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RESEARCH ARTICLE

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Why Are People Addicted to SNS? Understanding the Role of SNS Characteristics in the Formation of SNS Addiction

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Abstract

Research has shown that many people use social networking sites (SNS) excessively, which may lead to various negative consequences. With the aim of reducing SNS addition, this study investigates the role of SNS characteristics in the formation of SNS addiction. By applying incentive sensitization theory in the context of SNS addiction, we suggest that the compulsive motivation for using an SNS is developed by pleasurable and rewarding SNS use experiences. Social network characteristics and communication characteristics, which determine the rewards that users obtain from SNS use, moderate the relationship between habitual SNS use and SNS addiction. We develop novel behavioral measures of *habitual SNS use* and *SNS addiction* based on SNS activity logs and empirically test the research model using a large and unique dataset. Besides contributing to the theoretical development of SNS addiction, the results of this study offer practical options to help prevent SNS addiction. Moreover, the measures of SNS addiction enable the automated monitoring of user behavior on SNS, which could be useful for detecting potential SNS addicts.

Keywords: SNS Addiction, Habitual SNS Use, Social Network Characteristics, Communication Characteristics, Behavioral Measures

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1 Introduction

Social networking sites (SNS) are an important tool that people use to communicate with each other. As of September 2019, one of the most successful SNS, Facebook, had over 2.26 billion monthly active users, with more than 50% of them logging on to Facebook everyday (Facebook, 2020). Users spend an average of 1,200 minutes and share more than 140 billion pieces of content per month on Facebook. It has been reported that smartphone users check Facebook 14 times a day on average (Taylor, 2013), with 48% of 18-34-year-old users checking Facebook when they wake up and 28% doing so on their smartphones before even getting out of bed (Statistic Brain Research Institute, 2015). More than 50% of people even admit to checking Facebook while using the restroom (Jones, 2015). These statistics suggest that, beyond simply adopting SNS, many people use SNS intensively or even excessively. However, despite the benefits of SNS, studies have shown that intensive use of SNS can severely interfere with daily life and lead to various problems, such as the deterioration of academic or work performance and the neglect of important relationships (e.g., Kirschner & Karpinski, 2010; Nyland et al., 2007; Venkatesh et al., 2019). Moreover, studies have shown that addicted SNS users are more likely than non-addicted SNS users to exhibit clinical symptoms of psychiatric disorders, such as depression and schizophrenia (O'Keeffe & Clarke-Pearson, 2011; Rosen et al., 2013).

With the aim of reducing the negative consequences of SNS addiction, we conducted this study to explore how people become addicted to SNS and what factors can facilitate or inhibit the formation of SNS addiction. *SNS addiction* is defined as a psychological state of maladaptive dependency on the use of SNS to such a degree that the following symptoms arise: (1) salience, or SNS use dominating a person's thoughts and behaviors; (2) withdrawal, i.e., when negative emotions arise if a person cannot use an SNS; (3) conflict, or the conflict between SNS use and other tasks, which can impair normal function; (4) relapse and reinstatement, i.e., when a person is unable to voluntarily reduce the use of an SNS; (5) tolerance, i.e., when it becomes necessary to use an SNS to a greater extent in order to produce thrill; and (6) mood modification, i.e., when the use of an SNS offers thrill or relief and results in mood changes (Turel et al., 2011). The literature suggests that the formation of habit can be controlled in the initial stages of SNS use to prevent addiction (Turel and Serenko, 2012). *habitual SNS use* refers to routine repetitions of SNS usage that have become automatic responses to specific cues and are functional for obtaining certain goals or end states (Verplanken & Aarts, 1999).

In this study, instead of focusing on the antecedents of habitual SNS use, we investigate factors that can influence the transition from habitual SNS use to SNS addiction. First, because habit is formed unconsciously through the repetition of a behavior (Aarts & Dijksterhuis, 2000), it is hardly feasible to inhibit the formation of habitual SNS use without reducing the frequency of SNS use. Second, unlike addiction, which focuses on the compulsion to act despite negative consequences, habit emphasizes the automaticity of behavior and thus does not lead to individual or social problems until it becomes an addiction (LaRose et al., 2003; Limayem et al., 2007). Therefore, a more effective way to deal with the problem of addiction would be to reduce the likelihood of a habit developing into an addiction. However, the addiction literature has largely focused on how user personality traits and psychological factors impact addiction (Chen & Leung, 2016; Chen et al., 2020; de Bérail et al., 2019; Wang & Lee, 2020). Little is known about what factors influence the transition from habit to addiction.

Moreover, as a new type of internet addiction, SNS addiction is usually treated as general internet addiction in the literature (Kuss & Griffiths, 2011). However, a prior study revealed that people who have never been addicted to internet usage may nevertheless become heavily addicted to SNS (Karaiskos et al., 2010), which suggests that some novel features of SNS that are not shared by other online activities may facilitate the formation of SNS addiction. In this sense, the existing theories for general internet addiction, which do not take the unique characteristics of SNS into consideration, are not adequate to explain the development of SNS addiction. Therefore, we extend the addiction literature by examining the role of SNS characteristics (i.e., social network characteristics and communication characteristics) in the transition from habitual SNS use to SNS addiction.

In this study, we propose novel behavioral measures of habitual SNS use and SNS addiction, and empirically test the formation of SNS addiction on a large-scale longitudinal SNS activity dataset. According to the cognitive-behavioral model of pathological internet use, symptoms of internet addiction are reflected in both problematic cognitions and abnormal behaviors (Davis, 2001). While past studies have generally relied upon individuals' cognitive and emotional symptoms to measure addiction, we measure SNS addiction based on three typical addictive SNS use patterns that SNS addicts typically exhibit. Compared to the cognitive measures of SNS addiction, the behavioral measures of SNS addiction allow us to more accurately estimate the research model on a large-scale dataset. Moreover, they also provide an efficient approach to automatically monitoring individuals' SNS usage, which could detect those who may potentially become addicted to SNS. To demonstrate the validity of the behavioral measures of SNS addiction, we conducted a pilot study to show that the behavioral measures of SNS addiction are consistent with the cognitive measures of SNS addiction.

2 Literature Review and Theoretical Background

2.1 SNS Addiction

The term "addiction" has traditionally been used to describe repetitive routines aimed at obtaining psychoactive substances, namely alcohol and other addictive chemicals (Marks, 1990). However, research on the brain's reward system indicates that as long as there is a reward, regardless of whether it comes from a chemical or an experience, there is a risk of developing an addiction (Holden, 2001). Therefore, addiction can also refer to behavioral excesses in the absence of addictive psychoactive substances (Brown, 1997; Marks, 1990). SNS addiction is a psychological state of maladaptive dependency on the use of an SNS characterized by symptoms such as salience, withdrawal, conflict, relapse and reinstatement, tolerance, and mood modification (Turel et al., 2011).

Despite the increasing use of SNS, the formation of SNS addiction has received little research attention in the information systems (IS) literature. Most prior studies have used theories of internet addiction to explain the development of SNS addiction (Kuss & Griffiths, 2011). The literature includes three overarching theoretical perspectives that account for the formation of internet addition (Turel & Serenko, 2012). First, the cognitive-behavioral model explains how maladaptive cognitions, which are amplified by environmental factors, lead to pathological internet usage (Davis, 2001). Second, the social skill model suggests that people who lack self-presentation skills tend to prefer virtual communication to face-to-face interactions, which in turn promotes compulsive internet usage (Caplan, 2005). Third, the sociocognitive model of unregulated media use argues that addictive internet usage is caused by habit strength, deficient internet self-regulation, internet self-efficacy, and the expectation of self-reactive outcomes (LaRose et al., 2003).

In addition to these three perspectives, Turel and Qahri-Saremi (2016) took a dual-systems theory perspective to investigate how cognitive-emotional preoccupation with using SNS and cognitive-behavioral control over using SNS lead to problematic SNS use. Kwon et al. (2016) took a rational addiction perspective to show that users adjust their consumption of a social app over time to maximize the discounted utility derived from addictive social app usage. Furthermore, Vaghefi et al. (2017) relied on user liability to technology addiction, which referred to the extent to which a user was prone to addictive use, to categorize users into five profiles (i.e., addict, fanatic, highly engaged, regular, and thoughtful).

In sum, the literature provides strong evidence that internet or technology addiction is related to factors such as user personality traits, psychological factors, and previous usage. However, since individuals' personality traits and psychological factors can hardly be manipulated in practice, it would be difficult to prevent SNS addiction through changing these factors. Considering the positive relationship between habit and addiction, an alternative approach to alleviate SNS addiction would be to manipulate the antecedents of habit, which indirectly influence the formation of addiction (Turel & Serenko, 2012). Nevertheless, since habits are formed unconsciously through the repetition of behaviors (Aarts & Dijksterhuis, 2000), it would be difficult to intervene in the development of habitual SNS use unless users were willing to voluntarily reduce the frequency of usage. Given that habit does not lead to individual or social problems until it becomes addiction (LaRose et al., 2003; Limayem et al., 2007), a more effective approach would be to interrupt the transition from habit to addiction. However, little is known about the circumstances under which habitual SNS use develops into SNS addiction.

Moreover, because most prior studies seek to explain general internet or technology addiction, they generally focus on the factors that can be applied to all types of internet addiction and do not differentiate between different types of internet addiction (Beard & Wolf, 2001). Even among studies investigating SNS addiction, few account for the role of SNS characteristics in the formation of SNS addiction. Considering that individuals who have never been addicted to internet use may become heavily addicted to SNS use (Karaiskos et al., 2010), it may be misleading to study SNS addiction under the simple category of internet addiction because SNS provide certain pleasurable and rewarding use experiences that other internet activities do not. Therefore, despite the existing research on internet and technology addiction, this study investigates how SNS characteristics influence the transition from habitual SNS use to SNS addiction.

2.2 Moderators in the Transition from Habitual SNS Use to SNS Addiction

The literature has shown that habits do not necessarily become addictions (Robinson & Berridge, 2003). Habitual behaviors, such as tying shoelaces or brushing teeth, which are highly automatic and need little cognitive attention, are unlikely to be performed compulsively. Similarly, in the context of SNS use, some habitual users who check SNS automatically when they encounter certain environmental triggers may not feel compelled to use SNS. Habitual but not addicted SNS users can modulate their usage without any distress if they recognize that excessive SNS use may cause negative consequences. Considering that habit does not lead to adverse consequences until it becomes an addiction, it is important to identify the circumstances under which individuals are more likely to transition from habitual SNS use to SNS addiction.

By definition, habits are characterized by the automaticity of behavior whereas addiction is defined as the compulsive nature of behavior. The transition from habitual SNS use to SNS addiction occurs when individuals begin to use SNS compulsively. However, the underlying mechanism of how habitual users develop a compulsive motivation for using SNS remains unknown. Since the formation of behavioral addiction and substance addiction share similar neurobiological mechanisms (Ko et al., 2009), we use incentive sensitization theory, which was initially developed for drug addiction, to explain the formation of SNS addiction.

Incentive sensitization theory argues that the consumption of a rewarding-producing substance can alter brain "wanting" systems (i.e., nucleus accumbens-related brain systems) so that they become hypersensitive to specific drug effects and drug-associated stimuli (Robinson & Berridge, 2003). Consequently, excessive attribution of incentive salience to drug-related representations results in a pathological desire to take drugs (Robinson &

Berridge, 2003). In our study, since psychoactive substances are absent in the development of SNS addiction, the compulsive motivation of SNS use is instead developed by the execution of reward-producing behaviors (i.e., SNS use). In other words, pleasurable and rewarding SNS use activates brain "wanting" systems, which then overemphasize the incentive salience to SNS-related stimuli, causing a pathological desire to use an SNS.

This is consistent with the argument in the previous literature that people risk getting trapped in an addiction when they get a reward from a chemical or an experience (Holden, 2001). Because the major motivation for people to use SNS is to establish and maintain social relationships (Ellison et al., 2007; Kuss & Griffiths, 2011), the transition from SNS habit to SNS addiction is more likely to occur when past SNS use experiences provide continuous rewards that fulfill users' social needs.

Considering the differences between SNS and other online activities, this study focuses on how novel features of SNS fulfill users' social needs and affect the transition from habitual SNS use to SNS addiction. Past studies have shown that the combination of technology features provides a highly psychoactive experience that makes people more likely to engage in the technology and thus develop a psychological dependency on it (Choliz, 2010; Morahan-Martin & Schumacher, 2000). Compared to traditional content-based websites where content is usually produced by website editors, SNS are user-driven websites, where all the content that users can view is contributed by their online friends. Thus, the extent to which SNS can produce thrill and fill sociopsychological voids mainly depend on users' online social network and their communication with online friends. Therefore, according to incentive sensitization theory, SNS users' online social networks and communication with their online friends (i.e., social network characteristics and communication characteristics), which determine the rewards that users can obtain from SNS use, moderate the relationship between habitual SNS use and SNS addiction.

