TESTING A DUAL MODES RECONCEPTUALIZATION OF FACTORS INFLUENCING BEHAVIORAL CHANGE IN THE SOCIAL MEDIA CONTEXT

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Psychology—Doctor of Philosophy

2018

ABSTRACT

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The challenges of changing dysfunctional behaviors at work have puzzled organizational scientists and practitioners for several decades. Previous research on curbing dysfunctional behaviors in work domains rests on self-regulation models in which goals and conscious processes play a dominant role in driving behavioral change. I argue that self-regulation theory does not fully explain behavioral change because it does not fully take into account automatic processes that can hamper change. The approach here builds on a foundational tenet in dual modes theory (Smith & DeCoster, 2000)—that two systems drive behavior: (1) The controlled system and (2) the automatic system. The current study develops and examines an alternative explanation and model based on dual process theory for understanding behavioral change in the social media context. This study helps to reveal hidden factors (e.g., habits) that can shed light on the challenges of changing behavior. Using a field sample of participants from Amazon's Mechanical Turk, the data showed that at the between-person level, individuals with strong habits regarding social media spent more time on social media, as predicted. At the within-person level, intention strength for reducing time on social media negatively impacted time on social media, as expected. Finally, the results did not support the expected two-way interactions among state self-control, intentions, strength, and habits strength. I discuss these findings in terms of the theoretical implications for advancing understanding of behavioral change and practical implications for curbing dysfunctional behaviors at work.

Keywords: Behavioral change; habits; self-regulation; automatic processes

ACKNOWLEDGEMENTS

I want to thank my adviser, Dr. Kevin Ford, for his continual support with this dissertation research as well as being an excellent guide throughout my college and graduate school career. Feedback from my committee members—Drs. Ann Marie Ryan, Linn Van Dyne, and Joseph Cesario—have had a substantial and very positive effect on my research program on the topic of habits and self-regulation. Thank you so much!

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INTRODUCTION

INTRODUCTION

A 24-year-old female visited a psychiatry clinic because she had experienced severe life consequences due to checking social media more than 5 hours per day (Cohen, 2009). In the past 7 months, she had lost her job as a waitress, ceased normal activities, and spent the majority of time at home. Although she recognized her problem and sought treatment, she could not stop and even attempted to peruse Facebook during the clinical examination. Although extreme, this true story illustrates the difficulties individuals experience in changing dysfunctional behaviors. Organizations have spent enormous financial resources (e.g., wellness programs) on curbing various dysfunctional behaviors (e.g., unhealthy eating), yet the evidence so far is that these programs have had limited success (Watson & Fauthier, 2006). Use of social networking sites (SNS) is a particularly vexing dysfunctional behavior given that employees can use SNS without physically leaving their work desk (Tayor, 2007). This allows employees to appear to be working while actually browsing social media for non-work related matters (Wagner et al., 2012). Social media use is an example of cyberloafing—or a specific kind of loafing behavior whereby employees use work hours to visit websites not related to their work (Wagner et al., 2012). Not surprisingly, non-work related social media use contributes to 178 billion dollars in annual losses to organizations (Vitak, Crouse, & Lacrose, 2011; Wagner, Barnes, Lim, Ferris, 2012). Further, employees often state desires to change dysfunctional behaviors, yet these behaviors continue to persist. Hence, the question: Why is behavioral change so difficult?

To date, research on behavioral change more broadly emphasizes self-regulation models involving a deliberative process in which people select goals, strategically create and enact plans, and consciously monitor progress. Although self-regulation models have enhanced our understanding of the factors such as goal difficulty and intentions that influence dysfunctional behaviors, they are incomplete because they do not fully account for the puzzling phenomenon of inertia. Inertia is "attachment to, and persistence of, existing behavioral patterns (some of which are habituated) even if there were better alternatives and incentives to change" (Polites & Karahanna, 2012, p. 24). Self-regulation does not fully capture the role of automatic influences (e.g., habits) that obstruct behavioral change. As such, this dissertation provides an alternative explanation that acknowledges two systems: Automatic and controlled.

Broadening the approach to thinking about behavior change in this way is promising for two reasons. First, self-regulation explanations emphasize conscious drivers of behavior, such as goals and intentions (Vlaev & Dolan, 2015). However, meta-analytic evidence suggests that explicit intentions have some limitations in predicting behavioral change. For example, a fairly large change in intentions ($d = .66$) accounts for a small to medium change in behavior ($d = .36$) across 47 experimental studies (Webb & Sheeran, 2006). A significant homogeneity statistics indicates that the magnitude of intention-behavior relationships is inconsistent across studies. These findings suggest that self-regulation may provide incomplete understanding of behavior in certain situations. Indeed, in the case of SNS use in particular, self-regulation may not fully explain the phenomenon of addiction—or having symptoms such as preoccupation with SNS usage, tolerance, withdrawal symptoms, and relapse (Kuss & Griffiths, 2011). Relapse, for example, primarily involves automatic processes that are not fully captured in self-regulation theories (Marlatt & Donovan, 2005).

The aim of this dissertation is to develop and test a conceptual model based in dual modes theory that captures the main and interactive effects of both automatic and controlled constructs on behavioral change. This approach (Smith & DeCoster, 2000) draws on theoretical paradigms (e.g., dual modes theory) that acknowledge the existence of the controlled and automatic systems. This approach also draws on scholarship involving an automatic construct called *habits*—defined as routine sequences of actions that have become automated in response to specific cues (Verplanken & Aarts, 1999). Habits are important to consider because they can lead to inertia, making it difficult for individuals to change their behavior (Polites & Karahanna, 2012). The notion that *two* systems influence behavior is novel because current perspectives in organizational psychology and organizational behavior emphasize a *single* self-regulation system. For example, self-regulation suggests that reducing performance-goal discrepancies play a critical role in allowing individuals to change their behavior (e.g., Scheier & Carver, 1992).

The first two intended contributions of the dissertation are focused on helping researchers in organizational behavior and organizational psychology to make advancements in theory and empirical knowledge of behavioral change and dysfunctional behaviors. Contribution one centers on the following research question: Do constructs in the automatic and controlled systems predict day-to-day fluctuations in behavior (e.g., reductions in social media use). In attempting to address this question, I draw from dual modes theory in developing and testing an approach that aims to reconceptualize the factors influencing behavioral change. The approach presented here highlights the idea that individuals have explicit intentions (in the controlled system) that push in the direction of behavioral change AND habits (in the automatic system) that serve as a pulling force against behavioral change. From a theoretical viewpoint, acknowledging the main effects of habits is novel because the dominant perspective in self-regulation theory centers on goals and deliberative processes as primary drivers of behavioral change. Instead, organizational scholars might consider studying automatic constructs because they illuminate reasons why individuals experience so much difficulty in changing behavior. From an empirical standpoint, investigating the effects of habits is an important research gap. In particular, tests of hypotheses in the proposed model extend empirical work on self-regulation (e.g., Ilies & Judge, 2005; Northcraft, Schmidt, & Ashford, 2011; Wagner et al., 2012) by surfacing a hidden factor, habits, that underlie work behaviors.

Contribution two centers on the following research question: Do interactions in core constructs of the automatic and controlled systems predict day-to-day fluctuations in behavior (e.g., reductions in social media use)? In attempting to answer this question, I suggest that some tenets of self-regulation may need to be revised. For example, fluctuations in self-regulation constructs (e.g., intention strength) may not predict behavioral change when individuals have strong habits associated with the old behavior. State self-control—defined as the ability to voluntarily regulate thoughts and behavior in-the-moment—is an important lever that can influence both systems, by enhancing the effects of strength of intentions while also weakening the effects of habits on behavioral change. An investigation that fully captures these interactions among the constructs in dual modes theory and their effects on behavioral change is missing from empirical research.

Contribution three focuses on practical implications in regards to curbing dysfunctional behaviors. The focus on social media behaviors in this dissertation serves as a prominent example of dysfunctional behaviors in organizations. Social media may have particular practical significance given its rise in popularity. For example, Facebook has grown from just 8% of working adults in 2005 to 74% of employees in 2015 (Lenhart, Purcell, Smith, & Zickhur, 2010; Meshi, Tamir, & Heekeren, 2015) and has over 1.5 billion users (Meshi et al., 2015). Given the importance of curbing social media use, revealing hidden predictors of SNS behaviors may be important for organizations and employees to develop interventions for curbing this behavior. For instance, motivational interventions in organizations tend to be focused on self-regulation (e.g., goal-setting interventions), yet these interventions often have weak effects on behaviors that have become habit (Wood & Neal, 2007). The findings anticipated here may provide insight into interventions that can be used to directly target habits in order to influence lasting behavioral change (e.g., reducing SNS use). As another example, the study aims to identify mechanisms that fluctuate over time (e.g., state self-control, intention strength) and interact with habits to predict behavioral change. Knowledge of interactions can be applied to designing interventions in order to best influence behavioral change.

To begin, I describe and evaluate the prevailing self-regulation approach for understanding dysfunctional behaviors such as non-work related social media use. The paper then covers dual modes theory and habit research that addresses limitations of current approaches for explaining behavior change. This dual modes theory section forms the basis for developing the overarching model and individual hypotheses (Smith & DeCoster, 2000). I proceed by discussing the sample, procedure, measures, and analytics that comprise the methodology. The findings section summarizes the results and tests of hypotheses. Finally, the discussion section reviews the findings and highlights theoretical and practical implications.

Social Media and Self-Regulation

Social media use in this dissertation serves as a particularly relevant and useful way of shedding light on broader questions surrounding dysfunctional behaviors and behavioral change in organizations. Accordingly, in this section I define social media use and describe a dominant way scholars have conceptualized this topic. Social media use is defined as engaging in digital platforms that facilitate user-created content, collaboration across people, and information sharing (McFarland & Ployhart, 2015). In utilizing social media, employees can choose from a number of platforms—or technical vehicles that help them connect with others (e.g., Facebook, Twitter, Instagram, Snapchat). Scholars tend to adopt self-regulation perspectives for conceptualizing social media use (e.g., Liberman et al., 2011; Pelling and White, 2009).

