PP and EX made me blame the product, leading me to stop using the product.	• CC results in **internal attributions** (self-blame), while PP and EX lead to **external attributions**. • Internal attributions lead to changes in behavior, while external attributions affect the current platform usage.
21: Self-blame leads to self-doubt and generates negative and stressful emotions, while blame for the product results in more positive and comfortable emotions. 13: Notifying me of time cannot touch me and will make me anxious.	• CC is more likely to evoke **negative emotions** related to psychological conflicts, such as self-doubt.
22: I easily become immersed when scrolling phone. A prompt in here hardly affects me. 12: I become detached if the experience is poor. A prompt in here can easily make me stop. 13: Previous reminder resurfaces in my mind when I encounter unenjoyable content, making me self-aware and wanting to stop. 18: When I have other work to do, I cannot fully immerse and can easily stop on my own.	• Self-awareness requires **mental space**. It is hardly generated in immersed states. • Self-awareness requires **buffering time**. It takes some time to generate and is hardly generated instantly.
52: Gaining nothing equals a waste of time. It makes me regret and want to stop the behavior.	• People need to feel that they are **gaining** something from their behavior. The feeling of gaining nothing can trigger users' self-reflection, leading to behavior cessation.
16: I can stop with self-motivation, but hardly stop by external demands, it make me feel compulsive. 18: CC made me stop on my own. PP and EX were like the platform educating me to stop. 13: PP led me to stop on my own. CC were like someone educating me to stop.	• **Intrinsic motivations** make people voluntarily change. • **Extrinsic motivations** can easily make people feel obligated and evoke aversion or lead to purpose transfer. • **Nudged** interventions are preferable. Avoiding compulsive methods.
26: Negative emotions like guilt or feeling forced made me anxious. 8: Negative emotions helps me to stop. I feel like a disciplined and accomplished person after stopping. 10: Existing products mainly cause negative emotion.	• Intervention can evoke both positive and negative emotions. People prefer **positive emotion**.
12: The intervention was effective at first but becomes less so over repeated time. I gradually became annoyed.	• Users develop **tolerance** to repeated content, and its effectiveness decreases as the frequency of appearance increases.
41: I set the limit myself, but I often find myself wanting to remove it and continue using my phone when it reminds me.	• Completely shifting the responsibility for self-control to an external tool (**Proxy**) weakens users' self-awareness and self-control abilities.
42: It was too easy to skip interventions. So it's useless.	• Intervention that can be countered at a low **cost** is hardly effective.
11: The current products are complex and create more effort, causing additional troubles.	• Reducing the setup and usage costs of the approaches.
22: Existing products are hardly effective because	• Effective interventions must align with users'

they cannot adapt to my situation. I'd rather set my own rules.	**personalized characteristics.**
13: Notifying me of time cannot touch me and will make me anxious.	• People tend to resonate with **meaning**. Visualizing meanings of information is necessary.

5. Discussion

The research aims to decrease users' continuous smartphone usage. A theoretical model comprising three dimensions (PP, EX, and CC) was proposed. Empirical research was conducted to validate the effectiveness of reducing excessive smartphone usage. Participants exhibited a reduction in their continuous smartphone usage in the experimental conditions compared to the control condition. The impacts of each dimension of the model differed while also influencing one another.

5.1 Perceived performance

PP involves interventions in the user experience to influence users' perception of the performance of their current experience. When users perceive high PP, their behavior tends to continue. Conversely, users will stop the behavior when they perceive low PP. Reducing the quality of the user experience can impact the user's willingness to continue their behavior. This aligns with the current research aimed at increasing information system continuous intention, showing a positive correlation between user experience and information system continuous intention [43, 55].