2.3 Social Network Characteristics and Communication Characteristics

The first novel feature of SNS is the virtual social network created by users over the internet. A social network is a social structure made up of a set of people as well as the dyadic ties between them. Users have their own personal offline social networks, comprising relationships with family members, relatives, and friends. However, offline social networks may be difficult to maintain because of physical separation, time conflicts, or deficits in social skills (Caplan, 2005). To overcome these constraints, SNS allow users to construct a virtual social network over the internet. In the virtual social network, people can either maintain their existing friendship circles or make new online friends based on shared interests, political views, or other activities (boyd & Ellison, 2007).

In social network analysis, two of the most commonly used variables to describe a social network are degree centrality and closeness centrality. Using a node to represent an online user, friendship between two users can be represented by a tie linking the two nodes. Thus, a user's degree centrality, which is measured as the number of ties incident upon a node, equals the number of online friends a user has. Moreover, if the length of the path from a user to the user's friend is defined as the friend's frequency of SNS activities, closeness centrality, which is measured as the average length of paths between a node and all other linked nodes in a graph, equals the average activeness of a user's online friends. Considering that SNS are user-driven websites, having a large number of online friends ensures that one will have an audience to view posted content, while a high level of activeness among online friends ensures that one will have sufficient content (e.g., posts, pictures, videos, and comments) to consume. Both the number of online friends and the activeness of online friends influence the rewards that users obtain from SNS use and thus moderate the transition from habitual SNS use to SNS addiction.

In addition to the virtual social network, another novel feature of SNS is the communication means provided for users to interact with each other. Since social relationships are formed and maintained through communication with online friends (Ellison et al., 2007), how users communicate with others also influences the extent to which their social needs are met. Compared to traditional computer-mediated communication (e.g., email and instant messenger), SNS allow users to interact with their friends through both directed and undirected communication channels. Directed communication, which is similar to instant messaging, is composed of personal, one-to-one exchanges with a targeted user, whereas undirected communication, which is a novel feature of SNS, relies on one's virtual social network to broadcast information to a group of friends (Burke et al., 2011). Through the undirected communication channel, users are able to receive an aggregate stream of updates about their friends, which helps them keep in regular touch with their friends (Burke et al., 2011).

Moreover, SNS allow users to communicate with their friends in different content formats (e.g., text, pictures, and videos). Text is a descriptive form of information representation (Mayer, 2005); since text has no similarity with its referent, people can only understand its meaning based on convention. By contrast, picture and video are depictive forms of information representation that are associated with their referent (Mayer, 2005).

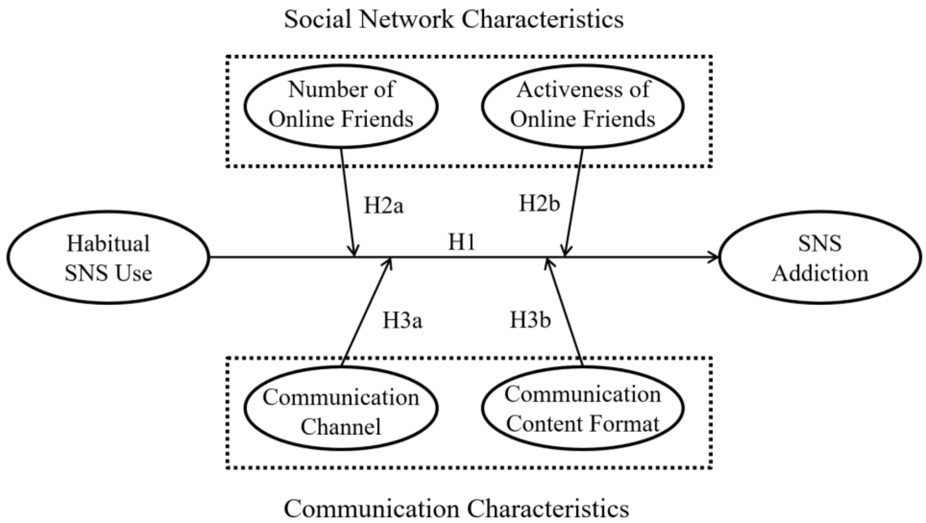

Figure 1. Research Model

Because new information can be read directly from depictive information representation but not descriptive information representation, it takes less processing effort to interpret results from a picture or a video (depictive information representation) than a paragraph of text (descriptive information representation) (Kosslyn, 1996; Larkin & Simon, 1987). Hence, compared to textual content, it is generally more efficient and relaxing for people to consume nontextual content (Mayer & Moreno, 2003). In sum, both the communication channel and the communication content format influence the rewards that users obtain from SNS use and thus moderate the transition from habitual SNS use to SNS addiction.

3 Research Model and Hypotheses

We propose a research model to account for the formation of SNS addiction—in particular, how habitual SNS use develops into SNS addiction (see Figure 1). In the research model, habitual SNS use is positively related to SNS addiction and the relationship is moderated by both social network characteristics and communication characteristics.

3.1 From Habitual SNS Use to SNS Addiction

Past research offers two perspectives demonstrating that IS use habit leads to addiction. First, because of the automaticity of habit, habitual SNS users often pay little attention to the potential harms imposed by expanding SNS use (Turel & Serenko, 2012). According to the theory of rational addiction, the reduced attention devoted to the potential future negative consequences of SNS use facilitates the transition from habit to addiction (Becker & Murphy, 1988). Second, from a neurobehavioral perspective, habitual SNS use may have an enduring impact on nucleus accumbens-related brain systems, leading to hypersensitivity to SNS related stimuli (Robinson & Berridge, 2003). Therefore, habitual SNS use may be more likely to develop into SNS addiction because of users' increased hypersensitivity to SNS-related stimuli and a consequently expanding gap between their expected rewards and their actual rewards (Robinson & Berridge, 1993; Turel & Serenko, 2012).

In addition, we argue that after people develop the habit of using SNS, they are likely to repeat SNS usage automatically when they encounter similar environmental stimuli. In this sense, users with a stronger SNS use habit would be expected to use SNS more frequently in order to increase the opportunity of experiencing the thrill of performing rewarding SNS use actions. Since addiction is developed through the execution of reward-producing behaviors, more pleasurable and rewarding SNS use experiences accelerate the changes in habitual users' brain "wanting" systems that overemphasize incentive salience to SNS-related stimuli, leading to SNS addiction. Hence, we hypothesize:

H1: Habitual SNS use is positively related to SNS addiction.

However, as discussed above, not every habit eventually becomes an addiction. Habitual SNS users risk becoming addicted to SNS when SNS use provides sufficient psychological rewards to fulfill users' social needs. Since SNS are user-driven websites, the extent to which SNS can produce thrill and fill sociopsychological voids primarily depend on users' online social networks and their communication with online friends. Therefore, the relationship between habitual SNS use and SNS addiction is moderated by social network characteristics and communication characteristics.

3.2 Social Network Characteristics

The first social network characteristic is the number of online friends a user has. Because the primary motivation for people to use SNS is to maintain existing relationships and develop new relationships (Ellison et al., 2007), a larger number of online friends implies a higher probability that a user's social needs are being met by SNS use. From a network structure perspective, previous studies have shown that users who are more centrally located in the network are able to obtain more rewards from the network (Afuah, 2013; Ahuja et al., 2003; Paruchuri, 2010). In our study, users with a higher degree centrality have a larger audience available to view their SNS posts. Moreover, some audience may "like" or reply to the posts or conduct one-to-one online conversations with users. Receiving attention from others fulfills the social needs of such users and offers pleasurable SNS use experiences. In contrast, users with low degree centrality would have a smaller audience available to view their SNS posts, likely leading to fewer interpersonal interactions. In this case, the social needs of such users may not be fulfilled because they do not receive adequate attention from others. As discussed above, if SNS use is able to fulfill users' heretofore unmet needs, habitual SNS use may lead to SNS addiction. However, if habitual SNS use is unable to fulfill users' needs, it is unlikely to transition into SNS addiction. Therefore, the number of online friends a user has affects the extent to which the user's social needs are met and thus moderates the positive relationship between habitual SNS use and SNS addiction. Hence, we hypothesize:

H2a: Habitual SNS use is more likely to lead to SNS addiction if the user has more online friends on the SNS.

The second social network characteristic is activeness of online friends, which refers to the average frequency of online friends' content production activities on SNS. Since SNS are user-driven websites, all content that users can view on SNS is contributed by their circle of online friends (Mislove et al., 2007). Hence, the activeness of SNS friends determines the amount of content that a user can view on an SNS. If a user's SNS friends are highly active on the site, the user's SNS homepage will be filled with friends' posts and other SNS activities, providing the user with a great deal of information and topics for future conversations. The user can use this information to communicate with SNS friends by replying to posts or status updates. Thus, if users have a highly active SNS network, the SNS is likely to provide pleasurable and rewarding use experiences through content consumption and interpersonal interactions, which can fulfill users' social needs. In contrast, users that do not have an active network of SNS friends would have little access to content on the site. Such users would know little about what their SNS friends are doing and would have fewer opportunities to interact with them. Under such circumstances, an SNS would be less likely to provide pleasurable and rewarding use experiences capable of fulfilling users' social needs. Since the transition from habitual SNS use to SNS addiction is influenced by the extent to which users' social needs are fulfilled, the activeness of SNS friends moderates the positive relationship between habitual SNS use and SNS addiction. Hence, we hypothesize:

H2b: Habitual SNS use is more likely to lead to SNS addiction if the user's online friends are highly active on the SNS.

3.3 Communication Characteristics

The first communication characteristic is the communication channel used to interact with SNS friends. As discussed above, SNS allow users to interact with friends through either directed or undirected communication channels. Directed communication channels allow information to be sent to a specific person; thus, the interaction occurs between the sender and receiver only. In contrast, undirected communication channels allow users to share their current status or any other information with a larger audience. Since friends' status updates are displayed in an aggregate stream on the user's SNS homepage, it is more convenient and efficient for users to gain information about their friends and communicate with them through undirected communication channels. In this sense, the broadcasting nature of undirected communication enhances the efficiency of information dissemination among users, and thus plays an important role in providing more pleasurable and rewarding SNS use experiences and fulfilling users' social needs.

Moreover, because users can view and comment on the original content posted through undirected communication channels, see the comments made by other users on these posts, and add to these comments, undirected communication provides greater opportunities for users to interact not only with the sender but also with other friends who reply to the post. Given that undirected communication leads to more interactions among users, and social relationships are maintained through regular interaction (Allan, 1979), users' social needs are more likely to be fulfilled if their online friends send information through undirected communication channels vs. directed communication channels. Since the transition from habitual SNS use to SNS addiction is influenced by the extent to which users' social needs are met, the communication channel moderates the positive relationship between habitual SNS use and SNS addiction. Hence, we hypothesize:

H3a: Habitual SNS use is more likely to lead to SNS addiction if the user's online friends send information through undirected vs. directed communication channels on the SNS.

The second communication characteristic is the format of communication content. Generally, SNS allow three forms of content to be shared—text, pictures, and videos. As discussed above, text is a descriptive form of information representation, whereas pictures and videos are depictive forms of information representation (Mayer, 2005). Because descriptive information requires more processing effort than depictive information (Kosslyn, 1996; Larkin & Simon, 1987), nontextual content is more efficient for users to consume than textual content (Mayer & Moreno, 2003). Therefore, if posts are presented in depictive form, users are able to acquire more information and communicate with more friends with the same amount of effort.

Moreover, the literature has shown that pictorial information outperforms textual information in capturing attention (Finn, 1988), enhancing recall of other semantic information (Childers & Houston, 1984), and evoking affective responses (Mitchell & Olson, 1981). Past research has also shown that people feel more relaxed and satisfied while viewing nontextual content vs. textual content (Kosslyn, 1996; Mayer & Moreno, 2003). Therefore, nontextual content may offer users more pleasurable and rewarding SNS use experiences than textual content. Since the transition from habitual SNS use to SNS addiction is influenced by the rewards obtained from SNS use, the communication content format moderates the positive relationship between habitual SNS use and SNS addiction. Hence, we hypothesize:

H3b: Habitual SNS use is more likely to lead to SNS addiction if the user's online friends post nontextual (e.g., pictures and videos) rather than textual content on the SNS.