The process of self-regulation is often characterized as largely goal-driven, purposeful, and conscious.[1] Consistent with this notion, self-regulation is defined as the regulation of conscious thoughts, emotions, and behavior aimed at goal accomplishment over time and across situations (Carver & Scheier, 1982). Exemplifying its goal-driven nature, self-regulation presumes that individuals form deliberative judgments about goals and strategically develop explicit intentions for pursuing that goal (Gollwitzer, 2012). After performing intentions, individuals actively seek information about their performance and compare this information to the goal. If performance falls short of goals (i.e., negative goal-performance discrepancies; Kluger & Denisi, 1996), individuals may consciously attribute poor performance to aspects of the environment or self such as dysfunctional behaviors (e.g., socializing too much). These attributions can lead to intentions for behavioral changes aimed at accomplishing the goal next time.

Goals and conscious reflection are prominent drivers of behavioral change in self-regulation theories. Consider a sales employee with the goal of achieving his or her sales quotas for the week. Upon learning they failed to reach the goal, the employee enters the reflection process. The employee may realize that, because they frequently visited social media, they did

[1] Self-regulation models such as control theory have acknowledged and incorporated automatic influences on behavior (e.g, Kernan & Lord, 1990; Klein, 1989). In reviewing some of the automatic components of self-regulation, Vancouver (2000) explains the distinction between serial processing (i.e., where individuals have to complete one process before beginning another one) and parallel processing (i.e., where individuals can execute multiple processes relatively automatically). Parallel processing allows individuals to, for example, coordinate the multiple behaviors and corresponding functions that aid walking in a single direction, which is often done subconsciously. Nevertheless, goals and intentions tend to play a prominent role in self-regulation models of thoughts and behavior, which hints at the need to more fully account for the role of automatic features in these theories (Smith & DeCoster, 2000).

not place enough calls to prospective clients. They attribute insufficient calls to prospective clients as why they failed to accomplish their sales goals. The employee therefore comes to appreciate that a dysfunctional behavior is contributing to lower than expected performance levels. The employee resolves to stop using social media throughout the week, which helps the individual accomplish their sales goals next week. In sum, self-regulation theories assert that individuals eliminate dysfunctional behaviors by choosing goals, comparing current performance with goals, reflecting on progress, making attributions for any lower than expected outcome, and purposefully changing behavior in active and ongoing pursuit of goals. In line with this depiction, some scholars view cyberloafing "purely as a conscious, rational behavior, applying models (Ajzen, 1991; Ajzen & Fishbein, 1980, Bandura, 1986) that predict behavior from conscious behavioral intentions" (Vitak, Course, & Larose, 2011, p. 1758).

Investigations from a self-regulation perspective have been helpful in identifying various predictors of dysfunctional behaviors. Adopting control theory, for example, Prasad, Lim, and Chen (2010) showed that one's ability to self-regulate thoughts had a negative but non-significant effect on cyberloafing. In measuring self-regulation, a 10-item measure of trait self-regulation was used by Schwarzer, Diehl, and Schmitz (1999). An example item is "When I worry about something, I cannot concentrate on an activity". They also found that high levels of self-efficacy, conscientiousness, and achievement orientation strengthened the effect of trait self-regulation on cyberloafing behaviors. Finally, Libermann et al. (2011) applied social cognitive theory and found that positive attitudes towards cyberloafing and Internet self-efficacy positively predicted cyberloafing whereas job involvement and intrinsic involvement negatively predicted cyberloafing. Social media is a fairly recent development and not much is known about the predictors of these behaviors, making it a gap for future research to address (Pelling & White, 2009). Researchers tend to focus on between-person variance, for example, by studying how self-regulation traits predict variance in behavior across individuals. However, using a within-person approach is necessary in order to study fluctuations in social media use and the factors that influence these fluctuations. Therefore, a within-person approach is needed in order to illuminate factors underlying behavioral change.

Reconsidering the Self-Regulation Account of Intentions to Change Behavior

Although self-regulation theories such as control theory (Scheier & Carver, 1992) have enhanced understanding of behavior (Deshon & Rench, 2009) and fueled studies that examine within-person relations (e.g., Chang, Johnson, & Lord, 2010; Eddington & Foxworth, 2012), there are also some limitations. Organizational scholars tend to draw from self-regulation theories that emphasize the role of goals and conscious reflection in driving behavioral change (Shantz & Latham, 2009; George, 2009). However, mounting evidence shows that automatic behaviors and automatic thoughts are pervasive and contribute to behavior in ways that should not be overlooked (George, 2009). In the following section I focus in on a core tenet of self-regulation (intention-behavior relationships) that is not fully understood and has particularly important consequences for behavioral change. I argue that a self-regulation perspective of the intention-behavior relationship falls short in explaining important behavioral change phenomena (i.e., inertia, addiction). I further suggest that the evidence for a self-regulation perspective of factors influencing the intention-behavior relationship is equivocal. Finally, I explain why it might be fruitful to broaden perspectives of intention-behavior relationships to include automatic factors that influence this relationship.

Inertia

The gap between intentions and behavior is often present when individuals experience inertia. Inertia refers to "attachment to, and persistence of, existing behavioral patterns (some of which are habituated) even if there were better alternatives and incentives to change" (Polites & Karahanna, 2012, p. 24). Inertia suggests individuals may have intentions for performing the 'better alternative'. Yet, there is a disconnect in their ability to follow through on this intention.

A self-regulation account of intention-behavior relationships sheds light on inertia under certain conditions, such as when individuals have sufficient attentional resources and time for acting. With sufficient attentional resources to engage in reflection, individuals may discover that factors outside of their control (e.g., unreasonable demands by supervisor) are responsible for their poor performance. Thus, there is no need to change their behavior. In addition, a self-regulation perspective might suggest that inertia can be due to procrastination—defined as voluntarily delaying intended actions despite expecting to be worse off because of the delay. Individuals may procrastinate highly aversive tasks (e.g., taking out the trash) in favor of more enjoyable tasks (e.g., watching TV). Although this strategy helps them to temporarily avoid spikes in negative mood owing to the aversive task, individuals often later experience negative mood in greater amounts when doing the aversive task at a later time. According to Anderson's (2003) rational-emotion model, individuals may experience inertia because they anticipate regret, leading individuals to avoid making a decision.

Under other conditions, however, a self-regulation account of intention-behavior relationships does not adequately predict or explain behavior. For example, all individuals will face limited attentional resources and low self-control at some point, which makes it difficult to retrieve and act on intentions for changing behavior (Smith & DeCoster, 2000). Under conditions of low attentional resources, strong intentions for changing current actions may not help individuals in overcoming inertia and changing their behavior. Strong habits and insufficient time for choosing the alternative behavior may lock in past behaviors despite intentions for change. In sum, while self-regulation and intention-behavior relationships have generated insight into inertia under certain conditions, additional perspectives are needed to provide a more comprehensive understanding of inertia.

Addiction

The disconnect between intentions and behavior is also apparent in the phenomenon of addiction. Individuals often experience difficulty in acting on planned intentions when they have an addiction. Addiction to behaviors such as social media use—refers to having symptoms such as preoccupation with SNS usage, tolerance, withdrawal symptoms, or relapse. Cyber-relationship addiction refers to addiction with online social relationships (for literature reviews on the topic, see Griffiths, 2013; Kuss & Griffiths, 2011). For example, individuals may become addicted to SNS use as they experience rewards associated with presenting themselves in a favorable light and receiving positive feedback about their profile, pictures, and posts. Even small social rewards (e.g., receiving a "like", positive comment, or a friend request in Facebook) can activate the brain's reward system and lock in future behaviors (Meshi, Tamir, & Heekeren, 2015). The opportunities for receiving these social rewards are potentially endless as individuals can share information with thousands of Facebook friends or Twitter followers. Individuals may also continue to repeat SNS behaviors because it helps them fulfill underlying desires for connection with others or to cope with negative events, leading to dependence and sometimes addiction. In support of cyber-relationship addiction, neurological evidence suggests that perusing a friend's profile can activate the appetitive system (Wise, Alhabash, & Park, 2010) in the same way in which it becomes activated among Internet game addicts (Ko et al., 2009). One empirical study has shown that individuals have addictive SNS tendencies and these tendencies can be predicted by high extraversion and low conscientiousness (Wilson, Fornasier, & White, 2010). In addition, research has shown that individuals who frequently use SNS experience common characteristics of addiction (e.g., neglecting personal life, preoccupation and rumination, mood modifying experiences and concealing the addictive behavior; Kuss & Griffiths, 2011). Individuals often have intentions to stop the addiction yet they may be unable to do so. In this way, the intention-behavior disconnect is apparent in the phenomenon of cyber-relationship addiction.

Self-regulation and intentions by themselves cannot fully explain inertia once individuals have become addicted to these behaviors. For example, self-regulation may not fully account for the automatic processes involved in relapse. Relapse is a largely automatic process by which a user reverts back to old behavioral patterns after a period of abstinence (Kuss & Griffiths, 2011; Marlatt & Donovan, 2005). In the case of relapse, behavioral change is primarily driven by external cues (e.g., smelling cigarettes), not necessarily goals (Marlatt & Donovan, 2005). Although self-regulation has utility in explaining initial behaviors that lead to addiction, the automatic processes involved in relapse often go beyond the scope of self-regulation theories.

Equivocal Findings of Intention-Behavior Relationships

Consistent with the arguments above, self-regulation research demonstrates gaps in intention-behavior relationships. Meta-analytic results show changes in intentions drive only 28 percent of variance in behavior change (Sheeran, 2002) and intentions drive only 3 percent of variance in behavior in experimental studies (Webb & Sheeran, 2006). According to meta-analytic evidence, a fairly large change in intentions (d = .66) accounts for a small to medium change in behavior (d = .36) across 47 experimental studies that were randomly assigned to either the intention strength condition or a control condition (Webb & Sheeran, 2006). A significant homogeneity statistic indicates significant variation in effect sizes across primary studies, suggesting inconsistencies in the strength of intention-behavior relationships. The small to medium change in behavior and the moderators (e.g., low attentional resources) suggest that self-regulation supplies only part of the variance in behavioral change. This evidence suggests conscious goals and self-regulation have somewhat limited predictive utility for understanding behavior and highlights the need to identify hidden sources of variance in behavior change.

Why Address the Intention-Behavior Gap

Although there are a number of core aspects to self-regulation (e.g., goal-performance discrepancies, attributions), in this dissertation I focus on the intention-behavior relationship and automatic factors influencing this relationship for a number of reasons. First, as mentioned previously, identifying automatic predictors of the intention-behavior relationships seems fruitful for enhancing knowledge of inertia and addiction. Applying the intention-behavior gap, for example, individuals who experience inertia have an inclination to stick with dysfunctional behaviors despite stated desires for change. Second, the ultimate research question of this dissertation is to understand why individuals experience difficulty in changing their behavior despite intentions for change. Identifying automatic factors influencing the intention-behavior relationship is directly relevant to addressing the question of why behavioral change is difficult. In the following sections I advance an alternative perspective for thinking about behavioral change at work and the intention-behavior relationship.