The qualitative results unveiled that user responses to interventions in the user experience follow an inverted U-shaped curve. Initially, the intention to continue the behavior increases when the experience is disrupted. Occasional low-quality experiences or disruptions do not prompt users to stop their behavior but rather encourage them to seek more interesting content to compensate for their unmet user experience needs. Moreover, the fluctuations introduced by occasional disruptions may create variable rewards within the experience, which encourages users to persist in their behavior [9]. However, continuous low-quality experiences or disruptions will reach a threshold that users can endure. After surpassing this threshold, users' desire to continue scrolling gradually decreases until it completely disappears. This suggests that occasional interventions not only fail to help users stop their behavior but may also increase sustained usage. Only if the intention persists beyond the user's threshold can it truly assist users in stopping their behavior. This discovery offers valuable insights into the specific trends in users' continuous behavior following interventions, addressing a gap in previous studies that often oversimplified this trend as a mere decline and reflexively employed PP interventions to assist users in discontinuation [56-60]. Our research findings suggest that inappropriate interventions can actually foster sustained behavior, resulting in an upward trend in continuous behavior intention. It's worth noting that the threshold of this inverted U-shaped curve varies among individuals. In practice, this threshold may be identified through user-authorized behavior monitoring, such as tracking user behavior operation frequencies. The study demonstrates that the higher the user's operation frequency, the more detached their state, and the more likely they are to stop actively.

5.2 Expectation

Managing users' expectations of future experiences can assist in behavior modification. The qualitative results suggest two ways to carry out: First, increase user expectations to a level the experience cannot meet or erase expectations. Second, encourage users to set clear and achievable goals for their smartphone usage, providing an endpoint for the behavior.

The study supported previous research indicating that people tend to maintain their behavior to sustain their satisfaction when their expectations are met [43, 61]. However, our study found that this often occurs when people use their smartphones without a specific goal. We also observed that their responses to situations where their expectations were unmet resembled their response to unliked PP, demonstrating an inverted U-shaped curve. Only when their expectations continuously fail to be met does this lead to the cessation of their behavior. Under such circumstances, two strategies can be considered: either widening the gap between expectations and experiences by raising expectations and lowering the quality of the experience to facilitate behavior cessation, or erasing user expectations to aid in behavior cessation. Curiosity and anticipation of upcoming unknown and variable content, as well as the search for entertaining material to satisfy the brain's reward system, can keep users engaged online [9]. The results suggest that several factors, such as familiar, unchanging, or unattractive content, can assist in managing user expectations. It is worth noting that the risk associated with the former strategy is that users may lower their expectations to adapt to low-quality experiences.

Unlike smartphone usage without a clear goal, our qualitative results revealed distinct user behavior in goal-directed smartphone use. Users tend to discontinue the behavior after reaching their goal when they have a clear objective for their behavior. Having a clear and achievable goal provides a specific endpoint for continuous smartphone use. Assisting users in defining a clear and attainable goal for their ongoing behavior shifts their expectations toward achieving it. Once the goal is attained, the ongoing behavior reaches its natural endpoint. Current application designs to combat digital addiction incorporate intervention practices like setting concrete time goals, concrete goal reminders, or comparing behavioral goals [58]. However, these interventions are often focused on helping users set goals to cease the behavior. We propose an alternative approach where goals are set for ongoing behavior, emphasizing the importance of having a clear purpose for the current behavior. In practical implementation, the design can visualize users' behavioral goals and remind them of their goal achievements after they have accomplished what they intended. This can enhance the likelihood of discontinuing the behavior once the goal is met.

In the theoretical model proposed in this study, we hypothesized a negative correlation between EX and behavior discontinuation. This implied that lower EX would lead to user discontinuation. However, the qualitative findings contradicted this hypothesis. They revealed that the effect of adjusting EX is significantly influenced by PP. In certain situations, such as when PP is low, higher EX may result in user discontinuation of continuous behavior. Conversely, in other situations, such as when PP is high, lower EX may lead to users continuing their behavior. This finding is contrary to our initial hypothesis.

Our findings contradict the hypothetical model proposed in this study, which posited a negative correlation between EX and behavior discontinuation. We hypothesized that lower EX would result in user discontinuation. However, the qualitative findings reveal that this correlation is just one of the possibilities for promoting discontinuation. The alternative scenario is in line with the ECT, suggesting that the confirmation of EX and PP encourages continuous information system use. In this context, lower EX than PP leads to continuous behavior [43, 61]. Conversely, our results show another possibility where the confirmation of EX and PP actually results in the discontinuation of behavior during goal-directed smartphone usage. Therefore, this study suggests that the strategies for regulating EX are complex and cannot be summarized as a unidirectional axis. Furthermore, it also unveiled that ECT theory is not universally applicable, paving the way for further in-depth and extensive research into ECT in information system continuance.