4 Methodology

4.1 Data and Sample

Our dataset was drawn from a large SNS. On this SNS, users need permission to connect with other users. The major use motivation on this SNS is to establish and maintain social relationships. There are three segments of the raw data: anonymous user profile data, time-series user friendship data, and time-stamped user activity logs. The user profile data include the demographic information of 34,979 undergraduate students born between 1985 and 1990 from 10 US universities. The user friendship data include the creation of friendships between these users and their friends on the SNS. The user activity logs include time stamps, user IDs, activity types, and the activity content produced by these users and their friends on the SNS between January 9, 2010, and March 12, 2010 (9 weeks). The SNS activity data are aggregated on a weekly basis. A week (instead of a day) was chosen as the unit of time for data analyses because SNS use, like other types of entertainment (e.g., online gambling or watching movies), typically has weekly patterns (Ma et al., 2014). Since people typically have more leisure time on weekends, their SNS use would likely differ between weekdays and weekends. Therefore, we divided the 63-day period of our dataset into 9 weeks to control for the weekend effect. The study was approved by the National University of Singapore's Institutional Review Board (IRB).

4.2 Operationalization of SNS Addiction

While most prior studies rely on self-reported surveys to measure internet addiction (i.e., cognitive measures of addiction), this study proposes a novel approach to measure SNS addiction based on users' abnormal SNS use behaviors recorded on SNS activity logs (i.e., behavioral measures of SNS addiction). The cognitive-behavioral model of pathological internet use indicates that symptoms of internet addiction are reflected in both problematic cognitions and abnormal behaviors (Davis, 2001). Since problematic cognitions and abnormal behaviors usually occur simultaneously, people who have cognitive symptoms of SNS addiction also exhibit addictive SNS use patterns. Thus, the diagnosis of SNS addiction based on abnormal SNS use behaviors should be consistent with diagnosis based on pathological cognitions. Importantly, the new behavioral measures provide an efficient approach to detecting SNS addiction based on users' SNS activity logs, which allowed us to estimate the research model on a large-scale longitudinal dataset. In this study, we identified three typical addictive SNS use patterns, and measured SNS addition based on these three patterns. Moreover, we conducted a pilot study to demonstrate the validity of diagnosing SNS addiction based on these three addictive SNS use patterns.

The first addictive SNS use pattern is always being active on SNS. $Addiction\ 1_{i,t}$ was measured as user *i*'s number of active time slots on SNS in week *t*. We divided each day into 24 hourly slots (i.e., 0:00 to 0:59 hours, 1:00 to 1:59 hours …… 23:00 to 23:59 hours). If user *i* had any activity in hour *h* of day *d* in week *t*, time slot $w_{i,t,d,h}$ was regarded as active. Otherwise, this time slot was deemed inactive. If users have a lot of active time slots on SNS, we believe that they likely have symptoms of addiction such as salience, withdrawal, conflict, relapse and reinstatement, tolerance, and mood modification. For these users, it is also likely that SNS use dominates their thoughts and behaviors (salience), that they are unable to voluntarily reduce their use of SNS (relapse and reinstatement), and that they have to use SNS to a greater extent to produce thrill (tolerance). Moreover, using SNS in many time slots likely conflicts with other tasks, which impairs normal function (conflict). In addition, if users are always active on an SNS, it is probably because the use of the SNS offers thrill and/or relief, which may result in mood changes (mood modification). Under such circumstances, if such users cannot use the SNS, negative emotions will likely arise (withdrawal).

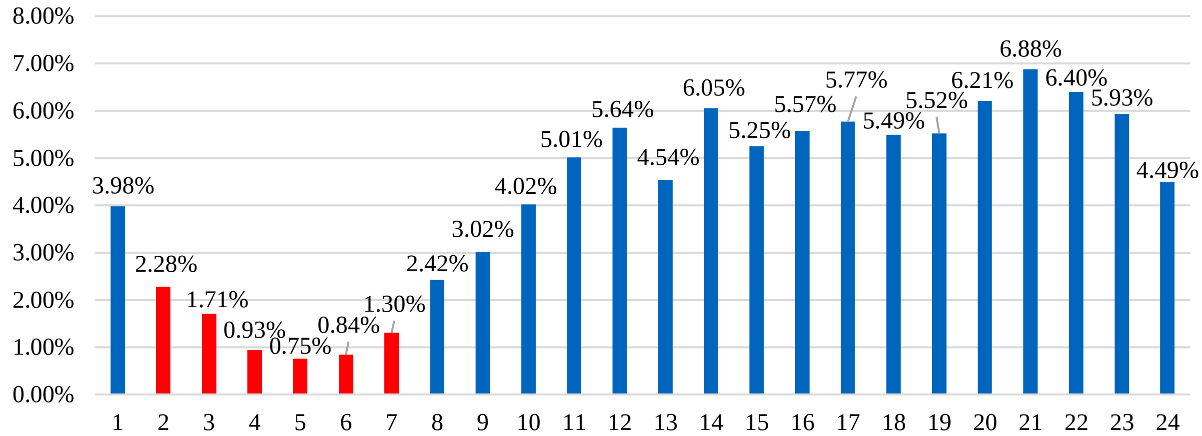

Figure 2. Percentage of SNS Activities by Hour

The second typical addictive SNS use pattern is using SNS frequently from late at night to early in the morning. $Addiction\ 2_{i,t}$ was measured as the number of SNS activities user *i* conducted from 1 a.m. to 7 a.m. in week *t*. Figure 2 presents the statistics of the percentage of SNS activities by hour. The percentages are based on the number of SNS activities within a certain hour divided by the total number of SNS activities in a day. As shown in Figure 2, SNS use declines rapidly between 1 a.m. and 7 a.m. In contrast to normal SNS users who may use SNS to kill time when they are bored or have free time, SNS addicts tend to use SNS frequently and compulsively even when they need to carry out other tasks or perform normal bodily functions such as sleep. Therefore, using SNS frequently late at night conflicts with the biological clock and is thus detrimental to physical and mental health (conflict) (Luyster et al., 2012). Moreover, heavy SNS usage late at night also likely reflects other addictive symptoms, such as salience, relapse and reinstatement, tolerance, mood modification, and withdrawal. Since late-night SNS use likely causes users to lose sleep, we presume that users engage in frequent late-night SNS use only because SNS use dominates their thoughts and behaviors (salience), they are not able to voluntarily reduce their use of the SNS (relapse and reinstatement), and they have to use the SNS to a greater extent to produce thrill (tolerance). Likewise, we presume that users are engaging in frequent late-night SNS use because it offers thrill or relief, because it results in mood changes (mood modification), and because not doing so would arouse negative emotions (withdrawal).

The third addictive SNS use pattern is responding quickly to SNS activities. We measured $Addiction\ 3_{i,t}$ as user i's average response time on the SNS in week *t*. Considering that some SNS users may prefer to consume content and do not initiate conversations or make posts on SNS, $Addiction\ 3_{i,t}$ allowed us to measure the addiction level of this type of user by calculating how quickly they respond to friends' activities on the SNS. If users always respond quickly, this indicates that they pay close attention to SNS updates and that they frequently check the SNS. For such users, it is reasonable to infer that SNS use dominates their thoughts and behaviors (salience), that they are not able to voluntarily reduce their SNS use (relapse and reinstatement), and that they have to use SNS to a greater extent to produce thrill (tolerance). Moreover, if users pay close attention to SNS updates, it is probably because checking the SNS offers thrill or relief and changes their mood (mood modification). Otherwise, they would not check the SNS so frequently. For such users, if they are no longer allowed to use the SNS, negative emotions such as anxiety would arise, because they would be worried about missing important updates from their SNS friends (withdrawal). In addition, frequently checking SNS likely conflicts with other tasks, thus impairing normal work and life routines (conflict).

In sum, we design three indicators of addictive SNS use patterns, which capture the six symptoms of SNS addiction. While each indicator describes a certain pattern of addictive SNS use, the combination of these three indicators provides a more accurate and robust measure for SNS addiction. Therefore, SNS addiction ($Addiction_{\ i,t}$) was computed as the product of $\ln(Addiction\ 1_{i,t} + 2)$, $\ln(Addiction\ 2_{i,t} + 2)$, and the reciprocal of $\ln(Addiction\ 3_{i,t} + 1)$ (See Equation 1). We used the log-transformed values of $Addiction\ 1_{i,t}$, $Addiction\ 2_{i,t}$, and $Addiction\ 3_{i,t}$ in the equation to ensure that the multipliers were normally distributed. 1 or

2 was added to each indicator to ensure that none of the log-transformed values were equal to zero.

$$Addiction_{i,t} = \frac{ln(Addiction\ 1_{i,t} + 2) \times ln(Addiction\ 2_{i,t} + 2)}{\ln(Addiction\ 3_{i,t} + 1)} \quad (1)$$

4.3 Operationalization of Other Variables

This study also proposes a novel behavioral measure of habitual SNS use based on routine repetitions of SNS use recorded on SNS activity logs. While most prior studies use self-reported surveys to measure IS use habit (i.e., cognitive measures of habit), Wood et al._(2002) measured habit based on subjects' diary records. Since habit reflects the routine repetitions of past behavior that are cued by stable features of the environment, they measured habit as the extent to which the behavior is performed "just about every day" and "usually in the same location" (Wood et al., 2002, p. 1285). In our study, because habitual users automatically repeat SNS use actions when they encounter similar features in the environment (e.g., arrival at school or getting up in the morning), their SNS use follows a routine pattern. Therefore, similar to Wood et al.'s approach, we measure habitual SNS use ($Habit_{i,t}$) as the extent to which user *i* followed a similar SNS use pattern between week *t*-1 and week *t*.

We constructed vector $W_{i,t}$ = ($w_{i,t,1,1}$, $w_{i,t,1,2}$, ……, $w_{i,t,1,24}$, $w_{i,t,2,1}$, $w_{i,t,2,2}$, ……, $w_{i,t,7,24}$) to describe user *i*'s SNS use pattern in week *t*. The vector $W_{i,t}$ has 168 dimensions (i.e., 24 hours × 7 days). For each dimension, $w_{i,t,d,h}$ is 1 if the time slot is active and 0 otherwise. We measured similarity in the patterns of SNS use between two consecutive weeks by calculating the angle between two weekly vectors using cosine distance (Deza & Deza, 2006). In Equation (2), if the angle between $W_{i,t-1}$ and $W_{i,t}$ is 0, then user *i* exhibits same pattern of SNS use in both week *t*-1 and week *t*. Hence, the strength of user *i*'s habitual SNS use in week *t* would be 1. An increase of the angle between $W_{i,t-1}$ and $W_{i,t}$ means a reduction in the strength of the habitual SNS use. When the angle reaches 90°, the strength of habitual SNS use would be 0, implying completely different patterns of SNS use in week *t*-1 and week *t*.

$$Habit_{i,t} = \frac{W_{i,t-1} \cdot W_{i,t}}{\left|\left|W_{i,t-1}\right|\right| \cdot \left|\left|W_{i,t}\right|\right|} \quad (2)$$

Social network characteristics and communication characteristics were also measured using SNS activity logs. When we measured the variables, we counted both original posts drafted by a user and news links or others' posts forwarded by the user. Number of online friends ($Number_{i,t}$) was measured as the number of user *i*'s friends on SNS in week *t*. Activeness of online friends ($Activeness_{i,t}$) was measured as the average number of SNS activities conducted by user *i*'s friends in week *t*. Communication channel ($Channel_{i,t}$) was measured as the percentage of content sent through the undirected communication channel out of the total content sent by user *i*'s friends in week *t*. Communication content format ($Format_{i,t}$) was measured as the percentage of nontextual content out of the total content sent by user *i*'s friends in week *t*. A message with both text and pictures/videos was considered to be a nontextual message; a message with text only was defined as a textual message.