A Dual Modes Account of Behavioral Change

Dual process theory is directly relevant to understanding the intention-behavior relationship and factors that influence behavioral change because it incorporates both controlled and automatic influences on behavior. Dual modes theory acknowledges two systems (Smith & DeCoster, 2000). The first system—called the controlled system—emphasizes effortful and conscious factors that underlie behavior. This system has also been referred to as the rule-based system (Wilson, Lindsey, & Schooler, 2000). The second system—the automatic system—suggests implicit processes drive behavior. This system has also been referred to as the associative system (Wilson, Lindsey, & Schooler, 2000). Table 1 depicts a sample of the many different dual-process theories. Indeed, "The dual-mode approach has become so established that one edited volume collected thirty-some chapters on this framework" (Fiske & Taylor, 2013, p. 31) and a substantial amount of empirical research supports dual modes perspectives (e.g., Evans & Stanovich, 2013; Kahneman, 2011). I draw from one fundamental tenet that connects all of these theories—that two systems guide behavior: One for automatic processes and the other for controlled processes.

Table 1: *The Variety of Dual Process Theories and Their Systems (Adapted from Fiske & Taylor, 2013)*

Theory	Domain	Automatic processes	Controlled processes
Dual modes theory (Smith & DeCoster, 2000)	Attitude-behavior	Associative system	Rule-based system
Dual-process model of impression formation (Brewer, 1988)	Impressions	Initial identification or categorization using images	Personalized concepts
Continuum model of impression formation (Fiske, Lin, & Neuberg, 1999)	Impressions	Immediate categorization	Intermediate processing
Elaboration likelihood model (Petty & Cacioppo, 1986)	Persuasion	Peripheral cues	Central cues
Heuristic-systematic model (Chen & Chaiken, 1999)	Persuasion	Heuristic shortcuts	Systematic processes

Dual modes theory further asserts that two different systems govern the process of encoding and representing information in memory (Smith & DeCoster, 2000): The slow-learning system (which primarily guides automatic processes) and the fast-learning system (which influences only controlled processes). According to Smith and DeCoster (2000), "Numerous theorists have advanced generally similar proposals focused on the idea that humans have two separate memory systems with distinct properties" (p. 109). Drawing upon these memory systems, in the following sections I describe the core features and constructs of the controlled system and then the automatic system.

Controlled System

The controlled system has direct relevance to better understanding intentions to change behavior and their effects on actual behavioral change. The controlled system—also called the rule-based system—primarily draws from the fast-learning memory system. Like self-regulation processes, controlled processes such as intentions to change behavior can be learned after just one experience, occur optionally when capacity is present, and involve conscious awareness. One function of the controlled system is to quickly encode new information (e.g., intentions to change behavior) that is sometimes learned through a single experience. As far as moderators of the intention-behavior relationship, dual modes theory suggests that capacity and motivation are critical variables that influence the extent to which intentions are actively guiding behavior. Indeed, "We hold that motivation and capacity are the key factors" [that influence how the dual modes lead to an overall response] (Smith & DeCoster, 2000, p. 116). Specifically, "The explicit [intention] requires more motivation and capacity to retrieve from memory" (Wilson et al. 2000). In the following section, I describe one construct related to capacity (i.e., state self-control) and one construct related to motivation (i.e., intention strength).

State self-control. State self-control is defined as the ability (that is malleable) to voluntarily regulate thoughts and behavior in a given moment (Galla & Duckworth, 2015). According to dual modes theory, attentional resources—or the amount of attention left to spare for performing task(s) and/or making decision(s)—is an important indicator of state self-control (Schiefele, Howland, Maris, Pschierer, Wipplinger, & Meuter, 2005; Smith & DeCoster). Attentional resources serve an important self-control function: the ability to recall information such as explicit intentions from the fast-learning system. Declines in attentional resources lead to parallel decreases in the ability to recall and act on explicit intentions—and in turn diminished state self-control. Individuals possess a limited amount of attentional resources and thus humans should efficiently allocate these resources.

Explicit intentions. Explicit intentions are defined as behavioral plans for achieving the higher-level goal (Kuhl & Koole, 2004). According to self-regulation perspectives of goal hierarchy, explicit intentions differ from goals in that explicit intentions are more concrete representations of actions whereas goals are more abstract. In this dissertation I am particularly concerned with intentions to change one's behavior because they are most relevant to behavioral change. The behavioral nature of intentions is what differentiates them from goals. For example, in coding for their meta-analysis, Sheppard, Hartwick, and Warshaw (1988) classified something as a goal or behavior based on if individuals are able to perform the behavior. For example, spending time on social media would be an example of a behavior because individuals can readily perform this activity.

Explicit intentions often serve higher-level goals. For example, employees may have a goal to be productive. To help them obtain that goal, individuals may retrieve and act on an explicit intention for avoiding social media use. Acting on explicit intentions generally requires effort, attentional resources, and conscious awareness of the intention. Indeed, both dual modes theory (Wilson, Lindsey, & Schooler, 2000) and traditional self-regulation theories such as ego-depletion theory (e.g., Muraven & Baumeister, 2000) suggest that the capacity to retrieve intentions are necessary for them to guide behavior. As intentions are enacted, individuals reflect about whether they have been fulfilled or whether additional action is required (Gollwitzer, 1990). Intentions are amenable to change as they stem from the system responsible for encoding new pieces of information. The above characterization of explicit intentions is consistent with self-regulation perspectives in which behavior is largely conscious, deliberative, and goal-driven.

Intention strength and measurement. Strength of explicit intentions captures the motivational determinants that influence whether individuals act on a given intention (from here on I refer to strength of explicit intentions as intention strength) (Hom & Hulin, 1989). According to the theory of planned behavior, intention strength indicates how much effort an individual is willing to exert or how hard they are willing to try to fulfill an intention (Armitage & Connor, 2001). For example, on Monday, an individual may have a moderate intention to reduce time on social media; on Tuesday, he or she may have a strong intention to reduce time on social media. The increase in intention strength might indicate the individual is willing to put forth more effort or worker harder in order to limit their social media use. For example, they may write reminders to themselves or monitor how many times they go on social media. As a general rule, the stronger the intention, the more likely an individual is to carry out that intention.

The intention (vs. prediction) distinction informs the types of measures of intention strength (Armitage & Connor, 2001). Intention refers to one's plans for carrying out the planned action; an example item is "I intend to perform behavior x". Prediction refers to one's estimates of whether they will perform the behavior; an example item is "How likely you will perform behavior x?”. As compared to intentions, self-predictions lead individuals to consider all factors that could influence performance of the behavior. Applied to social media use, self-predictions may prompt individuals to consider factors outside of motivation that influence their social media such as pre-existing habits. Thus, prediction of a given behavior may be confounded to some extent with other factors that influence performance of the behavior. To avoid this issue, in this dissertation I use measures that focus on intentions as opposed to prediction of behavior.

Measurement of intentions also differs with respect to valence, generality, and word choice. Beginning with valence, some intention measures have positive valence; “I intend to buy food from a fast-food counter or restaurant” (Ji & Wood, 2007). Other intention measures use negative valence: “I intend to watch the amount of fat in my diet” (Bruijn et al., 2008); “I intend to avoid sitting (Conroy et al., 2013). In this dissertation I am interested in the process of changing behavior away from a dysfunctional behavior. Thus, a negative valence is more relevant for predicting and understanding reductions of dysfunctional behaviors. Regarding the specificity of intentions, theoretical perspectives (e.g., theory of planned behavior) are consistent with the idea that individuals have global positive or negative evaluations of a given behavior and set general intentions for performing that behavior (Armitage & Connor, 2001). Although the specificity of intentions differ somewhat across measures, most measures of intentions tend to be general in nature—“I intend to avoid behavior X (Conroy et al., 2013); “I intend to watch the amount of times I engage in behavior X” (Bruijn et al, 2008); “I intend to reduce time spent on social media”—rather than more specific: “I intend to limit social media use to 20 minutes per day”. In other words, research tends to employ general measures of intentions. Setting specific intentions (e.g., limit your social media use to 20 minutes per day) would give an advantage to certain individuals over others. For example, those who use social media very frequently would find it almost impossible to achieve the goal; those who use social media very infrequently would find it easy to accomplish the goal. However, a general intention ("I intend to reduce the time I spend on social media") may be perceived as possible to achieve by both frequent and infrequent users of social media. Thus, a general intention is more likely to have a motivational effect on a wider range of individuals than a specific intention. Regarding word choice, examples in the literature include: "I intend to avoid behavior X" (Conroy et al., 2013); "I intend to watch the amount of behavior X" (Bruijn et al, 2008); "I intend to reduce time spent on social media". It may not be realistic for most individuals to completely avoid social media use. Therefore, researchers might consider using softer language when constructing intentions about social media use (e.g., reducing time spent on social media).

There is meta-analytic evidence for the validity of measures tapping into strength of intentions for changing behavior. For example, a meta-analysis by Web and Sheeran (2006) demonstrated a positive effect of change in intention strength on behavioral change. They also showed that increases in intention strength positively mediated the effect of interventions for changing behavior on actual behavioral change. Regarding intention strength, a meta-analysis by Armitage and Connor (2001) found positive relationships of intention strength with self-efficacy, attitudes, social norms, perceived behavioral control, and behavior. As expected, the relationships of intention strength with attitude, subjective norm, and perceived behavioral control were significant and positive.

The Automatic System

The automatic system relies on the slow-learning memory system in which humans encode typical information across many experiences. In contrast to the controlled system, automatic processes are characterized by being mentally efficient and fast, difficult to control, and subconscious in the sense that individuals may have awareness of the results but not the process itself (Smith & DeCoster, 2000). Information in this system is encoded incrementally and slowly over time in order for humans to hold a large sample of one's experiences. After encoding enough of these experiences that are consistent over time, individuals automatically extract patterns and form associations. Indeed, the "Associative processing mode is based directly on the properties of the slow-learning system and operates essentially as a pattern-completion mechanism" (Smith & DeCoster, 2000, p. 110). These features of dual modes theory are consistent the construct of habits. Indeed, dual modes theory "was inspired by the writings of James (1980) and Jastrow (1906) on habit formation" (Moors & Houwer, 2007, p. 13). The following section covers the topic of habits and its dimensions, the importance of habits for organizations, how habits form, and how scholars typically measure habits.