5.3 Cognitive consistency

Consistency between the behavior and cognition for the behavior leads to behavior continuation, while inconsistency prompts adjustment in either behavior or cognition to achieve alignment [49, 50]. Approaches related to CC help users recognize the gap between their behavior and cognition and enhance their cognitive inconsistency. Users rarely engage in continuous self-reflection on their behavior and they often fail to recognize the inconsistency between the two. Thus, users need help in becoming aware of their cognitive inconsistency, which can motivate them to stop unwanted behavior.

CC serves as a method to facilitate users' self-awareness. The qualitative results revealed that two essential conditions need to be satisfied when implementing methods to manage CC. The first condition is that users need mental space to generate self-awareness. Interview results indicate that people are not immediately influenced by CC reminders; these reminders often take effect when individuals are not enjoying their current experiences. When users are immersed in using their smartphones, they have little mental space for self-observation. Attempting to elicit self-awareness from users while they are in this immersive state may even provoke aversion.

The second condition is enough time to recognize cognitive inconsistency. The recognition of cognitive inconsistency does not occur immediately after receiving stimuli aimed at provoking self-reflection. Instead, users initiate introspection (inward reflection) after exposure to the stimuli. This process involves mobilizing users' reflection that guides them to self-observe and be self-aware. It takes longer than the time needed for users to react to stimuli related to PP (e.g., decreasing user experience). As observed in the experiment, participants' introspection often occurred after a certain duration of the detached state. In practical applications of CC adjustments, it is necessary to provide users with more mental space and time to respond accordingly, such as offering users the option to choose non-immersive or detachment modes.

Employing CC methods also entails certain limitations. Approaches that provoke cognitive-behavioral inconsistency often lead to the emergence of negative emotions, including regret, guilt, shame, and self-blame [48]. Some opinions support the idea that eliciting negative emotions like guilt or regret in users can enhance an individual's intention to discontinue excessive behavior [49, 62]. However, part of participants reported experiencing aversion due to the negative emotions induced by CC. Besides, the descriptive statistics in this study have revealed that negative emotions often result in continued smartphone usage. The application of CC-related approaches may carry the risk of encouraging users to maintain their usage as a way to counteract the negative emotions stemming from self-blame. Therefore, it is crucial to consider the psychological impact on users when implementing CC adjustment methods and aim to design interventions that evoke positive psychological experiences. Incorporating positive elements, such as demonstrating the benefits of each achievement in reducing usage or encouraging users to anticipate, be curious about, and explore things beyond their smartphones and into their lives, may yield more effective outcomes.

Furthermore, methods that encourage user introspection may lead users to feel pressured to change their behavior, potentially triggering resistance and yielding counterproductive results. As a result, nudging should be considered the prior approach to guide users in cultivating intrinsic motivation. Therefore, when implementing CC adjustment methods, it's essential to take precautions to prevent users from experiencing negative emotions and a sense of compulsion.

5.4 Relationships between PP and EX

The static relationship between PP and EX is well-established. Users tend to continue their behavior when their PP aligns with or exceeds their EX. However, if PP falls below EX, users will cease the behavior due to the experience not meeting their expectations. This static relationship aligns with the Expectation Confirmation Theory (ECT), which posits that consumers' intention to continue using a product or service hinges on the expectation-performance discrepancy. Positive confirmation indicates that consumer expectations are lower than perceived performance, while negative confirmation signifies the opposite. The former results in continued use, while the latter suggests an intention to discontinue [43]. Therefore, methods that leverage this static relationship can be implemented by elevating user expectations and diminishing the user experience, thereby widening the gap between the two. Users will discontinue the behavior when the experience consistently falls short of their expectations.