4.4 Econometric Model Specification

We model the main effect of habitual SNS use and the interaction effects of social network characteristics and communication characteristics on SNS addiction in Equation (3). Panel data was used to estimate the model for better causality. In the model, *i* denotes an SNS user; *t* denotes the time period in weeks; α_i denotes the individual-specific effect; and $\varepsilon_{i,t}$ denotes the residual error term. A set of weekly time dummies (θ_t) was included to capture the time-specific effect. To rule out confounding effects and possible alternative explanations, we included a set of control variables that could impact the formation of SNS addiction based on our review of the extant literature (e.g., Osatuyi & Turel, 2018; Pontes et al., 2018; Vaghefi et al., 2020). First, since individuals' previous SNS use experience might influence their addiction levels, SNS age ($SNSage_{i,t}$, the number of weeks from the time user *i* joined SNS to week *t*) and the square of SNS age ($SNSage\_Squared_{i,t}$) were included to control for possible linear and nonlinear use experience effects. Moreover, to eliminate the effects of sociodemographic variables (gender and age) on SNS addiction, possible effects of user gender ($Male_i$, a dummy indicator: 1 for male, 0 for female) and age (Age_i) were also controlled in the model estimation. To account for the chronological order of different constructs, habitual SNS use ($Habit_{i,t-1}$), social network characteristics ($Number_{i,t-1}$ and $Activeness_{i,t-1}$), and communication characteristics($Channel_{i,t-1}$ and $Format_{i,t-1}$) were lagged by one week in the model. This approach deals with simultaneity issues and allows the lagged effects on SNS addiction to be examined.

$$\begin{aligned} Addiction_{i,t} = \\ &\beta_1 Habit_{i,t-1} + \beta_2 Habit_{i,t-1} \times Number_{i,t-1} \\ &+ \beta_3 Habit_{i,t-1} \times Activeness_{i,t-1} \\ &+ \beta_4 Habit_{i,t-1} \times Channel_{i,t-1} \\ &+ \beta_5 Habit_{i,t-1} \times Format_{i,t-1} \\ &+ \beta_6 Number_{i,t-1} + \beta_7 Activeness_{i,t-1} \\ &+ \beta_8 Channel_{i,t-1} + \beta_9 Format_{i,t-1} \\ &+ \beta_{10} SNSAge_{i,t} + \beta_{11} SNSAge\_Squared_{i,t} \\ &+ \beta_{12} Male_i + \beta_{13} Age_i + \theta_t + \alpha_i + \varepsilon_{i,t} \end{aligned} \quad (3)$$

5 Pilot Study

Cognitive measures of addiction and habit, which can capture core symptoms of addiction and the automatic nature of habit, have been widely used in clinical settings and previous studies. To validate the behavioral measures of SNS addiction and habitual SNS use, we conducted a pilot study to show that the diagnosis of SNS addiction and habitual SNS use based on SNS activity logs is consistent with that based on self-reported surveys. Moreover, to differentiate SNS addicts from SNS non-addicts, we computed behavioral thresholds based on the diagnosis of SNS addiction using cognitive measures.

5.1 Pilot Study Data Collection

We developed a web app to collect users' SNS activity data and survey data. The behavioral indicators of SNS addiction and habitual SNS use were calculated based on SNS activity data while the cognitive indicators were obtained based on survey responses (see Appendix A). We recruited active SNS users from Amazon Mechanical Turk for the pilot study. They opted in to the app and granted us permission to access their SNS activity logs. After receiving authorization, the app automatically downloaded their SNS activity data, including time stamps, user ID, activity types, and content. Then, they were given a link to provide their demographic information. Finally, they completed an online survey about SNS addiction and habitual SNS use. Participants were each given $5 in compensation for their time and effort. A total of 275 subjects (136 women and 139 men) participated in the pilot study.

5.2 Pilot Study Data Analysis and Results

First, we showed that the scale items of the cognitive measures, which were adapted from established instruments, have adequate reliability and validity (See Appendix B). Second, we showed that the results of the cognitive measures are not significantly influenced by social desirability bias (see Appendix C). Third, we calculated the correlations between the behavioral measures of SNS addiction and habitual SNS use and their corresponding cognitive measures. Both correlation coefficients are high and significant (SNS addiction: $r = 0.863$, $p < 0.001$; habitual SNS use: $r = 0.732$, $p < 0.001$), which demonstrates the validity of the behavioral measures of SNS addiction and habitual SNS use. Moreover, we found that, compared to the behavioral indicators based on one addictive SNS use pattern, the combined behavioral indicator based on three addictive SNS use patterns has the highest correlation coefficient with the cognitive measures of SNS addiction.

In order to determine addiction to SNS based on SNS use behaviors, we computed behavioral thresholds to differentiate SNS addicts from SNS non-addicts. In general, if participants answered with "5" (*slightly agree*) or more on over half of the questions in the survey (See Appendix D), we classified them as addicts. Because of the consistency between the behavioral measures and the cognitive measures of SNS addiction, we determined the behavioral thresholds of SNS addiction based on the classification of SNS addicts using the survey method. A twofold cross-validation was performed to calculate and evaluate the behavioral thresholds of SNS addiction.

First, we randomly partitioned the whole sample into an estimation sample and an evaluation sample. The estimation sample was used to calculate the behavioral thresholds of SNS addiction whereas the evaluation sample was used to evaluate the accuracy of classification using these behavioral thresholds. Second, we selected users who were marginally addicted (i.e., users who answered *slightly agree*, *agree*, or *strongly agree* on 7 or 8 out of the 12 items) or marginally not addicted to SNS (i.e., users who answered *slightly agree, agree*, or *strongly agree* on 5 or 6 out of the 12 items) from the estimation sample. Based on these selected users, we calculated the average values of the behavioral indicators and used them as thresholds to diagnose SNS addiction (Addiction > 0.928). Third, for users in the evaluation sample, we classified them as SNS addicts if their behavioral indicators exceeded the thresholds of SNS addiction. Assuming the diagnosis of SNS addiction based on the cognitive measures was correct, we calculated accuracy by comparing the classification based on the behavioral measures with that based on the cognitive measures. The accuracy rate of the classification of SNS addicts using the combined behavioral indicator was 97.83%, which was the highest among classifications using different behavioral indicators. Moreover, we conducted robustness checks by changing the time unit of analysis from one week to two weeks or four weeks and obtained similar results (see Appendix E).

6 Data Analyses and Results

6.1 Main Analysis and Results

Users who were already addicted to SNS at the beginning of the time period of our dataset were omitted (using the threshold obtained in the pilot study). Hence, the final dataset for model estimation contained 30,847 users and their friends' SNS activity logs from January 9, 2010, to March 12, 2010. Among these SNS users, 51.33% were women, 46.60% were men, and the remaining 2.07% did not provide gender information. Their mean age was 22.48 (SD = 1.43, min = 20, max = 26). Each user conducted an average of 20.12 activities weekly (SD = 60.03, min = 0, max = 960). Table 1 presents the descriptive statistics and the correlation matrix for all variables.

Table 1. Descriptive Statistics and Correlation Matrix

	Variable	Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8	9
1	Addiction	0.320	0.288	0.038	10.836	1.000								
2	Habit	0.065	0.096	0	0.720	0.693	1.000							
3	Number	160.483	127.068	1	1,680	0.060	-0.007	1.000						
4	Activeness	22.010	9.469	0	733.143	0.106	0.113	-0.022	1.000					
5	Channel	0.678	0.097	0	1	0.008	0.007	-0.031	0.027	1.000				
6	Format	0.372	0.159	0	0.972	-0.159	-0.133	0.256	0.264	0.360	1.000			
7	SNSAge	164.847	50.197	1	296	-0.065	-0.067	-0.017	-0.363	0.025	0.103	1.000		
8	Male	0.476	0.499	0	1	-0.091	-0.108	0.009	-0.043	0.025	-0.008	-0.058	1.000	
9	Age	22.479	1.431	20	26	-0.152	-0.114	-0.159	-0.365	0.075	0.067	0.649	0.021	1.000

Note: All correlation coefficients were significant at p< 0.05

Table 2. Main Results

Variables	Model 1: FE basic	Model 2: FE full	Model 3: RE basic	Model 4:RE full	Hypothesis
	Addiction	Addiction	Addiction	Addiction	
Habit	1.530*** (0.070)	0.911*** (0.072)	1.728*** (0.073)	1.130*** (0.077)	H1: supported
Habit × Number		0.0009*** (0.00006)		0.0008*** (0.00006)	H2a: supported
Habit × Activeness		0.013*** (0.002)		0.013*** (0.002)	H2b supported
Habit × Channel		0.864*** (0.084)		0.962*** (0.090)	H3a: supported
Habit × Format		-1.210*** (0.050)		-1.439*** (0.051)	H3b: rejected
Number		0.0009*** (0.0002)		0.0001*** (0.000007)	
Activeness		0.0004 (0.0002)		0.0007*** (0.0001)	
Channel		0.105*** (0.009)		0.093*** (0.007)	
Format		-0.060*** (0.009)		-0.079*** (0.006)	
SNSAge	0.008*** (0.001)	0.006*** (0.0007)	0.0006*** (0.00007)	0.0003*** (0.00008)	
SNSAge_Squared	-0.00001*** (0.000002)	-0.00001*** (0.000002)	-0.000001*** (0.0000002)	-0.00000007 (0.0000002)	
Male			-0.014*** (0.002)	-0.014*** (0.002)	
Age			-0.022*** (0.0009)	-0.017*** (0.001)	
Intercept	-0.753*** (0.109)	-0.731*** (0.110)	0.623*** (0.019)	0.466** (0.022)	
R^2	0.153	0.202	0.487	0.508	
Number of obs	194,807	194,807	190,775	190,775	
Number of users	30,771	30,771	30,135	30,135	

Note: Robust standard errors in parentheses; **p* < 0.05, ***p* < 0.01, ****p* < 0.001. Because 636 users did not provide their gender information, the number of users and the number of observations in the RE models are less than those in the FE models.

Table 3. Effect Sizes for Different Levels of SNS Characteristics

	Number of online friends	Activeness of online friends	Communication channel	Communication content format
Mean - Std_Dev	0.942	1.074	1.413	0.654
Mean	1.056	1.199	1.497	0.461
Mean + Std_Dev	1.171	1.323	1.581	0.269

We estimated both fixed-effects (FE) and random-effects (RE) linear models of the relationship between habitual SNS use and SNS addiction, as well as the moderating effects of social network characteristics and communication characteristics on this relationship (See Table 2). In Models (1) to (4), robust standard errors are clustered at the individual level to control for heteroskedasticity. Time invariant control variables (Age_i and $Male_i$) are included in the RE models but not the FE models. We employed a series of alternative models to benchmark the results and statistical fit for both the FE and RE models. Models (1) and (3) are basic models with independent variables and control variables. Models (2) and (4) include independent variables, moderators, and control variables. R^2 increases substantially from Model (1) to (2) and from Model (3) to (4), indicating that the moderators provide additional explanatory power to the original models. We conducted a test of overidentifying restrictions (orthogonality conditions) to show that the RE estimators are inconsistent. Thus, the FE estimators in Models (1) and (2) are preferable. The FE models allow the user-specific unobserved heterogeneity to be correlated with observed variables.

The coefficients of *Habit* are consistently positive and significant in Models (1) to (4), suggesting that users with a stronger habitual SNS use are more likely to become addicted. Thus, H1 is supported. Specifically, Model (1) suggests that an increase of 1 unit in habitual SNS use leads to an increase of 1.530 units in SNS addiction when moderators are not considered.

Models (2) and (4) reveal the moderating effects of social network characteristics and communication characteristics. Parameters for *Habit*×*Number* are consistently positive and significant, supporting H2a. Our results show that habitual SNS use is more likely to lead to SNS addiction if the user has high numbers of SNS friends. Parameters for *Habit*×*Activeness* are also consistently positive and significant, supporting H2b. This means that habitual SNS use is more likely to lead to SNS addiction if the user's online friends are more active on the SNS. Parameters for *Habit*×*Channel* are consistently positive and significant, supporting H3a. This indicates that habitual SNS use is more likely to lead to SNS addiction if the user's online friends send information through undirected communication channels vs. directed communication channels on the SNS. Parameters for *Habit*×*Format* are consistently negative and significant, contradicting H3b. This indicates that habitual SNS use is more likely to lead to SNS addiction if the user's online friends post textual vs. nontextual content on the SNS.

Table 3 presents the effect sizes of the impact of habitual SNS use on SNS addiction for different levels of SNS characteristics. Column 2 shows that when the number of SNS friends equals *mean - SD, mean,* or *mean + SD*, an increase of 1 unit in habitual SNS use leads to an increase of 0.942, 1.056, and 1.171 units in SNS addiction, respectively. Column 3 shows that when the activeness of online friends equals *mean - SD, mean,* or *mean + SD*, an increase of 1 unit in habitual SNS use leads to an increase of 1.074, 1.199, and 1.323 units in SNS addiction, respectively. Column 4 shows that when the communication channel equals *mean - SD, mean,* or *mean + SD*, an increase of 1 unit in habitual SNS use leads to an increase of 1.413, 1.497, and 1.581 units in SNS addiction, respectively. Column 5 shows that when communication content format equals *mean - SD, mean,* or *mean + SD*, an increase of 1 unit in habitual SNS use leads to an increase of 0.654, 0.461, and 0.269 units in SNS addiction, respectively.