Habits. Habit is defined as routine sequences of actions that have become automated in response to specific cues (Verplanken & Aarts, 1999). Habits strength is defined as the degree to which these actions have become automated to specific cues, with greater habit strength reflecting stronger automatic responses. In general, stronger automatic responses are developed when the behaviors are repeated more frequently and in response to more similar environments. Habit strength accordingly goes beyond the mere repetition of behavior because it takes into account the degree of automaticity (for a review, see Polites & Karahanna, 2013).

There are several dimensions of habits: *Awareness*, *controllability*, and *mental efficiency* (Verplaken & Orbell, 2003). Habits fall outside of *awareness* in the sense that individuals are sometimes unaware of the situational triggers that prompt habitual behaviors. Or, they may be unaware that the trigger in the moment it occurs is driving the habitual behavior. Strong habits are difficult to *control* (Verplaken & Orbell, 2003), meaning that it may be difficult to overcome the urge to perform the habitual behavior in response to the situational trigger. Strong habits are *mentally efficient*, in the sense that individuals do not need to use much attentional resources in order to perform habitual behaviors. Thus, attentional resources can be used for *other* endeavors.

The dimensions of habits can be used to help explain why habits are important to study. First, habits are important to consider because, although they are often functional for achieving goals, they can become dysfunctional. It is difficult to change dysfunctional habits because they occur outside awareness and are harder to control than intentional actions. Indeed, because habits fall outside of awareness and are difficult to control, employees may experience great difficulty in stopping a launch into automatic routines even when those routines become inappropriate as a result of changing conditions (Gersick & Hackman, 1990). Second, studies have shown that about 45% of the actions participants listed in daily diaries are repeated behaviors that occur in the same location about every day (e.g., Wood, Quinn, & Kashy, 2002). These findings suggest that there is an automatic component to a wide range of behaviors. Indeed, "It is difficult to find any behavior that does not include some amalgam of processes with automatic features and control features" (Stewart & Payne, 2006, p. 299). Due to their pervasive nature, these repeated behaviors at home may also extend to the workplace. For example, George (2009) and Weiss and Ilgen (1985) recognize that a great deal of behavior in organizations is repeated in response to similar cues. Summarizing the importance of habits, a wide range of work behaviors contains automatic features, and these features can thwart efforts to change. Accordingly, the study of habits provides a valuable opportunity for scholars and practitioners alike to better understand and influence job performance.

Third, habits are distinct from other automatic variables including implicit attitudes and proceduralization. Implicit attitudes are summary evaluations that have unknown origins, can be activated automatically, and often have an affective tone to them (Greenwald & Banaji, 1995). In contrast, habits involve connections between cue and actions and typically do not involve affect. Implicit attitudes also differ from habits because summary evaluations can include affective components (Greenwald & Banaji, 1995), which are not included in the definition of habits. Proceduralization is a learning outcome and shares a number of characteristics with habits such as automatic processing, task accomplishment without conscious monitoring, and allows cognitive attention to be devoted to other endeavors (Kraiger, Ford, & Salas, 1993). Habits are different from proceduralization in two ways. First, proceduralization is a learning outcome and is comprised of skills that have become automatic. Although habits involve learned behaviors, the term is broader in the sense that it covers a wider range of automatic behaviors. For example, habits could involve connections between external cues such as seeing an alcoholic beverage and behaviors like drinking. Although this is a learned behavior, it would hardly be described as a proceduralized skill. Second, individuals can often pick up habits that are dysfunctional (e.g., smoking, unhealthy eating, drinking), whereas proceduralization is mostly concerned with skills that individuals are actively attempting to learn.

Consistent with dual modes theory (Smith & DeCoster, 2000), humans form strong habits as a result of three components: (1) external cues, (2) behavioral responses, and (3) rewards (Polites & Karahanna, 2013; Verplanken & Orbell, 2003). As an illustration of habit formation at work, employees sometimes habitually check Facebook once they begin work. In this example, the external cue could be sitting down and beginning work on the computer; the behavioral response could be checking Facebook; and the reward might be receiving ‘likes’ or favorable comments. Over time, individuals may begin to internalize a link between the external cue (e.g., the computer) and the behavioral response (e.g., checking Facebook) such that exposure to the cue may automatically trigger the behavior. The habit becomes stronger as repetition establishes this association in memory. The stronger this internalized association, the stronger the habit.

Dual modes theory and scholarship on habit formation provide insights into why habits may become removed from current goals (Polites & Karahanna, 2013; Neal & Wood, 2007; Smith & DeCoster, 2000). Initially productive habits can turn counterproductive over time as the circumstances and/or goals change. For example, although a habit to check email every few minutes is productive when rapid communication is required, it may become counterproductive when fast communication is no longer needed. Rather than being mediated by goals, habits utilize short cuts in triggering behavioral decisions (e.g., choose whatever behavior was done in the past in a similar situation). As a result, habits within the automatic system are approximations or estimations of the best behavioral option (Smith & DeCoster, 2000). These estimations are sometimes not accurate, suggesting the possibility of dysfunctional habits.

Measurement of habit strength. The discussion of habits above provides insight into how to measure this construct. Scholars have used a variety of definitions to capture habit strength (for a review, see Polites & Karahanna, 2013), resulting in multiple measures. Many of these definitions can be organized into two larger categories. The first category involves conceptualizing habit strength as a behavioral tendency. For example, Wood et al. (2005) defined habit as "behavioral dispositions to repeat well-practiced actions" (p. 918); Quellette and Wood (1998) conceptualized habits as "tendencies to repeat responses given a stable supporting context" (p. 55). However, some researchers have argued this definition does not capture the essence of habits—that they have features of automaticity (Bargh, 1989). Rather than capturing the automatic nature of habits, this definition may only capture the notion of repeated behaviors.

Indeed, “Many actions are performed repeatedly in the course of doing one’s job, yet not all these actions have truly habituated” (Polites & Karahanna, 2012, p. 4).

The second category involves characterizing habits as a type of automatic response. For example, Verplanken and Aarts (1999) defined habits as sequences of actions that have become automatic responses to environmental cues. Triandis (1980) defined habits as automatic, situation-behavior sequences. Similarly, Bamberg conceptualized habits as being automatically activated by environmental cues without reflection. Consistent with the automatic system of dual modes theory (Smith & DeCoster, 2000), this dissertation draws on the second category of definitions because it directly captures the automatic nature of habits.

The two categories of definitions have translated into two major ways of operationalizing habit strength. The first method for assessing habit strength is consistent with the first category of definitions—that characterizes habits as a behavioral disposition (Verplaken & Aarts, 1999). The first method is based on the notion that the strength of habit can be inferred from how frequently the individual performs the behavior and the stability of that performance environment (Verplanken & Aarts, 1999). The reason it signals a strong habit is because frequent repetition of behavior and a stable performance environment may prompt individuals to form internalized connections between the behavior and the cues in that particular environment. Therefore, some measurement approaches have captured not only the frequency of the behavior but also the stability of the physical performance context and the time of day the behavior is enacted (Wood & Neal, 2009). A critical deficiency of this measurement approach is that it may be assessing an antecedent to habit strength rather than the construct itself. Indeed, “Frequent repetition of a behavior in a stable context simply increases the likelihood of a behavior habituating, making context stability an antecedent, rather than a facet, of habit” (Polites &

Karahanna, in press, p. 4). Even more important, assessing behavioral frequency and stability of performance environment does not directly capture the automatic nature of the habit construct.

The second common method of assessing habits corresponds to the second category of definitions—characterizing habits as a type of automatic response. An advantage of this method is that it directly assesses the automatic nature of habits. In particular, it captures three automatic dimensions of dual modes theory—low awareness, low controllability, and high mental efficiency awareness (Polites & Korahanna, 2012; Smith & DeCoster, 2000)—described in the preceding section. From a theoretical standpoint, these dimensions are critical characteristics of automaticity that distinguish automatic processes from controlled processes, according to scholarship on automaticity and dual process theories (e.g., Bargh, 1989; Smith & DeCoster, 2000). From a measurement standpoint, therefore, these individual dimensions should be measured (Polites & Karahanna, 2012).

The self-report habit index (SRHI) index is a popular measure in which the authors purport to assess five dimensions of habits (Verplanken & Orbell, 2003): (1) Habits are repeated behaviors, (2) individuals have difficulty controlling and (3) becoming aware of the process generating the habit. Further, (4) habits are mentally efficient (e.g., habit performance requires little mental resources) and (5) individuals view them as part of their identity (e.g., individuals describe themselves with respect to the habit). Verplanken and Orbell (2003) developed a 12-item measure to capture these characteristics. For example, the item “I have no need to think about doing [this behavior]” captures the dimension of mentally efficient. The item “I do [this behavior] automatically” captures the dimensions of lack of control. Verplanken and Orbell (2003) present validity evidence for their measure of habits. It is important to note that this widely used measure of habits captures the three dimensions of habits described above including controllability, awareness, and mental efficiency. One major issue with this measure, however, is that it assesses dimensions that are *not* typically viewed as core to automatic processes. For example, the identity dimension is not considered a core aspect of habit or automatic process. Indeed, Polites and Karahanna (2012) state that “While we do not deny that one’s personal style and desire for self-expression may lead them to develop particular ways of performing regular activities, these personalized ways of completing tasks may or may not habituate over time. Thus, while self-identity may aid in the development of strong habits, it is not a part of habit itself” (p. 5). In addition, self-identity should not be considered as a dimension of automaticity according to dual modes theory and scholarship on automaticity (Bargh, 1989; Smith & DeCoster, 2000). As another example, repeated behaviors may not necessarily become habitual behaviors (Polites & Karahanna, 2012) and are not considered a dimension of automaticity (Smith & DeCoster, 2000). Thus, the SHRI index is contaminated, in the sense that it includes two dimensions that fall outside the scope of habits and automaticity: Self-identity and frequency.