Additionally, this study confirmed a dynamic relationship between PP and EX. When PP and EX are inconsistent, they dynamically influence each other and prompt adjustments. PP has an impact on the adjustment of EX. A high-quality experience can sustain high expectations or even elevate them, while a low-quality experience may lower user expectations. This is aligned with the suggest that good user experiences will raise user expectations for future product usage, and poor user experiences will reduce user expectations for future product usage [63]. However, the qualitative results revealed that individuals responding to a low user experience sometimes exhibit learned helplessness. Users' responses to low-quality experiences typically fall into two categories: they either discontinue the behavior or adapt by reducing their expectations and increasing their tolerance for the experience to continue the behavior. This illustrates a scenario resembling learned helplessness, a psychological concept describing a state of perceived powerlessness and a lack of control resulting from repeated experiences of uncontrollable adversity [64]. On the contrary, EX can also induce adjustments in PP. When EX surpasses PP, users exhibit a low tolerance for the experience, resulting in a decrease in PP and ultimately leading to the cessation of the behavior. Conversely, when EX falls below PP, users demonstrate a high tolerance for the experience, which in turn leads to an increase in PP and the continuation of the behavior. Thus, it is imperative to consider the dynamic interplay between these two factors in practical applications.

The authors postulate that the impact of PP, EX on different digital behaviors may vary in degree. In this study, watching short videos served as the experimental task to represent a form of continuous linear behavior. Interestingly, as show Figure 3, participants' evaluations of MEX were found to be positively correlated with MPP and slightly lower than MPP in all conditions, even in the experimental condition designed to encourage discontinuation of the behavior. This finding contradicts conventional research, which typically suggests that higher PP than EX leads to behavior continuity, while lower PP than EX leads to discontinuity [34, 43, 61, 63]. We suppose that the quantitative results validated the model's effectiveness in a specific scenario of continuous and coherent activity. In this context, the level of PP primarily determines user continuity, and its influence outweighs that of EX. This outcome may be attributed to participants' expectations strongly influenced by PP, especially since it was a continuous experience. Expectations pertain to anticipation for the future, while PP pertains to evaluating past and current experiences. We hypothesize that in continuous and coherent behaviors, such as watching short videos, users' cognitive space is largely consumed by the current experience, leaving less room for anticipating the future experience. This may account for the positive correlation between MEX and MPP in this study. Conversely, we assume that EX may exert a greater influence than PP in other digital behaviors like email and social media platforms primarily used for messaging (e.g., WhatsApp, Instagram, Line, and WeChat). This is because these digital behaviors feature discrete point experiences rather than continuous linear actions, resulting in varying degrees of influence by PP, EX, and CC. In future research, a quantitative investigation should be conducted to assess the varying degrees of impact that PP, EX, and even CC have on different digital behaviors.

5.5 Relationships among the model's constituent elements

The methods involving PP or EX are implemented to influence the user's current experience. In contrast, CC methods aim to evoke users' self-awareness and bring about behavioral changes through self-reflection and self-regulation. We can learn from the interview that PP and EX directly elicit immediate responses from users, while CC follows a more intricate path involving the activation of self-reflection and self-awareness before reacting to stimulus, which require additional cognitive space and response time. Participants generally believe that CC has a longer-lasting influence than PP and EX. Furthermore, CC has a greater impact on the behavior itself, while PP and EX primarily affect the product or platform. This raises a limitation in adjusting PP and EX, as it may primarily affect users' persistence in using the product that has undergone adjustments rather than causing them to cease continuous smartphone usage. In response, users might opt to switch to using another product to continue their smartphone usage. Differently, adjustments in CC are more likely to encourage users to make changes to their excessive smartphone usage. Studies related to promoting continuous digital behavior or enhancing user satisfaction with digital use conventionally focused on investigating the influence of PP and EX on user behavior [34, 43, 61, 63]. This study suggests that CC plays a vital complementary role within the established framework of PP and EX. The conceptual structure of CC does not overlap with PP and EX but rather complements them.

PP, EX, and CC are interrelated factors that collectively influence rather than operate independently. The interview results remind that individuals inherently possess self-awareness capabilities and tend to engage in autonomous self-reflection when they perceive their behavior as meaningless, unworthy, or unproductive. However, the capacity for self-reflection and awareness requires users to have mental space. Attempts to provoke users' self-awareness in their immersed state may prove ineffective and lead to user aversion. In situations where users undergo interventions related to PP and EX, they disengage from their immersive state and generate the necessary mental space to recognize the inconsistency between their behavior and cognition. Consequently, the methods for inducing cognitive inconsistency are more effective when combined with adjustments in PP or EX. The main objective of CC-related solutions is to highlight the disparity between users' cognition and behavior, with a variety of methods can achieve this goal. Hence, the three quadrants of the PEC model are not isolated from one another; instead, they mutually influence, adjust, and support each other. In practice, intervention design should comprehensively consider three quadrants.