6.2 SNS Addiction as a Binary Variable

In the main analysis, SNS addiction was treated as a continuous variable. However, in clinical settings, it is common for psychologists to diagnose SNS users as addicts or non-addicts (i.e., using binary states). Therefore, in addition to the change in addiction levels, we also coded SNS addiction as a binary variable and focused on the change in state from non-addiction to addiction. Specifically, we used the behavioral threshold of SNS addiction obtained from the pilot study to classify SNS users into SNS addicts (*Addiction* > 0.928) and non-addicts (*Addiction* $\leq$ 0.928). The dependent variable was coded as 1 if a user who was not addicted to SNS in week *t*-1 became addicted to SNS in week *t*, and 0 otherwise. Since the dependent variable is a binary variable, a panel logit model was employed to analyze the probability of habitual SNS use developing into SNS addiction.

Table 4 presents the results of the FE and RE panel logit model estimations. The number of observations in the FE logit model drops significantly because this model requires within-subject variation in the dependent variable (Wooldridge, 2010). The Hausman test indicates that the FE estimation is preferable. In Models (5) and (6), the coefficients for *Habit*, *Habit*×*Number*, *Habit×Active*, and *Habit×Channel* are consistently positive and significant whereas the coefficients for *Habit×Format* are consistently negative and significant. This indicates that habitual SNS use has a significant effect on the state transition from non-addiction to addiction, and this relationship is moderated by SNS characteristics. In addition, we found that among the 30,847 users in our dataset, only 139 (less than 0.5%) of users were addicted to SNS but did not use SNS habitually. This is mostly consistent with the findings in the literature that habit is a mandatory prerequisite for the development of addiction (Everitt et al., 2001; Robbins & Everitt, 1999; Turel & Serenko, 2012). To explain the small percentage of SNS addicts who do not use SNS habitually, we argue that a relatively stable context is a prerequisite for habit development. Nevertheless, some addicts might break their habit when the context changes—for example, because of school schedules. However, the brain's "wanting" systems would still compel them to use SNS addictively during other time periods. Under such circumstances, users who have been diagnosed as SNS addicts might not use SNS habitually at all times.

6.3 Autocorrelation

Autocorrelation refers to the cross-correlation of a construct with itself at different points in time, which is common in time-series data (Baltagi & Li, 1991). It results in autocorrelated error terms (which violate the linear regression assumption that error terms should be independent) and causes standard errors of regression coefficients to be underestimated (Wooldridge, 2010). In this study, a user's addiction level in week *t* might correlate with the user's addiction level in week *t*-1. To estimate models with a first-order autoregressive disturbance (AR(1) disturbance), we included a within estimator in the FE linear model and a GLS estimator in the RE linear model. By performing a Cochrane-Orcutt procedure on the data, the influence of the first-order serial correlation was eliminated in the model estimation (Baltagi & Wu, 1999).

Table 4 presents the results of FE and RE linear models with an AR(1) disturbance. The Hausman test suggests that the FE estimation is preferable. In Model (7) and (8), the coefficients for *Habit*, *Habit×Number*, *Habit×Active*, and *Habit×Channel* are consistently positive and significant whereas the coefficients for *Habit×Format* are consistently negative and significant. Therefore, the findings are similar when first-order serial correlation is considered in the model estimation.

6.4 Instrumental Variable

Despite having control variables in the models, there might still be omitted unobserved variables that could influence SNS addiction. Moreover, it is possible that habitual SNS use might be reversely influenced by SNS addiction. To address these endogeneity issues, we employed an instrumental variable (IV) $SpringBreak_{i,t}$, indicating whether week *t* was Spring Break at user *i*'s university, in the FE and RE linear model estimation. Spring Break is a one-week break in the middle of the spring semester at most US universities. Among the 10 US universities in our data sample, seven universities had Spring Break after March 13 in 2010 (outside the time frame of the dataset), while the other three universities had spring break between February 27 and March 5 (within the time frame of the dataset).

Since habitual SNS use is influenced by context changes (Limayem et al., 2007), students would be more likely to change their habitual SNS use to pursue other activities during Spring Break versus normal weeks (Wood et al., 2005). Thus, Spring Break in week *t* had a direct effect on habitual SNS use in week *t*. However, Spring Break in week *t* would not be expected to have a direct effect on SNS addiction in week *t*+1 (aside from the indirect route via $Habit_{i,t}$). According to incentive sensitization theory, SNS addiction develops when users obtain continuous rewards to fulfill their social needs. Other than the changes in rewards obtained from SNS use caused by the change in habitual SNS use (indirect effect of Spring Break on SNS addiction through habitual SNS use), being on Spring Break likely does not increase or decrease the rewards that users could obtain from SNS use and thus would have no direct effect on SNS addiction. In other words, although Spring Break in week *t* might change users' SNS use patterns in week *t*, which would, in turn, influence SNS addiction in week *t* +1, this effect would be absorbed by the indirect effect of Spring Break on SNS addiction through habitual SNS use. Thus, we used $SpringBreak_{i,t}$ as an IV, and employed FE and RE panel IV regressions to examine the causal relationship between habitual SNS use and SNS addiction (See Table 4). The Hausman test suggests that the FE estimation is preferable. In Models (9) and (10), the coefficients for *Habit* are consistently positive and significant. The results reveal that habitual SNS use has a positive effect on SNS addiction, thereby ruling out potential endogeneity issues.

6.5 Examining Underlying Mechanism of Social Needs Fulfillment

To justify the hypotheses in the research model, we argue that number of SNS friends, activeness of SNS friends, communication channel, and communication content format moderate the relationship between habit and addiction through the mechanism of social needs fulfillment. Since the focus of the study is how social network characteristics and communication characteristics facilitate or inhibit the formation of SNS addiction, we do not include social needs fulfillment in the research model.

Table 4. Alternative Model Specifications

Variables	Model 5 FE Logit	Model 6 RE Logit	Model 7 FE AR(1) Disturbance	Model 8 RE AR(1) Disturbance	Model 9 FE IV	Model 10 RE IV
	Addiction (binary)	Addiction (binary)	Addiction	Addiction	Addiction	Addiction
Habit	4.401* (1.988)	4.815** (1.552)	0.820*** (0.041)	1.103*** (0.035)	1.121*** (0.232)	1.564*** (0.215)
Habit × Number	0.005* (0.002)	0.007*** (0.001)	0.0009*** (0.00005)	0.0008*** (0.00004)	0.0007* (0.0003)	0.0004 (0.0003)
Habit × Activeness	0.125*** (0.028)	0.140*** (0.021)	0.014*** (0.0006)	0.013*** (0.0005)	0.017*** (0.004)	0.013*** (0.003)
Habit × Channel	5.987* (2.753)	9.721*** (2.117)	0.858*** (0.057)	0.963*** (0.049)	0.708* (0.338)	0.785* (0.309)
Habit × Format	-7.612*** (1.622)	-9.227*** (1.263)	-1.071*** (0.036)	-1.405*** (0.031)	-1.690*** (0.200)	-2.024*** (0.186)
Number	0.001 (0.006)	0.001*** (0.0004)	0.0003 (0.0002)	0.0001*** (0.000007)	0.0009** (0.0002)	0.0002*** (0.00002)
Activeness	-0.011 (0.008)	-0.014* (0.006)	0.0007*** (0.0001)	0.0007*** (0.00009)	-0.00008 (0.0004)	0.0006 (0.0003)
Channel	8.033*** (0.779)	3.773*** (0.552)	0.125*** (0.010)	0.095*** (0.007)	0.106*** (0.030)	0.092*** (0.026)
Format	-2.973*** (0.441)	-2.457*** (0.330)	-0.084*** (0.007)	-0.080*** (0.005)	-0.018 (0.020)	-0.028 (0.018)
SNSAge	0.069 (362545.8)	0.005 (0.002)	0.001* (0.0005)	0.0003*** (0.00007)	0.006*** (0.0008)	0.0002*** (0.00007)
SNSAge_Squared	0.00003 (0.0001)	0.00001 (0.000008)	-0.000006** (0.000002)	-0.00000007 (0.0000002)	-0.000009*** (0.000002)	0.0000001 (0.0000002)
Male		-0.163*** (0.049)		-0.014*** (0.001)		-0.013*** (0.002)
Age		-0.366*** (0.023)		-0.017*** (0.0007)		-0.016*** (0.0007)
Intercept		-1.368* (0.645)	0.090** (0.031)	0.469*** (0.017)	-0.717*** (0.081)	0.437*** (0.025)
Log likelihood	-3,405.564	-10,590.557				
(Pseudo) R^2	0.384		0.204	0.508	0.204	0.507
Number of obs	17,017	181,254	164,036	190,775	194,807	190,775
Number of users	2,431	30,209	30,669	30,135	30,771	30,135
Note: Standard errors in parentheses; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; (Pseudo) R2 for Model (5)						

However, to verify that social needs fulfillment serves as the underlying mechanism in the formation of SNS addiction, we propose a new conceptual model in which the number of SNS friends, activeness of SNS friends, and undirected and textual communications lead to greater social needs fulfillment, and the fulfillment of social needs positively moderates the relationship between habit and addiction[1] (see Figure 3).

We conducted additional analysis to empirically examine the underlying mechanism of social needs fulfillment in the formation of SNS addiction. Because we were not able to measure social needs fulfillment using SNS activity logs, we collected more survey data. We recruited 230 SNS users who were undergraduate students at US universities on Amazon Mechanical Turk to take an online survey about their SNS use. The survey items of SNS addiction and habitual SNS use were the same as those used in the pilot study (see Appendix A). The survey items of social needs fulfillment were adapted from established instruments (see Appendix F).

[1] We thank an anonymous reviewer for the suggestion of testing the underlying mechanism of social needs fulfillment in the formation of SNS addiction.

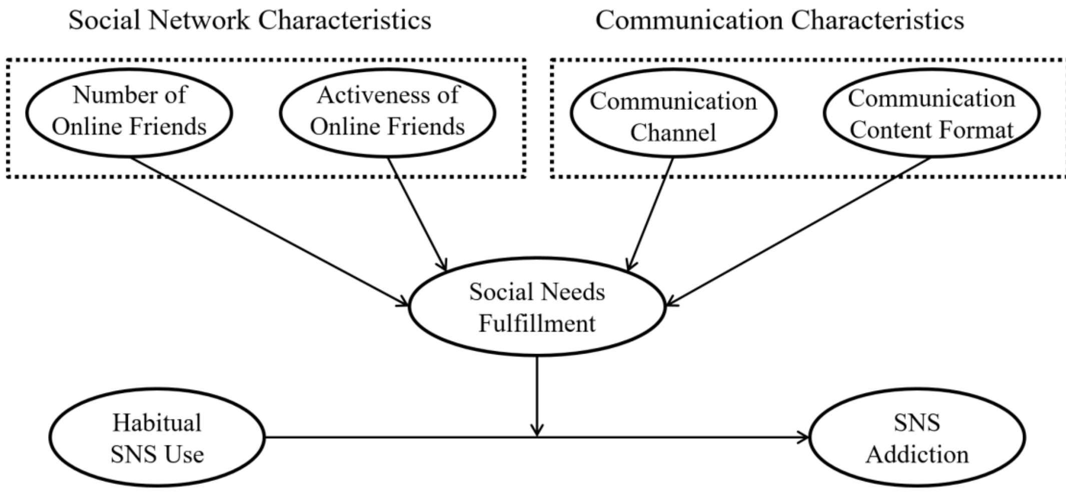

Figure 3. Underlying Mechanism of Social Needs Fulfillment

Table 5. Examining Underlying Mechanism of Social Needs Fulfillment

Hypothesis	Path coefficient	Standard deviation	P-values
Number → Fulfillment	0.174	0.054	0.001
Activeness → Fulfillment	0.275	0.054	0.001
Channel → Fulfillment	0.233	0.053	0.001
Format → Fulfillment	-0.200	0.065	0.002
R^2 Adjusted: 41.7%			
Habit → Addiction	0.438	0.063	0.001
Habit * Fulfillment → Addiction	0.150	0.043	0.001
R^2 Adjusted: 49.5%			

We created new items for number of online friends, activeness of online friends, communication channel, and communication content format (see Appendix F). We followed Moore and Benbasat's (1991) approach to verify the convergent and discriminant validity of the newly created and existing items by examining how they were sorted into various construct categories.

Before we examined the conceptual model in Figure 3, we first showed that the survey items of all constructs had adequate reliability and validity (see Appendix G). We also showed that the reported scores for SNS addiction and habitual SNS use were not influenced by social desirability bias (see Appendix C). We performed bootstrapping with 500 resamples to test the significance levels of path coefficients in the conceptual model. Table 5 presents the model estimation results. The obtained path coefficients and their levels of significance suggest that number of online friends, activeness of online friends, and undirected communication channel are positively related to SNS users' social needs fulfillment, while nontextual content (e.g., pictures and videos) is negatively related to social needs fulfillment. Moreover, habit is positively related to addiction and this relationship is positively moderated by social needs fulfillment. The results are consistent with our main analysis results and provide empirical evidence for the underlying mechanism of social needs fulfillment in the research model. That is, SNS characteristics influence users' fulfillment of social needs, which further moderates the positive relationship between habit and addiction.