In light of these deficiencies, Polites and Karahanna (2012) developed and validated a measure of habit strength that directly assesses the three dimensions of automaticity. This measure makes theoretical sense because it assesses the dimensions of dual modes theory that distinguish automatic processes from controlled processes. An example item of awareness is “Oftentimes when on my computer or phone, I choose to browse social media without even being aware of making that choice”. An example item of controllability is “It would be hard for me to restrain my urge to use social media while on the computer or phone”. An example item of mental efficiency is “Selecting the behavior of using social media at work does not involve much thinking.” Exploratory factor analysis and confirmatory factor analysis support the three-dimensional structure of this measure of habit strength. Correlations among the dimensions of habits range from .28 to .55, providing support that the dimensions are related but distinct from each other.

Using this habits measure, Polites and Karahanna (in press) conducted multiple studies and the findings provide evidence for validity. One advantage of their validation effort for the purposes of this dissertation is they used the target of Facebook use, similar to the target of this study. As expected, the measure of Facebook habit strength demonstrates moderate to strong relationships with perceived ease of use of Facebook, perceived usefulness of Facebook, explicit intentions to use Facebook, and actual use of Facebook. In study 1, the authors used several tests to either avoid or identify common method bias. First, they collected data over two time periods. Second, they used different Likert scales in the system usage items as compared to other items in the survey. Third, they ran a confirmatory factor analysis that includes a method factor that helped them calculate the amount of method bias in the dataset. As a result, the estimated amount of common method bias was 12.7 percent for study 1. In study 2, the authors repeated Steps 2 and 3. The evidence from both studies suggests that, while common method bias was present, it was not severe.

Foundations of Dual Modes Theory and Implications for Studying Behavioral Change

Dual modes theory (Smith & DeCoster, 2000) serves as a foundational building block for developing the core argument in the next section that the two systems hold limited or no direct impacts on each other. The idea that *two systems* influence behavioral change expands on traditional thinking based on self-regulation perspectives that a single system governs behavioral change. For example, current self-regulation perspectives assume that reducing the discrepancy between goals and performance is a primary means by which individuals change behavior (e.g., Carver & Scheier, 1981). Acknowledging two systems allows for unlocking additional means or factors by which individuals change behavior. In the following sections, I present theoretical arguments and empirical evidence that the two systems hold limited or no direct impacts on each other. These features of dual modes theory have implications for behavioral change, such as studying main and interactive effects between the two systems and exploring fluctuations over time.

The two systems exert limited or no direct impacts on each other. According to dual modes theory (Smith & DeCoster, 2000), changes to one system (e.g., the controlled system) will not necessarily have a direct influence on changes to the other system (e.g., the automatic system) for the following reasons. First, the two systems encode different kinds of information (Smith & DeCoster, 2000). The automatic system is slow-learning because humans encode typical information into memory across many experiences, over the long run. For example, individuals may feel a strong impulse to use Facebook when they sit down to their computer in the morning because they have formed a strong association between sitting at the computer and Facebook over time. In contrast, the controlled system is fast-learning because new and unexpected information, sometimes gained from a single experience, can be quickly encoded into memory. For example, an individual may decide to quit using Facebook upon learning that the organization is monitoring the social media activity of its employees. Collectively, the two systems allow memory to reflect aspects of the environment that are both typical and novel. Second, individuals can have strong habits even if they do not explicitly endorse these habits. For example, individuals can feel the impulse to browse Facebook even while recognizing that this behavior is dysfunctional. As another example, in the domain of attitudes, Wilson, Lindsey, and Schooler (2000) argued that Caucasians could have implicit negative attitudes towards

African Americans yet explicitly endorse positive attitudes. Third, the controlled system does not play a direct role in the operation of the automatic system. Consistent with this notion, habits in the automatic memory system can influence behavior without the need for conscious goals in the controlled system to mediate this process (Wood & Neal, 2007). For example, when relevant cues are present (e.g., sitting down to work), employees may find themselves automatically checking Facebook despite the absence of an explicit intention for performing this behavior. Taken together, the automatic and controlled systems have different characteristics, which ensure that changes to one system do not directly influence changes to the other system.

Research on habits is consistent with the idea that controlled and automatic systems have limited effects on each other. Research demonstrates modest relationships between automatic constructs (e.g., habits) and controlled system concepts (e.g., explicit intentions). While there is sometimes a moderate or even strong positive relation between intention strength and habits (e.g., Chatzisarantis & Hagger, 2007; de Bruijn, Keer, Conner, and Rhodes, 2012), this is not always the case. For example, Gardner, Sheals, Wardle, and McGowan (2014) studied habitual dietary behavior and had subject matter experts rate participants' goals about how helpful they were in leading to habit formation. Contrary to expectations, these expert ratings did not significantly predict habit formation. As another example, Neal, Wood, Labrecque, and Lally (2012) concluded, based on two empirical studies, that habits "are relatively unaffected by goals" (p. 492). In further support, Neal et al. (2012) found that contextual cues associated with past performance such as locations strongly predicted habitual behaviors but not explicit intentions. In sum, the two systems are clearly not redundant and empirical research has established that individuals may hold several combinations of levels of constructs across the automatic system and controlled system. For example, some employees may hold strong and stable habits that maintain social media while experiencing strong intentions for reducing social media use.

In this paper, I argue that opposition between the two systems is particularly likely during the process of behavioral change. Simply put, employees who desire behavioral change (e.g., reducing social media use) likely have explicit intentions to do so. At the same time, they may also hold habits that foster continued use of the old behavior, particularly for individuals who have been performing the old behavior for a long period of time. Individuals may be particularly prone to developing habits associated with Facebook because there are clear cues and rewards associated with this behavior. Habits are difficult to control because the decision process underlying these behaviors is very quick and often subconscious. Therefore, habits can be powerful and persist even after employees develop explicit intentions to reduce the dysfunctional behavior. The reason habits may persist is because they reside in the automatic and slow-learning system that falls slightly below awareness. Consistent with the notion of opposition across systems, individuals can possess “a habitual negative evaluation and a more recently constructed positive attitude (i.e., explicit attitude)” (Wilson et al., 2000, p. 103). Indeed, “Associative knowledge at the implicit level sometimes conflicts with proposition-based conclusions at the explicit level” (Johnson & Tan, 2009, p. 103). One important consequence of the potential for opposition between systems is that there may be a fuller range of combinations of scores in habits and intentions. For example, some individuals may have *strong habits* and *low intentions* whereas other individuals may possess *strong habits* and *strong intentions*. It is therefore important to capture this full range of potential scores in order to best predict behavioral change.

In order to account for the full range of potential scores, it is important to acknowledge and study constructs from both systems, particularly when the two systems are opposing. For example, if the two systems are matched in terms of how they influence behavior, then studying constructs from one system will provide good prediction of behavior. However, when the two systems are not aligned, as is often the case with behavioral change, omitting the effects of one system can lead to difficulties in predicting and understanding behavior. As such, the influence of both systems and how they interact must be captured in order to best understand behavioral change. In what follows, I further describe the importance of investigating these main and interactive effects across the two systems and investigating fluctuations over time.

Important to study main effects of each system. Given this potential for misalignment between systems (Smith & DeCoster, 2000; Wilson, Lindsey, & Schooler, 2000), it becomes particularly important to acknowledge and study how each system affects behavioral change. As one example of misalignment, some individuals may hold strong habits towards engaging in non-work related use of social media, which serve as a pulling force against behavioral change. Yet, these same individuals may also experience increases in intention strength for avoiding social media use over time that push in the direction of behavioral change. Understanding both pushes and pull forces may illuminate difficulties involved in behavioral change. In sum, to understand and influence behavioral change, it is important to recognize and study the main effects of constructs from both systems.

Important to study interactive effects between systems. It is critical to understand interactive effects of the automatic and controlled system. Although the two systems may not directly influence each other, it is possible for one system, when active, to stifle the effects of the other system on behavior (Smith & DeCoster, 2000). For example, the stronger an individual's habit, the less likely that a change in his or her intention strength over time will predict corresponding changes in their behavior. On one extreme, individuals with a very strong habit may not experience any tracking of his or her behavior with intention strength. On the other extreme, individuals with very low strength of habit may experience close tracking between intention strength and the corresponding behavior. In sum, features of the controlled system (e.g., intention strength) may have very different effects on behavior depending on features of the automatic system (e.g., habit strength) and vice versa.

Fluctuations over time. Fluctuations are important to capture in this dissertation for the following reasons. First, the research questions involve fluctuations over time. The two key questions are: (1) do the core constructs of the automatic and controlled systems predict day-to-day fluctuations in social media use and (2) do interactions in core constructs between the automatic and controlled systems predict day-to-day fluctuations in behavior (e.g., reductions in social media use). Second, the perspective used here for understanding behavioral change—dual modes theory—incorporates fluctuations in behavior over time and factors that influence these fluctuations (Smith & DeCoster, 2000). For example, dual modes theory paints control over one's behavior as a constant struggle between two systems. For example, increases in state self-control may promote individuals to act on intentions; decreases in state self-control may prompt them to behave in a way consistent with habits. Finally, studies of behavioral change imply the need to study fluctuations over time. Indeed, investigating behavioral change with a single data point leaves little understanding regarding the extent to which the employee experienced difficulty in changing their behavior.

Findings and Gaps in Studying Habits, Intentions, and Self-Control

The previous section covered the argument for studying main and interactive effects of constructs across the two systems and exploring fluctuations over time. With this in mind, I now turn to summarizing the current state of research and knowledge gaps regarding the main and interactive effects of constructs relevant to dual modes theory. The section begins with main effects and then turns to interactive effects.

Main effects: Findings and gaps. Although organizational scholars admit that much of behavior in organizations is habitual (George, 2009; Weiss & Ilgen, 1985), few studies have examined this topic in organizational psychology or organizational behavior. As one exception, Ohly, Sonnentag, and Pluntke (2006) demonstrated that the strength of positive work habits (e.g., handling emails, interacting with subordinates, quality checking) positively predicted creative behaviors, above and beyond time pressure, job control, supervisor support, job complexity, job experience, education, gender, leadership position, research and development, production, and marketing and sales. Hinsz, Nickell, and Park's (2007) demonstrated the role of strength of work habits in positively predicting food safety behaviors. These studies provide initial evidence for the importance of work habits. Habit strength is important to consider because strong habits can lead to inertia, making it difficult for individuals to change their behavior (Polites & Karahanna, 2012). Studies incorporating habit strength may provide insight into interventions for mitigating the negative influence of this construct on behavioral change at work.