5.6 Suggestions

This research supports the finding that externally imposed controls or assistances reduce users' efforts at self-control or self-regulation [65-67]. Users tend to become less self-aware and fully absorbed in their behavior when they delegate self-management responsibilities to external tools. The conflict between external control and users' intention to continue can hinder users from ceasing the behavior. Therefore, it is crucial to find a balance between self-control and external assistance while avoiding a complete takeover of users' self-control responsibilities in the design of interventions.

Careful consideration is required when determining the cost of skipping interventions in the design of these measures. A high cost for skipping the intervention can make interventions compulsory [59]. This study also found that excessively low skipping costs significantly reduce the effectiveness of interventions. Most participants reported minimal effectiveness with the current intervention approaches because these interventions can be easily skipped at a very low cost, leading users to consistently opt to skip the intervention to maintain their usage. Therefore, deciding how much users should pay as a cost for bypassing restrictions is a matter that requires careful consideration. Determining the appropriate cost of skipping the intervention should give users the freedom to choose whether to skip the intervention while also encouraging them to make more deliberate decisions about continuing their behavior. Moreover, the frequency of intervention presentations is also a significant concern. Users develop a tolerance for repeated information. The utility of interventions decreases as the frequency of their presentation increases. Therefore, endlessly repetitive reminders should be considered a last resort.

Individuals have unique preferences for experiences, expectations, and content that can prompt reflection. The same information can hold different meanings for different users. Current solutions for CSU often rely on general methods that fail to account for individual circumstances, making it challenging to resonate with every user. This is in line with that suggested in reference [67]. Therefore, introducing personalized settings can contribute to designing more effective interventions. For instance, pre-setting various intervention methods within the product to correspond to different user characteristics or concerns, allowing users to choose the approach that best suits them. Alternatively, algorithms can play a role in personalization settings.

5.7 Limitation

This study has several limitations that should be addressed in future research. Due to constraints in the research conditions, laboratory experiments were employed. Ideally, field experiments involving programming interventions on participants' smartphones and tracking their actual smartphone usage and other responses could yield more authentic and objective data. Given the use of laboratory experiments, several potential biases may affect the results:

1. The laboratory setting for watching short videos differs from real-life situations. Moreover, the phones and TikTok accounts used in the experiment did not belong to the participants. TikTok typically employs precise algorithms to track user preferences, and participants may react differently when using their own accounts. These differences may influence participants' experiences and reactions.
2. Participants may exhibit a social desirability bias, tending to respond or behave in socially acceptable and expected ways to present themselves in a more favorable light. Participants were aware that they were part of an experiment and could behave decently within the limited duration of the experimental scenario. Social desirability might lead to the consistent evaluation that the CC condition is the most effective method among the three quadrants in the model, as they may have tried to portray themselves as self-reflective and self-controlled individuals.
3. The experimenter effect is another consideration. Participants might have tried to guess the purpose of the experiment, and the presence of the experimenter could lead participants to exhibit behaviors that conformed to the experimenter's expectations.

4. The study's limited time frame may also be a factor. The experiments were conducted within a restricted timeframe and failed to capture the long-term evolution of behavior and effects. Different time durations might yield varied results in the effectiveness of interventions.
5. The external validity of the findings from this study's experiments is somewhat limited, given that the study exclusively validated the model's effectiveness in the context of continuous behaviors, specifically, viewing short videos. Further research is needed to assess the generalizability of this model to other instances of excessive smartphone usage and digital overuse.
6. Lastly, the external validity of the research findings is limited because the participants mainly consisted of students aged between 20 and 35. These specific participant features may restrict the generalizability of the findings to broader populations. To enhance the external validity of future research, it is necessary to incorporate participants with diverse attributes.

The consistent tendency of evaluating CC as the most effective element should be interpreted with caution, as the authors believe the effectiveness of these elements depends on the specific scenario and may not be consistent in real-world settings. While the research demonstrates significant differences between the experimental and control conditions, indicating the model's effectiveness, it is necessary to conduct field experiments that include long-term evaluations during users' daily smartphone usage to verify the model's effectiveness in real-life situations. Overall, these limitations highlight areas for improvement in future research. Despite these limitations due to research constraints, the model development and validation show promise. The model offers practical potential solutions for addressing excessive smartphone usage and exhibits potential applicability not only in the context of continuous smartphone use but also in addressing other addictive behaviors.