6.6 Robustness Checks

First, we used four weeks as the time unit of analysis. Because of the persistency of behavior, behavioral patterns might last for more than a week. Also, the effects of habitual SNS use, social network characteristics, and communication characteristics on SNS addiction might lag for several weeks. To confirm the robustness of our results and capture possible lagged effect of independent variables and moderators, we used four weeks as the time unit of analysis, and the whole dataset was divided into two halves (Week 2 to Week 5 and Week 6 to Week 9). We measured habitual SNS use and SNS characteristics based on SNS activities from Week 2 to Week 5 while SNS addiction was measured based on SNS activities from Week 6 to Week 9. We employed the ordinary least squares (OLS) model to examine the formation of SNS addiction (See Table 6). In Model (11), the results of the OLS model estimation with the time unit of four weeks are consistent with the results in the main analysis.

Second, we operationalized *Addiction 2* using different boundaries for late night and early morning to check the sensitivity of the results. In the main analysis, *Addiction 2* was measured as the number of SNS activities from 1 a.m. to 7 a.m. However, since each person's biological rhythm might be slightly different, *Addiction 2* was measured as the number of SNS activities from 12 midnight to 7 a.m. and from 1 a.m. to 8 a.m., respectively, in the robustness checks. We employed panel linear models to examine the formation of SNS addiction using an alternative operationalization of *Addiction 2* (See Table 6). The Hausman test suggests that the FE estimation is preferable; thus, only FE estimation results are reported. In Models (12) and (13), the results of the FE linear model using alternative operationalization of *Addiction* 2 are consistent with the results in the main analysis.

Third, we also checked the sensitivity of the results using different time windows. Alternative approaches to dividing the time slots were considered: (1) dividing each day into 12 time slots of two hours each, (2) dividing each day into 48 time slots of 30 minutes each, and (3) shifting time slot by half an hour (i.e., the first time slot would go from 0:30 to 1:29 and the last time slot would go from 23:30 to 0:29 the next day). We employed panel linear models to examine the formation of SNS addiction using alternative time windows (See Table 7). The Hausman test suggests that the FE estimation is preferable; thus only FE estimation results are reported. The model estimation results for these three alternative approaches to diving the time slots are reported in Model (14), Model (15), and Model (16). The results are consistent with the results of the main analysis.

Table 6. Robustness Checks 1

Variables	**Model 11** **OLS 4-week**	**Model 12** **FE 12 am - 7 am**	**Model 13** **FE 1 am - 8 am**
	Addiction (4w)	**Addiction (12-7)**	**Addiction (1-8)**
Habit	1.765*** (0.324)	0.828* (0.079)	0.926*** (0.075)
Habit × Number	0.001*** (0.0002)	0.0005*** (0.00007)	0.0007*** (0.00006)
Habit × Activeness	0.013*** (0.003)	0.005** (0.002)	0.010*** (0.002)
Habit × Channel	1.156** (0.407)	0.654*** (0.096)	0.646*** (0.086)
Habit × Format	-2.840*** (0.206)	-0.786*** (0.057)	-0.985*** (0.052)
Number	0.0002*** (0.00001)	0.001*** (0.0003)	0.0008** (0.0002)
Activeness	0.0006** (0.0002)	0.002*** (0.0003)	0.001*** (0.0003)
Channel	0.010 (0.024)	0.211*** (0.012)	0.158*** (0.011)
Format	-0.084*** (0.015)	-0.178*** (0.012)	-0.109*** (0.010)
SNSAge	0.0003** (0.0001)	0.007*** (0.001)	0.008*** (0.0008)
SNSAge_Squared	0.000000005 (0.0000003)	-0.00001*** (0.000003)	-0.00001*** (0.000002)
Male	-0.012*** (0.002)		
Age	-0.020*** (0.001)		
Intercept	0.595*** (0.032)	-0.904*** (0.088)	-0.872*** (0.074)
R^2	0.404	0.085	0.129
Number of obs	30,026	194,807	194,807
Number of users	30,026	30,771	30,771

Note: Robust standard errors in parentheses; *p < 0.05, **p < 0.01, ***p < 0.001

Table 7. Robustness Checks 2

Variables	Model 14 FE 2h-slot Addiction (2h)	Model 15 FE 30m-slot Addiction (30m)	Model 16 FE Shifted Addiction (shifted)
Habit	0.719*** (0.067)	0.780*** (0.076)	0.438*** (0.069)
Habit × Number	0.0008*** (0.00005)	0.0009*** (0.00006)	0.0006*** (0.00005)
Habit × Activeness	0.012*** (0.002)	0.015*** (0.002)	0.011*** (0.002)
Habit × Channel	0.896*** (0.079)	1.053*** (0.088)	1.053*** (0.078)
Habit × Format	-1.294*** (0.047)	-1.425*** (0.053)	-1.294*** (0.043)
Number	0.001*** (0.0002)	0.001*** (0.0003)	0.001*** (0.0002)
Activeness	0.0002 (0.0002)	0.00008 (0.0002)	-0.00008 (0.0002)
Channel	0.098*** (0.009)	0.108*** (0.010)	0.089*** (0.009)
Format	-0.052*** (0.008)	-0.055** (0.010)	-0.036*** (0.008)
SNSAge	0.006*** (0.0007)	0.007*** (0.0008)	0.007*** (0.0007)
SNSAge_Squared	-0.00001*** (0.000002)	-0.00001*** (0.000002)	-0.00001*** (0.000002)
Intercept	-0.728*** (0.062)	-0.752*** (0.070)	-0.788*** (0.069)
R^2	0.153	0.174	0.098
Number of obs	194,807	194,807	194,807
Number of users	30,771	30,771	30,771
Note: Robust standard errors in parentheses; **p* < 0.05, ***p* < 0.01, ****p* < 0.001			

7 Discussion and Implications

7.1 Discussion of Findings

We developed and empirically tested a model to account for the formation of SNS addiction. Going beyond past research that focuses on the normal and habitual use of information systems, we examine the circumstances under which habitual SNS use is more likely to develop into SNS addiction. In line with the hypotheses, we find that habitual SNS use is more likely to lead to SNS addiction if the user has more friends on the SNS, (2) their friends are more active on the SNS, and (3) their friends send information through undirected communication channels on the SNS. Therefore, in addition to the effects of the user's personality traits and psychological factors, which have been examined in previous studies, the number and behavior of SNS friends also significantly impacts the formation of SNS addiction. Notably, such mutually reinforcing behavior among a circle of SNS friends can potentially lead groups of SNS users into a vicious cycle of succumbing to SNS addiction.

Contradicting H3b, we found that habitual SNS use is more likely to lead to SNS addiction if the user's friends post textual content rather than nontextual content on the SNS. A possible explanation for this result is that there are two types of SNS, e.g., Facebook vs. Twitter.[2] Facebook users need permission from targeted users to follow them /connect with them whereas Twitter users do not. Thus, Facebook is primarily based on networking people whereas Twitter is primarily based on networking ideas and topics. The major motivation for users to use the type of SNS we focus on in our study is to establish and maintain social relationships. Given the advantage of textual content for engaging in in-depth communication and maintaining social relationships with SNS friends (Mayer, 2005), textual content likely better satisfies people's social needs and facilitates the transition from habitual SNS use to SNS addiction in this context. This may explain why H3b was rejected. However, had we instead addressed an SNS that focuses on networking

[2] We thank an anonymous reviewer for providing this explanation for why H3b was rejected.

ideas and topics (like Twitter), H3b may have been supported because people feel more relaxed and satisfied while viewing nontextual content vs. textual content (Kosslyn, 1996; Mayer & Moreno, 2003). Thus, for this alternative type of SNS, habitual SNS use may be more likely to lead to SNS addiction if the user's online friends post nontextual (e.g., pictures and videos) vs. textual content. We plan to examine whether H3b is supported in the context of SNS like Twitter in future research.

7.2 Theoretical Contributions

This study makes theoretical contributions to IS and addiction research. First, this is the first IS study to investigate factors that influence the transition from habit to addiction. While previous studies suggest controlling the formation of habit to prevent addiction, we contribute to the literature by showing that a more feasible and effective approach is to intervene by reducing the possibility of habit developing into addiction. Moreover, by applying incentive sensitization theory in the context of behavioral addiction, we explain the underlying mechanism of how habitual users develop compulsive motivations for using SNS. We indicate that the transition from habitual SNS use to SNS addiction is more likely to occur when users' brain "wanting" systems are sensitized by pleasurable and rewarding SNS use experiences. This explanation offers insight into the conceptual connection between habitual SNS use and SNS addiction and provides a theoretical basis for identifying possible moderators in this relationship. Meanwhile, this study contributes to incentive sensitization theory by revealing that, instead of psychoactive substances, pleasurable and rewarding SNS use experiences can also cause people to become addicted.

Second, we demonstrate that social network characteristics and communication characteristics, which are new to the addiction literature, can be salient moderators in the transition from habitual SNS use to SNS addiction. Although internet addiction has been studied for the last two decades, little attention has been paid to the phenomenon of SNS addiction. Since novel features of SNS provide pleasurable and rewarding use experiences, previous studies on general internet addiction are not adequate to account for the formation of SNS addiction. To fill in this research gap, this study provides a theoretical foundation for the role of SNS characteristics in promoting SNS addiction. Based on incentive sensitization theory and the differences between SNS use and other online activities, we identify two social network characteristics and two communication characteristics that determine the rewards that users obtain from SNS use. The findings of this study enrich incentive sensitization theory by demonstrating that the activation of a user's brain "wanting" systems is contingent upon the user's social network characteristics and communication characteristics. The results show that unlike other forms of addiction, the behavior of a network of SNS friends can be mutually reinforcing, leading to all of them becoming addicted.

Third, this is the first study that measures SNS addiction and habitual SNS use based on users' abnormal and automatic SNS use behaviors recorded in SNS activity logs. We detected three addictive SNS use patterns (i.e., always being active on SNS, using SNS frequently from late at night to early in the morning, and responding quickly to activities on SNS), which capture six addiction symptoms, and used the cosine similarity of two SNS activity vectors to indicate the strength of habitual SNS use. After being validated by the pilot study, the behavioral measures allowed us to go beyond previous cross-sectional research in this area and find empirical support for causal inferences about the moderating effects of SNS characteristics based on a large-scale dataset. In addition, the robustness of the results, evident from the outcomes of our robustness tests, suggests that the behavioral measures developed for the variables in this study can be used for similar studies in the future.

7.3 Practical Contributions

Our results offer practical options to prevent the formation of SNS addiction. SNS users can be informed that taking the following actions can help them prevent SNS addiction. First, habitual users are advised not to have too many friends on SNS. Second, we recommend that habitual users set limits on the number of online friends' activities displayed on their homepage. Third, we suggest that habitual users create filters to selectively display textual content sent through undirected communication channels on SNS (this function is available on most SNS). While it may not be possible or advisable to make all these measures mandatory on SNS, habitual users should be informed that these approaches can prevent addiction and be given the option to implement these measures if they wish. Since the mutually reinforcing behavior of a circle of friends can cause the group to become SNS addicts, the implementation of these measures can help inhibit the influence of online friends' behavior on the transition from habitual SNS use to SNS addiction.

In addition, given that people who have an addiction problem may be unwilling to seek clinical help, the behavioral measures proposed in this study, which have been proven to be consistent with cognitive measures, provide an alternative approach to automatically detecting people who may be at risk of SNS addiction. Compared to the diagnosis of addiction by mental health professionals, the diagnosis of addiction using SNS activity logs and big data analysis techniques is much more efficient and thus can be applied to a large number of online users. Since data privacy issues may prevent healthcare workers from accessing users' SNS activity logs, SNS would be an initial screening and warning agent to prevent SNS addiction. Meanwhile, users could choose whether to share their SNS usage data with healthcare workers so that healthcare workers could analyze the data and intervene when users are at risk of developing an SNS addiction. Based on users' addictive SNS use patterns, SNS or healthcare practitioners could send alert messages to automatically identify potential addicts and other interested parties (e.g., addicted teenagers' parents) to warn them about the dangers of SNS addiction. Users with addictive SNS use patterns can be given priority for screening by mental health professionals. For potential severely addicted users who are unwilling to seek help in clinics, mental health professionals could intervene to help them alleviate psychological dependency on SNS. More importantly, this study provides novel insights for future research to automatically detect other types of online addiction or other psychological problems based on objective data.