Using theories such as self-regulation and ego-depletion, some studies have connected state self-control or similar constructs (e.g., sleep) with behavior and they range from conducting analyses only at between-person level to some that incorporate the within-person level. Using a correlational design, Reneicke, Hartmann, and Eden (2014) found a negative correlation between state self-control and unhealthy snacking. Employing a longitudinal design, Ghumman and Barnes (2013) found that day-today fluctuations in sleep quantity of employees positively predicted their organizational citizenship behaviors. Given the tight correspondence between sleep and attentional resources, the finding provides indirect insight into the relation between attentional resources and behavior. Wagner, Barnes, Lim, and Ferris (2012) demonstrated that low quality sleep positively predicted cyberloafing behaviors by monitoring students overnight in a laboratory study. They also showed that a shift to daylight saving time sparked a sizeable increase in cyberloafing using a field sample. Finally, using experience sampling methodology, Lanaj, Johnson, and Barnes (2014) found that smart phone use at night positively influenced depletion the next morning, which in turn negatively predicts levels of engagement throughout the work day. In sum, work on sleep and depletion has advanced understanding of how these constructs interrelate over time. This research, however, omits critical concepts such as habits and intentions despite their importance in revealing how the two systems jointly influence behavior.

Although the primary focus and contribution of this dissertation is to work subdomains, similar gaps in other psychology field domains are also important to note. Social psychology has paid some attention to the role of habit strength in influencing behavior, often by employing perspectives such as the theory of planned behavior. For example, Verplaken and Melkevic (2008) demonstrated a positive relationship between habit strength for exercising and exercising. Using two experiments, Neal, Wood, Labrecque, and Lally (2012) demonstrated that context but not goals predicted that individuals would recall and perform highly habitual behavior.

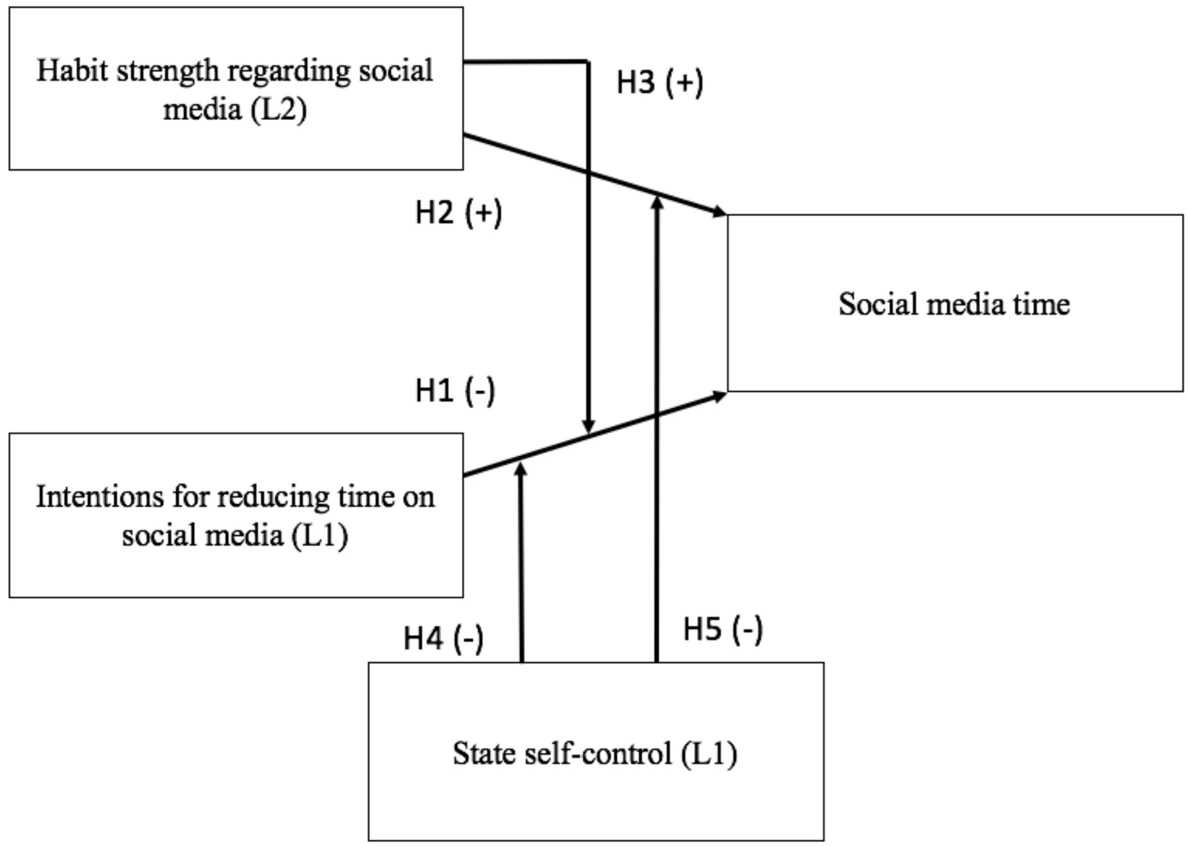
While the above studies have made some progress in understanding how constructs relevant to dual modes theory influence behavior, gaps remain. One such gap is that relationships are primarily studied at the between-person level despite evidence that many constructs relevant to dual modes theory vary over time (Rebar, Elavsky, Maher, Doerksen, & Conroy, 2014). This practice obstructs advances in understanding why behavioral change is difficult. As one exception, Rebar et al. (2014) found that, over a week-long period, individuals were more likely to engage in physical activity on days when they had strong habits for engaging in physical activity. Rebar et al. (2014) also found that more than half of the variability in explicit intentions over a week-long period resided at the within-person level of analysis. Yet, this study provides less insight into decreasing undesirable behaviors because it focuses primarily on increasing desirable ones. Desirable (undesirable) behaviors are actions that are perceived by the individual to be congruent (incongruent) with common goals. A final gap is that scholars do not tend to capture the automatic nature of habits, even though this is necessary for understanding main effects of habits on behavior. For example, scholars often operationalize habit strength using behavioral frequency and stability of context without measuring automaticity dimensions (e.g., Neal, Wood, & Drolet, 2013; Neal, Wood, Wu, & Kurlander, 2011). One important deficiency of this practice is that it does not directly assess the automatic nature of the habit construct. As one exception, Polites and Karrahanna (in press) conducted an initial validation attempt of the three dimensions of automaticity. They found positive correlations of each dimension of automaticity with Facebook use. However, the researchers did not measure other aspects that are important to dual modes theory such as state self-control. In addition, the study is not well positioned to shed light on behavioral change because the researchers did not examine fluctuations over time or within-person relationships.

Interactive effects: Findings and gaps. Compared to research on main effects, less scholarship has been devoted to interactive effects. Work subdomains in particular have rarely investigated interactive effects of intentions, self-control, and habits. One reason for this is that organizational scholars have rarely considered the habit construct. In contrast, the psychology literature more broadly has devoted some attention to interactive effects. The interactive effects most commonly studied tend to involve habit strength and intention strength. For example, using two field studies, Ji and Wood (2007) showed that intention strength predicted consumer behavior only in the absence of strong habits. Other studies have demonstrated similar patterns of relationships among habits, intentions, and behavior (e.g., van Bree, van Stralen, Bolman, Mudde, Vries, & Lechner, 2015; de Bruijn, Kroeze, Oenema, & Brug, 2008). Yet, these relationships tend to be studied at the between-person level. As one exception, Rebar, Elavsky, Maher, Doerksen, and Conroy (2014) found a significant interaction such that habit strength for physical activity positively predicted physical activity behavior only on days when intentions were weak. A second gap is that studies do not generally cover some of the interactions suggested by dual modes theory. For example, the study just described could be supplemented by including additional variables from the controlled system (e.g., state self-control) and the automatic system (e.g., controllability, awareness, mental efficiency) to have a fuller picture of how the systems interact in influencing behavioral change. In particular, it is uncommon for scholars in the social psychology literature to study the concept of state self-control alongside habits. As one exception, Neal, Wood, and Drolet (2013) conducted a series of field and laboratory studies to test the notion that people engage in habitual behavior when they have low self-control resources. The findings support their main thesis that individuals become locked into performing habitual behaviors when experiencing low state self-control. However, the study does not capture fluctuations or within-person relations, thus the findings provide only limited insight into behavioral change. In addition, the authors do not capture explicit intentions or goals, even though this is a critical construct residing in the controlled system.

Theoretical Model

Figure 1 provides a conceptual model that aims to address the abovementioned gaps and contribute to the behavioral change literature. The model captures how fluctuations in explicit intentions and state self-control influence behavioral change over time. The focus on fluctuations helps address the research questions of how main and interactive effects of constructs in the two systems influence day-to-day fluctuations in behavior. As another example, the model is one step closer to testing how the constructs in both systems influence behavior. To do so, the model includes the three dimensions of habits from the automatic system as well as the constructs of state self-control and intention strength from the controlled system. The model suggests these constructs influence behavior in various directions. The hope is that testing the conceptual model will provide a fuller picture of how the systems jointly affect behavioral change, revealing difficulties of behavioral change.

Figure 1: Pictorial representation of the hypothesized relationships



Assumptions underlying model. A few assumptions serve as boundary conditions for the theoretical model. For instance, the outcome of interest is time spent on social media on the job for non-work relevant purposes. Although many social behaviors are important for one's work activities, the focus here is on social media behaviors that are *not* done with the intent of aiding the organization. As another example, the model assumes that individuals view non-work related social media use on the job as a dysfunctional behavior, at least to some extent. Consistent with this assumption, it is expected that some employees believe that engaging in non-work related social media use while on the job is dysfunctional. In regards to academic performance, a study of 219 students found that individuals who used SNS spent less time studying and had a lower GPA than individuals who refrained from using SNS (Kirschner & Karpinski, 2010). Almost three quarters of these students believed their SNS use had a negative effect on their studies. This study suggests that individuals are aware of the dysfunctional nature of social media behaviors. Although some suggest that cyberloafing in certain instances may serve to replenish resources, research indicates that social media use can deplete attentional resources and state self-control in part because it often involves reading and analyzing written text (Greenfield, 2009). Employees may themselves wish to reduce their cyberloafing in order to better obtain their work goals and the resulting benefits (e.g., promotions). In addition, social media use is also dysfunctional because it does not have a clear beneficial effect on one's social life. For example, an online study showed that the longer individuals spend on SNS, the less involved they are perceived to be in their real life communities. Individuals with low self-esteem may become dependent on SNS use as a substitute for real life social networks, resulting in a lack of investment in their real networks and less social support. Unfortunately, building large social networks online does not seem to influence real life network size or emotional closeness to one’s network (Pollet, Roberts, & Dunbar, 2011). For all of the above reasons, I expect that at least some employees will view their social media use on the job as counterproductive.