6. Conclusion

This study has introduced a theoretical model to address the issue of excessive smartphone use. The verification of the model and its components has confirmed their effectiveness in addressing continuous smartphone use. Theoretically, the proposed model serves as a valuable addition to the ongoing discourse on resolving the pressing matter of excessive smartphone use. Although the model has been validated under certain experimental constraints, it holds significant potential for further exploration. In addition to confirming the model's effectiveness in dealing with various forms of excessive digital use, it has the potential to expand into solutions for other addictive behaviors. In practical application, this study provides a theoretical foundation and a comprehensive, novel perspective for product design aimed at assisting users in reducing excessive smartphone usage.

This study operates under the assumption that the likelihood of users discontinuing their behavior depends on the volume formed by three dimensions (PP, EX, and CC) and can be regulated by adjusting the three quadrants. The specific parametric influences along each axis merit further quantitative research. Moreover, this study has identified the interaction effects and mutual support among the three quadrants, opening up avenues for more in-depth research into correlations and path analysis within these three quadrants. Furthermore, the model and findings of this study contribute not only to addressing problematic smartphone use but also have the potential to address other addictive behaviors. Applying or developing this model in the research of other addictive behaviors represents a promising avenue for future exploration.

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Chapter 4

Discussion and Conclusion

The reliance of users on digital use has become a prevalent issue in contemporary society. Research on excessive digital use, often referred to as digital dependence, digital overuse, problematic digital use, or digital addiction, has received attention from various research fields [1]. Digital detox, as a research topic addressing this issue, aims to assist users with different levels of digital dependence in reducing their use of digital products and content. This study aims to contribute to digital detox by exploring intervention methods and their effectiveness. The primary objective is to help individuals with varying degrees of digital dependence achieve different levels of digital detox. In essence, the goal is to assist users in reducing their digital usage, thereby enhancing their digital well-being.

Previous research suggests that self-perceived addiction is a prerequisite for individuals to overcome addiction. Existing studies often utilize the objective phenomenon of being unable to stop as the basis for perceiving addiction, leaving a gap in the exploration of how subjective perceptions of one's own behavior influence the perception of addiction. In the chapter 2, we hypothesize that two subjective cognitive factors, namely regret and quit intention, have an impact on individuals' perception of addiction. We empirically validate this hypothesis and identify cognitive inconsistency as a key factor through which subjective cognitive factors influence the perception of addiction. Building on these findings, we propose intervention strategies aimed at helping users recognize and address cognitive inconsistency to enhance their perception of addiction and facilitate the process of overcoming it. As a result, we introduced the concept of behavior-cognitive consistency to the next study.

Based on the findings from the first studies, we have developed a theoretical intervention model for digital use to facilitate digital detox. This model integrates cognitive factors, specifically cognitive consistency, as identified in the first study, which relates to the degree of consistency between an individual's behavior and cognition. Alongside this, it incorporates objective factors associated with intervening behavior, discovered in the second study, notably perceived performance and expectation. The resultant model is referred to as the PEC model. Due to experimental constraints, we chose a common behavior linked to excessive digital use, continuous consumption of short videos, as the experimental context to validate the model. The research results affirm the effectiveness of the model. Furthermore, the study uncovered that users' intentions to continue their behavior exhibit an inverted U-shaped curve when perceived performance (PP) is applied. To encourage users to lean towards discontinuation, it is essential to surpass the threshold of this curve by adjusting the degree or duration of PP regulation. Prior to this threshold, the intervention may inadvertently strengthen users' intentions to continue their behavior. Additionally, we identified two methods for regulating expectation (EX): expectations elevating or expectations erasing, and goal setting. In contrast to the approaches employed by PP and EX to objectively alter behavior, the adjustment of cognitive consistency (CC) aims to influence individuals' subjective consciousness. It is crucial to ensure that the affected individuals have sufficient cognitive space and response time. A lack of these prerequisites may lead to a counteractive effect, potentially reinforcing users' intentions to continue their behavior. Ultimately, the three quadrants are interconnected and mutually supportive.