7.4 Limitations and Future Research

The results of this study must be interpreted and applied bearing in mind its limitations. First, changes in brain systems, which cause pathological "wanting" to use SNS, were not measured in this study. Since substance addiction and behavioral addiction share similar neurobiological mechanisms, we applied incentive sensitization theory in the context of SNS addiction and argue that pleasurable and rewarding SNS use experiences can alter brain "wanting" systems so that they overemphasize the incentive salience of SNS-associated stimuli. To determine whether neural sensitization would work for SNS addiction, future research could leverage MRI technology to examine the changes in brain systems caused by rewarding SNS usage.

Second, the research model seeks to explain the formation of SNS addiction. Since the mechanisms of addiction formation and addiction cessation (reduction) are different, suggestions on how to reduce the chance of becoming addicted may not be applicable to users who are already addicted to SNS. Considering the large number of SNS addicts, future studies could focus on the cessation of SNS addiction and figure out possible approaches to reduce their addiction level. For example, researchers could collaborate with SNS to implement the interventions suggested in this study. For users who are beginning to show signs of addictive behavior, future research could examine whether warnings or interventions can effectively course-correct their SNS use behavior.

Third, considering that the sample used in the main analysis comprises only undergraduate students, with an average age of about 22.5 and standard deviation of about 1.5, the findings may be limited to the young adult population. However, in addition to this demographic, academic studies and popular media have also expressed concern over adolescent (13-18) and middle-aged (25-45) SNS users manifesting addictive behaviors. In order to verify that SNS characteristics play a similar role in the formation of SNS addiction for both adolescent and middle-aged SNS users, future research could examine our research model based on adolescent and middle-aged SNS users.

8 Conclusion

The use of SNS is likely to grow unabated in the years ahead (Taylor, 2013). While there are good reasons for using SNS, excessive SNS use can lead to undesirable consequences. With the aim of reducing SNS addiction, this study investigates the role of SNS characteristics in the transition from habitual SNS use to SNS addiction. By extending the boundary of incentive sensitization theory to behavioral addiction, we argue that changes in brain "wanting" systems, which cause pathological "wanting" to use SNS, are activated by pleasurable and rewarding SNS use. Thus, social network characteristics and communication characteristics, which determine the rewards that users obtain from SNS, affect the extent to which the transition from habitual SNS use to SNS addiction occurs.

As the first IS study to focus on the role of SNS characteristics in the formation of SNS addiction, this study lays the foundation for theory development on SNS addiction, upon which future research can continue to build and extend. The models and measures used in this study provide insights for future studies in terms of how to operationalize and relate such variables. The behavioral measures developed and tested in this study make it possible to build a scalable and automated means to monitor a large number of SNS users for symptoms of addiction. Research in the vein of this study could contribute to society by further informing the massive and growing SNS user population about the dangers of SNS addiction as well as possible remedies.

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Appendix A: Cognitive Measures of SNS Addiction and Habitual SNS Use

The cognitive measures of SNS addiction and habitual SNS use were adapted from established instruments. Specifically, SNS addiction was measured using questions adapted from Turel and Serenko (2012) and Turel et al. (2011). Based on the definition of SNS addiction, each question reflected one or several core symptoms of SNS addiction. The 12 questions included in the pilot study thus captured all six symptoms of SNS addiction. Among these 12 questions, we included one reversed item to reduce common method bias (Hinkin, 1995). Table A1 outlines the 12 scale items of SNS addiction and shows how these scale items are mapped onto the six symptoms of SNS addiction. Habitual SNS use was measured using questions adapted from Limayem et al. (2007) and Kim et al. (2005). Table A2 presents the questions used to measure habitual SNS use. Questions pertaining to SNS addiction and habitual SNS use were measured using seven-point scales anchored on a scale from "strongly disagree" to "strongly agree."

Table A1. Cognitive Measures of SNS Addiction (Source: Turel & Serenko, 2012; Turel et al., 2011)

Items	Salience	Withdrawal	Conflict	Relapse and reinstatement	Tolerance	Mood modification
ADT1: I sometimes neglect important things because of my interest in using (name of the SNS).	√		√			
ADT2: My life has sometimes suffered because of me interacting with (name of the SNS).	√		√			
ADT3: Using (name of the SNS) sometimes interferes with other activities.			√			
ADT4: When I am not using (name of the SNS), I often feel agitated.	√	√				√
ADT5: I have made unsuccessful attempts to reduce the time using (name of the SNS).	√			√		
ADT6: I tend to want to spend increasing amounts of time using (name of the SNS).	√				√	
ADT7: I rarely think about using (name of the SNS) when I am not using a computer/mobile phone. (reversed)	√					
ADT8: I often fail to get enough sleep because of using (name of the SNS).	√		√			
ADT9: Arguments have sometimes arisen because of the time I spend on (name of the SNS).	√		√			
ADT10: My use of (name of the SNS) sometimes seems beyond my control.	√			√	√	
ADT11: I become anxious and/or distressed when I am prevented from using (name of the SNS).	√	√				√
ADT12: I think I am addicted to (name of the SNS).	√	√	√	√	√	√

Table A2. Cognitive Measures of Habitual SNS Use (Source: Kim et al., 2015; Limayem et al., 2007)

Construct	Items
Habitual SNS use	HBT1: Using [name of the SNS] has become automatic to me.
	HBT2: Using [name of the SNS] is natural to me.
	HBT3: When I want to communicate with friends, using [name of the SNS] is an obvious choice for me.
	HBT4: I use [name of the SNS] without even being aware of making the choice.
	HBT5: Using [name of the SNS] is something I do unconsciously.
	HBT6: Using [name of the SNS] is routine without a deliberate plan beforehand.

Appendix B: Reliability and Validity of Cognitive Measures in Pilot Study

The cognitive measures of constructs were assessed for reliability using SmartPLS version 3.2.1. Previous studies suggested that the values of Cronbach's alpha should exceed 0.70 to indicate adequate reliability (Fornell & Larcker, 1981; Nunnally, 1978). In our study, both SNS addiction and habitual SNS use had Cronbach's alpha that met the recommended threshold values (see Table B1). Thus, the cognitive measures of both constructs had adequate reliability.

The cognitive measures of constructs were then assessed for convergent and discriminant validity. Convergent validity indicates the extent to which the items of a construct are related to each other whereas discriminant validity indicates the extent to which a construct is different from other constructs. Factor analysis with principal components analysis and varimax rotation was conducted to test convergent and discriminant validity using SPSS version 19. Factor analysis yielded two components with eigenvalues above 1, that corresponded to SNS addiction and habitual SNS use. Table B2 shows that factor loadings of questions on intended constructs were more than 0.50, indicating adequate convergent validity, while factor loadings of questions on other constructs were less than 0.40, indicating adequate discriminant validity.

Moreover, Table B1 shows that the average variance extracted was greater than 0.50, which was the generally recognized threshold value of convergent validity. In addition, the square root of the average variance extracted for each construct was higher than the correlation between that construct and other constructs, showing discriminant validity. In sum, these results confirmed that the scale items had adequate convergent and discriminant validity.

Table B1. Descriptive Statistics, Reliability, and Correlations of Cognitive Measures of Constructs in Pilot Study

	Mean	*SD*	Min	Max	Cronbach's alpha	Addiction	Habit
Addiction	2.934	1.177	1	6.333	0.909	**0.711**	
Habit	4.534	1.402	1	7	0.883	0.483**	**0.794**
Note: Values for square root of average variance extracted are shown in the diagonals in bold. * p < 0.05, ** p < 0.01							

Table B2. Validity of Questions

Question	Factor	
	1	2
ADT1	**0.742**	0.237
ADT2	**0.735**	0.164
ADT3	**0.656**	0.214
ADT4	**0.723**	0.056
ADT5	**0.631**	0.218
ADT6	**0.667**	0.179
ADT7	**0.590**	0.286
ADT8	**0.653**	0.130
ADT9	**0.665**	0.131
ADT10	**0.686**	0.158
ADT11	**0.745**	0.152
ADT12	**0.734**	0.260
HBT1	0.083	**0.798**
HBT2	0.179	**0.784**
HBT3	0.219	**0.750**
HBT4	0.241	**0.775**
HBT5	0.218	**0.768**
HBT6	0.224	**0.745**
Eigenvalue	7.519	2.392
Variance explained (%)	41.772	13.289
Cumulative variance explained (%)	41.772	55.061

Appendix C: Social Desirability Bias

Since SNS addiction is a sensitive issue that may have negative social reflections on the subjects, the results of the cognitive measures may be influenced by social desirability bias (Crowne & Marlowe, 1960; Williams et al., 1992). In other words, users may under-report their addiction levels because they want to be viewed favorably. To assess the presence of social desirability bias in our study, we included a 13-item short version of Marlowe-Crowne scale in the questionnaire (Reynolds, 1982). Table C1 lists the 13 questions for social desirability bias.

We examined the potential influence of social desirability bias by calculating Spearman's correlations between reported scores and social desirability bias scores. Negative correlation suggested the measures for certain constructs might be influenced by social desirability bias through under-reporting unfavorable behavior and cognition, whereas a lack of correlation suggested the measures for certain constructs measures might not be influenced by social desirability bias.

In the pilot study, we show that social desirability bias scores are not significantly correlated with the cognitive measures of SNS addiction ($r = -0.083$, $p = 0.169$), which implies that self-reported addiction symptoms are not significantly influenced by social desirability bias. This is consistent with past findings that social desirability bias might exist but is not a major issue for measuring addiction using the survey method (Turel & Serenko, 2012; Turel et al., 2011). Unsurprisingly, we found no significant correlation between social desirability bias and the cognitive measures of habitual SNS use ($r = -0.052$, $p = 0.394$).

In the mechanism test, we also show that social desirability bias scores are not significantly correlated with the reported scores for SNS addiction ($r = -0.082$, $p = 0.217$). Moreover, we found no significant correlation between social desirability bias scores and the reported scores for habitual SNS use ($r = -0.059$, $p = 0.371$). Thus, the reported scores for addiction and habit are not influenced by social desirability bias in the mechanism test.

Table C1. Measurement of Social Desirability Bias (Source: Reynolds, 1982)

Construct	Items
Social desirability bias	SDB1: It is sometimes hard for me to go on with my work if I am not encouraged. (F)
	SDB2: I sometimes feel resentful when I don't get my way. (F)
	SDB3: On a few occasions, I have given up doing something because I thought too little of my ability. (F)
	SDB4: There have been times when I felt like rebelling against people in authority even though I knew they were right. (F)
	SDB5: No matter who I'm talking to, I'm always a good listener. (T)
	SDB6: There have been occasions when I took advantage of someone. (F)
	SDB7: I'm always willing to admit it when I make a mistake. (T)
	SDB8: I sometimes try to get even, rather than forgive and forget. (F)
	SDB9: I am always courteous, even to people who are disagreeable. (T)
	SDB10: I have never been irked when people expressed ideas very different from my own. (T)
	SDB11: There have been times when I was quite jealous of the good fortune of others. (F)
	SDB12: I am sometimes irritated by people who ask favors of me. (F)
	SDB13: I have never deliberately said something that hurt someone's feelings. (T)
Note: T = true, F = false	

Appendix D: Diagnosis of SNS Addiction Using Cognitive Measures

Most previous studies have diagnosed internet addiction based on self-reported surveys. For example, Young (1998) developed an eight-item questionnaire to assess internet addiction. Participants who answered "yes" to more than half of the eight questions were diagnosed as internet addicts. In our pilot study, the questions measuring SNS addiction were similar to the items in the previous research (Young, 1998; Young, 1999). Therefore, a user was deemed addicted to SNS if the user scored at least "5" (slightly agree) in more than 6 of the 12 questions in the survey. Using this cut-off, 13.09% of the sample (36 users) were identified as SNS addicts whereas the remaining 86.91% of the sample (239 users) were classified as SNS non-addicts. The bivariate comparisons show that SNS addicts have significantly different behavioral indicators of SNS addiction and habitual SNS use compared with SNS non-addicts. There were no significant differences between SNS addicts and SNS non-addicts in terms of demographic information except that SNS addicts were more likely to use SNS to obtain contact information and to get to know people better (see Table D1).