Theoretical Development of Hypotheses

In the previous sections I described the core tenets of dual modes theory, culminating in a description of the overarching model (Figure 1). A core focus of this dissertation is to develop and test a model based in dual modes theory that captures the main and interactive effects of constructs across the two systems in influencing behavioral change. I first focus on hypotheses regarding how explicit intention strength and habit strength influence behavior. Next, I focus on effects of state self-control, including its interactions with other variables in influencing fluctuations in behavior.

Hypotheses

According to dual modes theory, intention strength predicts behavior. Simply put, individuals are more likely to perform their intended actions on days they are strongly motivated for doing so. Strong explicit intentions indicate high motivation for performing intentions, resulting in the performance of the intended action (Armitage & Connor, 2001). Intentions differ from goals in that the former is a low-level representation of a planned action whereas the latter resides at a higher-level and does not capture specific actions. Because intentions involve specific behaviors, individuals tend to perform behaviors on days they have strong intentions for doing so (Armitage & Connor, 2001). Supporting this notion, meta-analytic evidence demonstrates a positive relationship between intention strength and behavior, though this linkage is generally small to moderate in size and not always present (Web & Sheeran, 2006). Studies in the domain of cyberloafing (e.g., Mahatanankoon, 2006) show that attitudes and intention strength to engage in cyberloafing positively predict cyberloafing at a between-person level. At the within-person level, there is theoretical evidence for the relation of intention strength with behavior (e.g., control theory; Carver & Scheier, 1981). Accordingly, intention strength for reducing social media use should negatively influence time on social media at a within-person level.

> H1: At a within-person level, intention strength (for reducing time on social media) will negatively predict time on social media.

Dual modes theory emphasizes the important role of the automatic system in influencing behavior. Individuals may be likely to develop habits for maintaining social media use in particular given these behaviors are simple and not complicated (e.g., checking Facebook), can be triggered by clear environmental cues (e.g., working on the computer), and often lead to immediate gratification/rewards (e.g., receiving 'likes', positive comments from friends). Continued social media use and receiving immediate rewards can lead some individuals to form strong connections between particular cues (e.g., opening browser at beginning of work day) and behavioral responses (e.g., perusing Facebook). These strong connections can lead individuals to frequently check social media platforms, increasing the time they spend on social media. Once formed, strong habits tend to promote the same behavior in the future because "Habitual behavior is apparently guided by implicit processes that operate outside of conscious awareness" (Wood, Quinn, Kashy, & 2002, p. 1294). Individuals often get locked into performing habitual behaviors because they have low awareness and control over the performance of these behaviors. Indeed, preliminary empirical evidence suggests a positive relation of habit strength with cyberloafing (e.g., Garrett & Danziger, 2008; Lim, 2002). Accordingly, the following is hypothesized.

> H2: At a between-person level, habit strength regarding social media will positively influence time spent on social media.

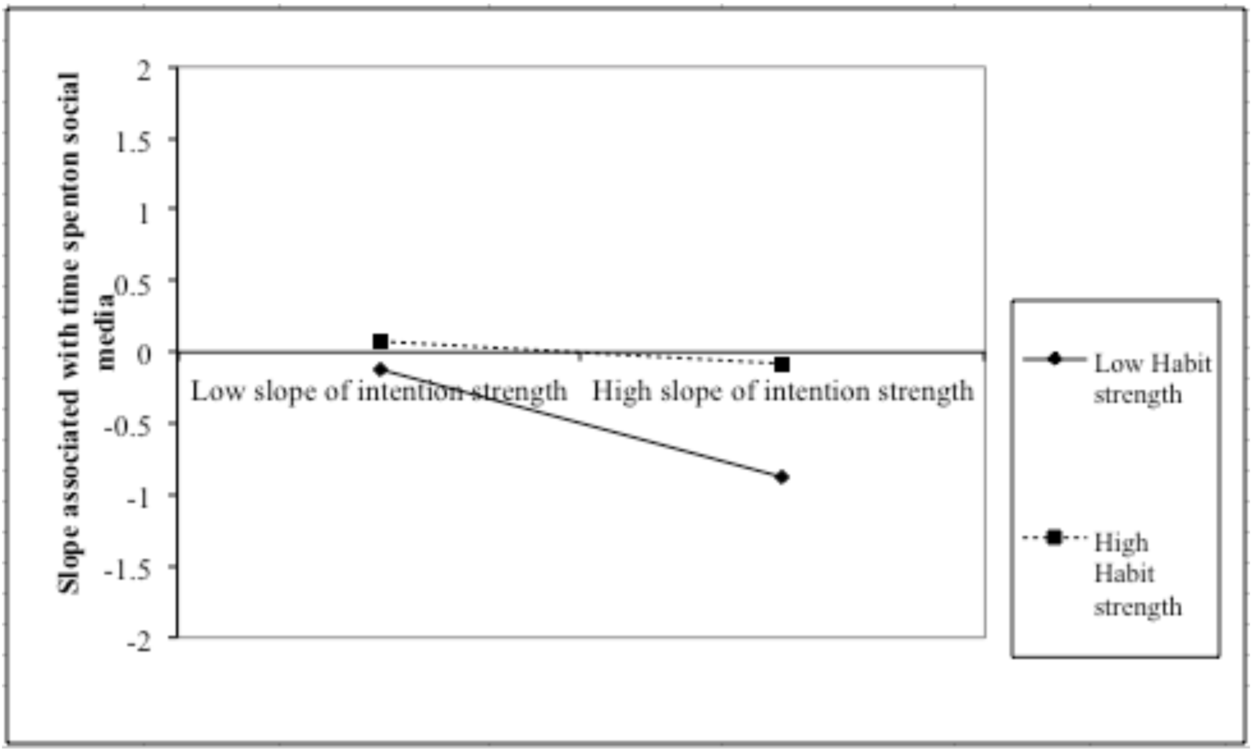
The notion that habits weaken the effects of explicit intentions on behavior is consistent with dual modes theory. While experiencing increases in intention strength for reducing social media use from day to day, individuals may nevertheless cling to old habits, perpetuating social media use. Old habits can persist because they reside in the automatic and slow-learning system that is inflexible to new pieces of information such as strong intentions. Habits have powerful and lasting effects on behavior because the automatic system does not have the same requirements for attentional resources as the controlled system in order for the system to guide behavior. Because they involve low awareness and controllability, habit strength can weaken the effects of intention strength on behavior. Regarding low awareness, individuals may be unaware of the environmental triggers, in the moment they occur, that automatically trigger the performance of a habitual behavior. Without awareness of these triggers, individuals have little warning before they find themselves engaging in the habitual behavior. Thus, even those with strong intentions may have trouble acting on them if they have strong habits. Accordingly, the stronger the habit (e.g., low awareness), the weaker the relationship of day-to-day increases in intention strength with the resulting behavior. Low controllability works in a similar way. Simply put, individuals are less likely to perform strong intentions for behaviors they have difficulty controlling. Habits are difficult to control in part because the decision process underlying these behaviors is efficient and often subconscious. Accordingly, for individuals with stronger habits (e.g., low controllability), intention strength from day-to-day will have a weaker effect on the resulting behavior.

Supporting the habits and intentions interaction, empirical studies have verified that intention strength predicts behavior more often when people possess weak but not strong habits (e.g., Aarts, Verplanken, & Knippenberg, 1998; Ji & Wood, 2007; Neal, Wood, Labrecque, &

Lally, 2012; Neal, Wood, Wu, & Kurlander, 2011). Although most of these findings reside at the between-person level of analysis, one study (Rebar, Elavsky, Maher, Doerksen, & Conroy, 2014) demonstrated that physical activity habits positively predicted physical activity behavior only on days when intentions were weak. Taken together, the strength of social media habits will weaken the within-person relation of intention strength for reducing time on social media for non-work use with time spent on social media. Figure 2 suggests that strong habits regarding social media will attenuate the within-person effect of intentions to reduce social media on social media time.

> H3: Habit strength regarding social media will weaken the negative within-person effects of intentions (to reduce time on social media) on social media time.

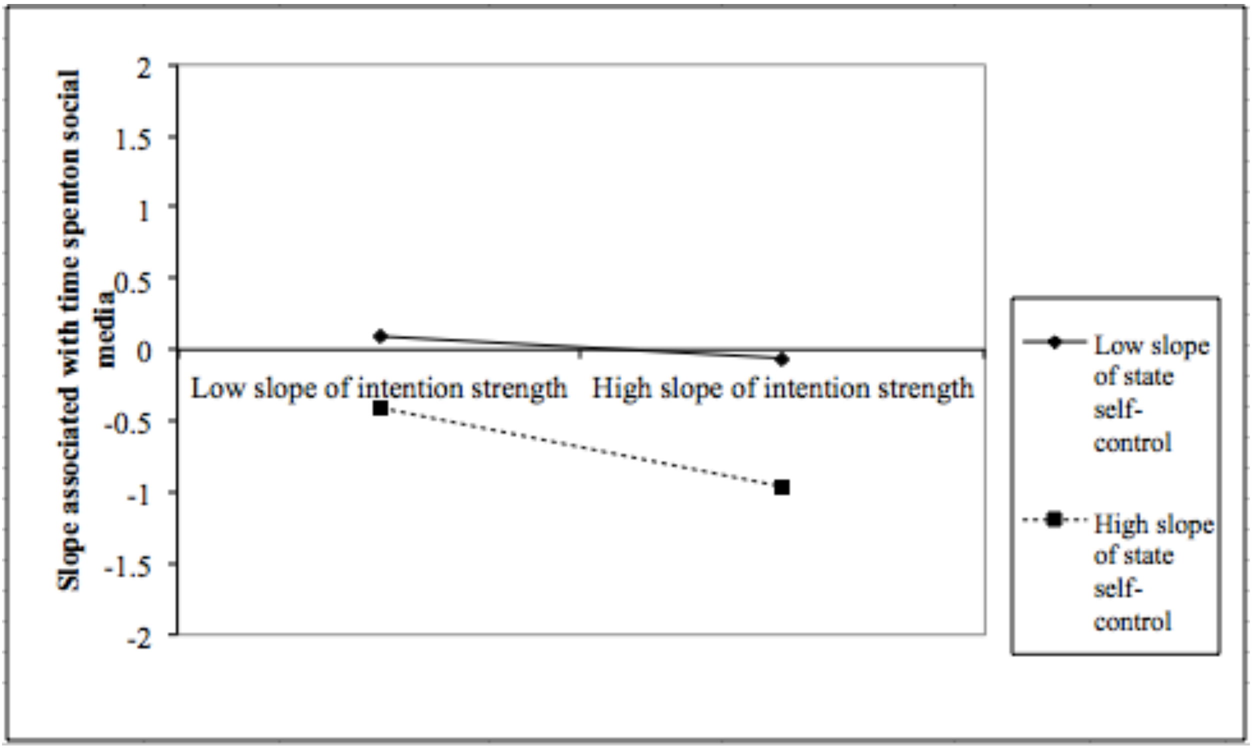
Figure 2: Within-person relationship between rate of change of intentions to reduce social media use and rate of change associated with time spent on social media, moderated by habit strength