1. Theoretical Contribution

This study has identified a gap in existing research concerning how individuals subjectively perceive addiction. The academic definition of digital addiction, also referred to as digital overuse or problematic digital use, exhibits variations in the literature but generally involves excessive or compulsive use of digital devices or digital content, resulting in negative consequences across various life domains. Conventional studies often utilize the objective phenomenon of being "unable to stop" as the basis for perceiving addiction, leaving a gap in the exploration of how subjective perceptions of one's own behavior influence the perception of addiction. This study provides an additional perspective for perceiving addiction by focusing on how individuals subjectively perceive digital addiction. We explored and verified how two subjective cognitive factors, namely regret and quit intention, influence individuals' perception of addiction. The findings suggest that people assess whether an individual is digitally addicted by considering an individual's subjective perception of one's behavior. When an individual with cognition inconsistency, that is their subjective thoughts significantly deviates from their actual behavior, this is seen as an indicator of being at risk for digital addiction. This research broadens the scope of identifying digital addiction form objective phenomenon to the subjective perspective.

The confirmation between PP and EX can promote Information Systems Continuance [2]. Chapter 3 of our study addressed a research gap related to reducing Information Systems Continuance using these two factors. PP and EX influence objective behaviors, and this study extends the current framework by introducing the subjective perception of individuals, known as CC, which complements and enriches the original solely objective perspective. In contrast to the predominant single perspective found in current research, our study delves into how both subjective and objective factors jointly influence digital user behavior. The theoretical model developed in this study encompasses factors that impact product quality and factors that affect an individual's perception of their own behavior. This enrichment extends beyond the conventional research that relies on a single perspective. The theoretical model proposed in this study provides a novel perspective and theoretical foundation for other research related to digital detox.

Conventional studies have extensively explored strategies for enhancing continuous behavior through improved user experience or product quality. Conversely, this study takes a divergent approach to validate the effectiveness of reducing perceived performance (PP) in discouraging continuous behavior. Additionally, this study reveals that when user experience is reduced or disrupted, the intention for continuous behavior does not exhibit a linear decline but rather follows an inverted U-shaped curve. The intervention of reducing PP initially exacerbates the intention for continuous behavior, and it is only after surpassing a certain threshold that users' intentions shift towards discontinuation. This research finding provides insights into the specific variation trend of user continuous behavior following these interventions, filling a theoretical gap in prior research that broadly summarized this change as interference or decreased PP leading to user discontinuation [3-5].

This study is in line with existing research by supporting the idea that individuals experiencing cognitive inconsistency may adjust their behavior or cognition to achieve alignment between their cognitive and behavioral aspects [6-8]. However, it also suggests that reinforcing user behavior can be another potential outcome if the intervention is inappropriate. The study's findings address a theoretical gap concerning the mechanisms of intervening in cognitive consistency (CC). This research reveals that influencing CC is an indirect process; it does not directly impact users' behavior but rather follows an indirect process, initially affecting users' cognition and subsequently influencing their behavior. The study posits that cognitive space and response time are essential prerequisites for intervening in CC. Cognitive space provides the conditions for individuals' self-perception, while response time is required for the indirect process through which CC exerts its influence. These findings enhance and clarify our understanding of the mechanisms underlying CC.

Furthermore, our first study adopted the HQs card sorting method in the experimental design. This approach represents an innovative exploration of experimental methods, broadening the possibility of empirical research design. It streamlines the experimental process and enhances the engagement of participants in the experimental procedure. Moreover, this method holds great potential for wide-ranging applications in research contexts where recruiting specific participants poses challenges. Therefore, other researchers might find value in incorporating this method into their own investigations.