Table D1. Bivariate Comparisons for SNS Addicts and SNS Non-Addicts

Variable	**SNS non-addicts**		**SNS addicts**		***P*-value**
	Number	**Mean (SD)**	**Number**	**Mean (SD)**	
Age	239	32.05 (9.101)	36	31.47 (7.474)	0.715[a]
Gender					
Male	122	44.4%	17	6.2%	0.669[b]
Female	120	42.5%	16	6.9%	
Education					
High school	91	33.1%	11	4.0%	0.781[b]
Associate's degree	53	19.3%	11	4.0%	
Bachelor's degree	71	25.8%	11	4.0%	
Master's degree	22	8.0%	3	1.1%	
Doctoral degree	2	0.7%	0	0%	
[Name of the SNS] experience in years	239	6.89 (2.135)	36	6.74 (2.150)	0.685[a]
Primary use of [name of the SNS]					
Looking at or posting photos	190	69.1%	30	10.9%	0.592[b]
Sending or receiving messages	156	56.7%	28	10.2%	0.137[b]
Making or reading wall posts	180	65.5%	30	10.9%	0.291[b]
Finding out or planning events	48	17.5%	11	4.0%	0.154[b]
Communicating with friends	184	66.9%	29	10.5%	0.633[b]
Getting to know people better	42	15.3%	14	5.1%	0.003[b]
Getting contact information	24	8.7%	9	3.3%	0.010[b]
Entertainment	178	64.7%	27	9.8%	0.946[b]
Others	17	6.2%	5	1.8%	0.162[b]
Addiction	239	0.343 (0.240)	36	1.362 (0.411)	0.001[a]
Habit	239	0.081 (0.104)	36	0.206 (0.088)	0.001[a]

[a] *p*-value from two-sample *t*-test
[b] *p*-value from Pearson Chi-Square test

Appendix E: Behavioral Measures Using Longer Time Units

In the pilot study, all behavioral measures of SNS addiction and habitual SNS use were calculated based on users' SNS activities in the last week before they took the survey. In order to check the robustness of the behavioral measures of SNS addiction and habitual SNS use, we changed the one-week time unit to longer time units, such as two weeks or four weeks, to see whether the behavioral measures were still consistent with the cognitive measures. Specifically, $Addiction\ 1\ (2w)_{i,t}$ was measured as user i's number of active time slots on SNS in week *t* and week *t-1* (week *t* refers to the last week before user *i* took the survey); $Addiction\ 2\ (2w)_{i,t}$ was measured as the number of SNS activities user *i* conducted from 1 am to 7 am in week *t* and week *t-1*; $Addiction\ 3\ (2w)_{i,t}$ was measured as user i's average response time on SNS in week *t* and week *t-1*. $Addiction\ (2w)_{i,t}$ was measured using the combination of $Addiction\ 1\ (2w)_{i,t}$, $Addiction\ 2\ (2w)_{\ i,t}$, and $Addiction\ 3\ (2w)_{i,t}$. $Habit\ (2w)_{\ i,t}$ was measured as the average of $Habit_{\ i,t}$ and $Habit_{\ i,t-1}$. Similarly, we had $Addiction\ 1\ (4w)_{i,t}$, $Addiction\ 2\ (4w)_{i,t}$, $Addiction\ 3\ (4w)_{i,t}$, $Addiction\ (4w)_{i,t}$, and $Habit\ (4w)_{\ i,t}$, which were measured based on users' SNS activities in the last four weeks before they took the survey.

Under the condition of using two weeks as the analysis time unit, the correlation coefficients between the behavioral measures of SNS addiction and habitual SNS use and their corresponding cognitive measures were high and significant (SNS addiction: $r = 0.800$, $p < 0.001$; habitual SNS use: $r = 0.651$, $p < 0.001$). Similarly, under the condition of using four weeks as the analysis time unit, the correlation coefficients between these two types of measures were still high and significant (SNS addiction: $r = 0.748$, $p < 0.001$; habitual SNS use: $r = 0.607$, $p < 0.001$). Therefore, the behavioral measures of SNS addiction and habitual SNS use were robust with longer analysis time units. Moreover, under the condition of using two weeks as the analysis time unit, the accuracy rate of SNS addiction classification based on the behavioral thresholds was 94.20%. Under the condition of using four weeks as the analysis time unit, the accuracy rate was 92.75%. These tests demonstrated the robustness of SNS addiction classification based on the behavioral thresholds.

In addition, we found that both correlation coefficients and accuracy rate of classification decreased with increased time unit lengths. This might be due to the fact that users' addiction level was changing during the two-week (four-week) period. While the behavioral measures evaluated users' addiction level during the whole time period, the cognitive measures evaluated users' addiction level at the time they took the survey. Therefore, the consistency between these two types of measures decreased with the increase of time unit length. Considering the possible changes in users' addiction levels and the difficulty in measuring SNS addiction longitudinally using the survey method, the behavioral measures provide an efficient approach to monitor users' addiction levels and detect users who are likely to be addicted to SNS.

Appendix F: Survey Items of Social Needs Fulfillment and SNS Characteristics

Social needs fulfillment was measured using questions adapted from McConnell et al. (2011) and Wang et al. (2012). We created new items for number of online friends, activeness of online friends, communication channel, and communication content format. Table F1 presents the questions used to measure social needs fulfillment and four SNS characteristics.

Table F1. Survey Items of Social Needs Fulfillment and SNS Characteristics

Construct	Items
Social needs fulfillment	SNF1: My social needs are gratified by using SNS. SNF2: Using SNS satisfies my needs to connect with others. SNF3: Using SNS strengthens the contact with my family and friends. SNF4: I feel poorly accepted by others when I am using SNS. SNF5: I feel I have made a connection or bonded with others when I am using SNS. SNF6: I feel like an outsider when I am using SNS.
Number of online friends	NUM1: I have many online friends on SNS. NUM2: I am connected with a lot of friends on SNS.
Activeness of online friends	ACT1: My friends are active on SNS. ACT2: My friends conduct activities frequently on SNS. ACT3: My friends make a lot of posts on SNS. ACT4: My SNS homepage is filled with my friends' posts and other SNS activities. ACT5: I am able to view a lot of posts made by my friends on SNS.
Communication channel	CHN1: My friends contact me more often through the undirected communication channel (i.e., broadcasting posts) than the directed communication channel (i.e., private messages) on SNS. CHN2: I interact with my friends more often through the undirected communication channel (i.e., broadcasting posts) than the directed communication channel (i.e., private messages) on SNS. CHN3: Compared to the directed communication channel (i.e., private messages), I have more interactions with my friends through the undirected communication channel (i.e., broadcasting posts) on SNS.
Communication content format	FMT1: My friends send more non-textual contents (e.g., pictures and videos) than textual contents on SNS. FMT2: Compared to textual contents, there are more non-textual contents (e.g., pictures and videos) sent by my friends on SNS. FMT3: I view more non-textual contents (e.g., pictures and videos) than textual contents sent by my friends on SNS.

Appendix G: Reliability and Validity of Constructs in Mechanism Test

All constructs were assessed for reliability using SmartPLS version 3.2.1. Previous studies have suggested that the values of Cronbach's alpha should exceed 0.70 to indicate adequate reliability (Fornell & Larcker, 1981; Nunnally, 1978). In the mechanism test, all of the constructs had Cronbach's alpha that met the recommended threshold values (see Table G1). Thus, all constructs had adequate reliability.

The survey items of all constructs were then assessed for convergent and discriminant validity. Convergent validity indicates the extent to which the items of a construct are related to each other, whereas discriminant validity indicates the extent to which a construct is different from other constructs. Factor analysis with principal components analysis and varimax rotation was conducted to test convergent and discriminant validity using SPSS version 19. Factor analysis yielded seven components with eigenvalues above 1 that corresponded to SNS addiction, habitual SNS use, social needs fulfillment, number of online friends, activeness of online friends, communication channel, and communication content format. Table G2 shows that the factor loadings of questions on intended constructs were more than 0.50, indicating adequate convergent validity, while the factor loadings of questions on other constructs were less than 0.40, indicating adequate discriminant validity.

Moreover, Table G1 shows that the average variance extracted was greater than 0.50, which was the generally recognized threshold value of convergent validity. In addition, the square root of the average variance extracted for each construct was higher than the correlation between that construct and other constructs, showing discriminant validity. In sum, the results confirmed that the scale items had adequate convergent and discriminant validity.

Table G1. Descriptive Statistics, Reliability, and Correlations of Contructs in Mechanism Test

	Mean	*SD*	Min	Max	Cronbach's alpha	Addiction	Habit	Fulfillment	Number	Activeness	Channel	Format
Addiction	3.423	1.297	1	6.500	0.939	**0.776**						
Habit	4.649	1.316	1	7	0.927	0.579**	**0.851**					
Fulfillment	4.412	1.374	1	6.833	0.903	0.583**	0.460**	**0.818**				
Number	4.187	1.660	1	7	0.898	0.497**	0.271**	0.453**	**0.952**			
Activeness	4.895	1.348	1	7	0.927	0.492**	0.273**	0.512**	0.423**	**0.871**		
Channel	4.548	1.318	1	7	0.853	0.526**	0.280**	0.467**	0.377**	0.349**	**0.871**	
Format	3.312	1.234	1	7	0.880	-0.488**	-0.354**	-0.468**	-0.385**	-0.409**	0.390**	**0.898**

Note: Values for square root of average variance extracted are shown in the diagonals in bold. *$p < 0.05$, **$p < 0.01$

Table G2. Validity of Questions in Mechanism Test

Question	Factor						
	1	2	3	4	5	6	7
ADT1	**0.696**	0.202	0.107	0.135	0.138	0.143	0.200
ADT2	**0.750**	0.154	0.177	0.226	0.001	0.063	0.056
ADT3	**0.606**	0.203	0.219	0.189	0.167	0.234	0.028
ADT4	**0.674**	0.069	0.103	0.125	0.151	0.107	-0.002
ADT5	**0.661**	0.299	0.125	0.180	0.085	0.131	0.060
ADT6	**0.689**	0.196	0.162	0.161	0.121	0.140	0.181
ADT7	**0.604**	0.151	0.206	0.098	0.030	0.140	0.194
ADT8	**0.739**	0.250	0.142	0.086	0.116	0.075	0.072
ADT9	**0.665**	0.211	0.227	0.144	0.237	0.173	-0.013
ADT10	**0.683**	0.236	0.198	0.223	0.052	0.108	0.123
ADT11	**0.766**	0.143	0.153	0.074	0.101	0.068	0.150
ADT12	**0.730**	0.255	0.159	0.125	0.131	0.158	0.022
HBT1	0.218	**0.811**	0.093	0.038	0.107	0.070	0.172
HBT2	0.142	**0.811**	0.187	0.008	0.135	0.148	-0.049
HBT3	0.216	**0.770**	0.225	0.075	0.112	0.078	-0.019
HBT4	0.310	**0.781**	0.091	0.061	0.158	-0.046	0.084

HBT5	0.312	**0.785**	0.101	0.075	0.044	0.015	0.049
HBT6	0.321	**0.775**	0.172	0.134	-0.062	0.036	0.005
SNF1	0.262	0.169	**0.672**	0.069	0.221	0.196	0.237
SNF2	0.233	0.252	**0.716**	0.218	0.059	0.198	0.031
SNF3	0.282	0.129	**0.710**	0.186	0.138	0.133	-0.003
SNF4	0.171	0.153	**0.761**	0.209	0.063	0.102	0.088
SNF5	0.271	0.082	**0.665**	0.176	0.169	0.076	0.117
SNF6	0.142	0.184	**0.794**	0.182	0.093	0.051	0.098
NUM1	0.246	0.055	0.201	0.190	0.134	0.171	**0.825**
NUM2	0.295	0.094	0.186	0.210	0.131	0.083	**0.833**
ACT1	0.182	0.029	0.301	**0.809**	0.076	0.008	0.100
ACT2	0.201	0.024	0.155	**0.819**	0.061	0.097	0.089
ACT3	0.224	0.065	0.125	**0.827**	0.098	-0.012	0.102
ACT4	0.187	0.134	0.143	**0.811**	0.145	0.109	0.088
ACT5	0.210	0.105	0.205	**0.764**	0.180	0.222	0.058
CHN1	0.241	0.036	0.137	0.106	0.109	**0.822**	0.057
CHN2	0.228	0.103	0.172	0.050	0.085	**0.788**	0.101
CHN3	0.299	0.078	0.204	0.180	0.149	**0.748**	0.099
FMT1	-0.170	-0.152	-0.167	-0.144	**-0.817**	-0.131	-0.142
FMT2	-0.215	-0.180	-0.177	-0.161	**-0.824**	-0.099	-0.075
FMT3	-0.259	-0.068	-0.175	-0.175	**-0.794**	-0.115	-0.054
Eigenvalue	14.745	3.210	2.424	1.975	1.619	1.356	1.210
Variance explained (%)	39.852	8.677	6.060	5.337	4.377	3.666	3.269
Cumulative variance explained (%)	39.852	48.529	54.589	59.926	64.303	67.968	71.237

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