2. Practical Implications

We have previously discussed the practical applications of our research findings in Chapter 2. In this section, we will further explore the applications of the PEC model. Reducing users' digital usage through interventions and adjustments to objective factors PP can be achieved by diminishing the overall user experience. This can be approached by considering users' sensory perceptions since the user experience is directly perceived through the five senses. For instance, it may involve subtle alterations to visual, auditory, olfactory, or tactile sensations. Interventions in user experience design should adhere to the principles of nudging. Additionally, intervention can also be accomplished by modifying the relationship between PP and EX. The static connection between PP and EX implies that users tend to discontinue actions when PP falls short of their EX expectations. On the other hand, the dynamic correlation between PP and EX suggests that elevated user experiences lead to higher expectations. In practice, a more effective method for discontinuation may involve initially enhancing the user experience, subsequently raising user expectations, and then reducing the overall user experience. Furthermore, interventions in user experience can be followed by stimulating cognitive inconsistency in users. For instance, if a user's visual experience is impacted, presenting the visual disparities between their intentions and actual behavior through prompts may expedite discontinuation. Combining biotechnological approaches to measure user focus levels and delivering reminders to users with reduced concentration can be an effective form of assistance. Moreover, strategies and interventions can be personalized through algorithms to enhance their effectiveness for different user profiles.

The theoretical model introduced in Chapter 3 has the potential to be applied to various types of digital behaviors to facilitate digital detox. Furthermore, it can be explored, extended, and optimized for application to other behaviors characterized by excessive use or addiction. Further examination and refinement of the model hold promise for future research.

It is essential to acknowledge that the subject matter of this research may conflict with commercial interests, potentially leading to skepticism and constraints in the practical implementation of the findings. Nevertheless, research in the field of assisting with digital detox remains valuable. In the practice of promoting digital detox, designers must confront this conflict and consider it more carefully. They need to strike a balance between not undermining business interests and enhancing users' digital well-being.

3. Limitation and Future Direction

There are numerous factors influencing users' subjective perception of addiction. However, Chapter 2 of this study exclusively examined the impact of behavior and individuals' thoughts about their behavior on user perception. Nevertheless, this study offers a subjective perception perspective for future research on digital addiction. Subsequent studies can explore additional factors that affect subjective perception, leading to a better understanding and establishing a more comprehensive approach to assisting users in digital detox.

Our study unveiled an inverted U-shaped curve in users' continuous intentions for behavior influenced by perceived performance, as discussed in Chapter 3. However, the precise threshold of this curve remains undetermined. Our future research will conduct a thorough investigation to pinpoint and define this curve's threshold and slope. The threshold signifies the point at which continuous intentions shift towards discontinuity. Specifying the slope of the curve will provide insights into whether users' intentions and behaviors rise sharply or gradually before the threshold and decline sharply or gradually after the threshold. The steepness of this curve will significantly impact the adjustments we make to our intervention strategies.

This study found that the higher the inconsistency between cognition and behavior, the more likely users are to discontinue their behavior. However, this description remains vague, as the quantitative relationship between the degree of inconsistency and behavior termination has yet to be explored. In our upcoming research, we will conduct parameterized studies to pinpoint the threshold at which this inconsistency leads to actual behavior termination. Specifically, we aim to determine the extent of misalignment between cognition and behavior that results in user discontinuation.

The research introduced a theoretical model consisting of three dimensions: perceived performance (PP), experiential excellence (EX), and cognitive consistency (CC). Upon concluding the study, we have clarified the mechanisms of CC. However, we have also observed that the relationship between PP and (EX) is intricate and intertwined, making it challenging to express their relationship adequately within the framework of two axes. The exploration in this aspect still needs to be completed. PP and EX are pivotal factors and sub-concepts of user satisfaction. Therefore, we can merge PP and EX into a comprehensive concept: satisfaction. It should be jointly integrated into the theoretical model for further investigation and discussion with CC.

Due to the limitations of the laboratory setting, this study conducted experiments on users' transient behaviors in an artificial environment. In future research, we need to leverage more extensive technological support to develop applications that enable the assessment and experimentation of users' long-term behaviors under real-world conditions. This approach will contribute to a deeper understanding of how the theoretical model functions in people's behavior and will provide a more reliable and meaningful validation of the theoretical framework.

Finally, the theoretical model proposed in this study was experimentally tested within the context of smartphone-related digital behaviors, leaving room for further exploration into various other digital behaviors. In future research, this study's theoretical findings can serve as a basis for enhancing and refining the proposed theoretical model in the context of a broader range of behaviors, not limited to digital behaviors alone. Such research can reveal both the distinct and shared mechanisms through which the theoretical model operates across different behaviors, allowing for the adaptation and refinement of the theoretical framework based on the specific characteristics of these behaviors.

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