Dual modes theory is consistent with the idea that the strength of one's intentions will only influence behavior if individuals have the attentional resources to recall that intention. Attentional resources is an important indicator of one's state self-control levels. Specifically, high state self-control and attentional resources, according to dual modes theory, allow individuals to better recall explicit intentions. Without the ability to retrieve intentions (i.e., low attentional resources) on a given day, stronger explicit intentions—or motivation for performing intended actions—will not necessarily increase the likelihood of performing that intention on that day. For example, individuals may be strongly motivated to avoid social media outlets because they believe it negatively influences their work performance. Without sufficient attentional resources, however, individuals will have difficulty recalling intentions. Thus, intention strength for reducing social media use will be less consequential in determining behavior on a given day. High attentional resources also aid individuals in *acting* on intentions. Thus, intention strength may be more likely to influence behavior on days when individuals have the resources necessary to carry out those planned intentions. All in all, increases in state self-control will strengthen the within-person relations between intention strength and behavior (Smith & DeCoster, 2000). Figure 3 suggests that, at a within-person level, greater increases in state self-control will strengthen the within-person effect of intention strength for reducing social media use on social media time.

> H4: At a within-person level, greater increases in state self-control will strengthen the negative effect of intention strength (for reducing social media use) on social media time.

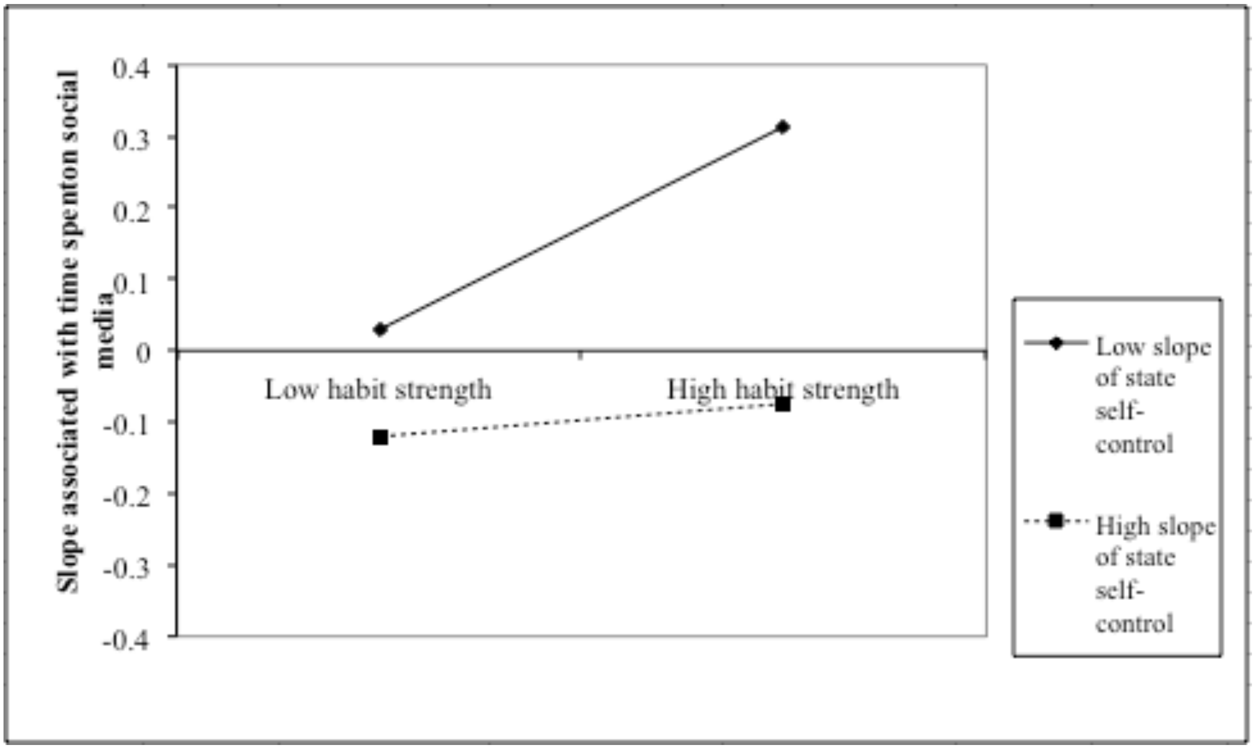
Figure 3: Within-person relationship between intention strength and time spent on social media, moderated by state self-control



According to dual modes theory, facets of the automatic system (e.g., habits) and aspects of the controlled system (e.g., state self-control) may interact with each other in influencing behavior. As individuals continually repeat behaviors in a given context, they may form an association such that aspects of the context automatically trigger the behavior to come to mind (Wood & Neal, 2007). Importantly, this automatic cuing function is not dependent on goals or intentions; thus, individuals may perform habitual acts even in the absence of attentional resources. On some days, individuals may find themselves low on state self-control such that intentions (from the controlled system) no longer have much influence on their behavior throughout the day and the only system left for guiding much of their actions is the automatic system. On other days, individuals may have enough state self-control to reject habitual responses and choose a novel behavior (Neal, Wood, & Drolet, 2013). In other words, the negative link of habit strength regarding social media and time on social media is likely to be weakened on days when individuals have higher state self-control. As a graphical representation, Figure 4 suggests that, at a within-person level, a greater increase in state self-control will weaken the positive effects of habit strength regarding social media on time spent on social media.

> H5: At a within-person level, greater increases in state self-control will weaken the positive effects of habit strength regarding social media on time spent on social media.

Figure 4: Relationship between habit strength and time spent on social media, moderated by slope of state self-control



In this section, I have revealed hidden factors (e.g., strong habits towards old behavior) that underlie reasons why behavior change is so challenging. These factors include the following—(H1): within-person main effect of intention strength on performance of new behavior; (H2): Main effect of habit strength regarding social media on social media behavior; (H3): Interaction between habit strength regarding social media and explicit intentions for reducing social media use on time spent using social media use (H4): Interaction between state self-control and intention strength at the within-person level; (H5): Interaction between state self-control and habit strength regarding social media. Scholars in work domains have devoted considerable theory and some research to H1 and H4, yet scant theory and research has been devoted to the rest of the hypotheses: H2, H3, H5. As such, hypotheses involving automatic processes represent the most understudied linkages needed to understand why behavioral change at work is difficult and to identify solutions for addressing these difficulties.

METHODS

METHODS

An overarching focus of this dissertation is to understand the difficulties employees experience in changing their behavior. The first research question is: Do constructs in the automatic and controlled systems predict day-to-day fluctuations in behavior (e.g., reductions in social media use). The second research question is: Do interactions in core constructs of the automatic and controlled systems predict day-to-day fluctuations in behavior (e.g., reductions in social media use)? To help answer these questions, I tested the conceptual model and hypotheses above using the following proposed methodology.

Pilot Studies

An overarching focus of the pilot studies were to ensure that parameters set in the filters for study 1 were rigid enough to obtain the desired population but also flexible enough to obtain enough participants. Secondary purposes were to ensure that enough participants were retained from the baseline survey to the morning and evening surveys, and to establish evidence for reliability and validity of the study variables. Amazon Mechanical Turk was used to find participants across the pilot studies.

Pilot 1 focused on testing these filters. One filter involved setting the percent approval rating that Mechanical Turkers have achieved and the number of tasks they have performed in the past. For example, we initially included Mechanical Turkers who spoke English as their primary language and had at least a 95% or higher approval rating and had performed at least 1,000 tasks. A second filter was to include participants with a full-time job outside of Mechanical Turk in which they worked five days and at least 30 hours per week. A third filter was to include only those participants that had access to at least one of the four forms of social media either in their phone or on their computer while on the job. Participants received a reward of one dollar for a single survey lasting 20-30 minutes. This reward for the baseline survey was 1 dollar. After data collection, I calculated a percentage of the number of Mechanical Turkers that passed the filters divided by the number of Mechanical Turkers recruited. 39 out of 74 (52.7%) of Mechanical Turkers successfully passed the above filters and these results were obtained within a single hour. These findings suggest there is room for establishing more rigid criteria in order to obtain a sample that is closer to the desired population.

Thus, in pilot study 2, I evaluated a more stringent set of criteria and evaluated reliability and correlations among primary study variables. Regarding the more stringent criteria, I eliminated individuals who used non-work related social media at work only once a week or less. In addition, I also eliminated participants who viewed social media as marginally good, good, or very good for work goals and those who responded “no” to their wiliness to complete 5-10 minutes surveys every day for a two week period. The reward for completing the baseline survey was again 1 dollar. 43 out of 145 (29.7%) individuals successfully passed the above filters.

I also evaluated reliability and correlations among the measures in the data. To assess habits strength, I used the validated measure by Polites and Korahanna (2012). Here is an example of an item: “While on my computer or cell phone at work, oftentimes I find it difficult to overrule my impulse to use social media” (see Appendix C for all items). To assess state self-control, I used a shortened measure of ego depletion by Twenge et al. (2004) that captures state self-control, which was used in the morning surveys (e.g., “Today, I feel drained”; See Appendix E for all 4 items). I included two variants of this measure. The first and primary method covered one’s current state of state self-control. The second method captured feelings of state self-control while engaging in social media use.

Regarding reliability, the coefficient alpha for the 11-item habits measure was .917; the coefficient alpha for the 4-item state self-control measure was .938; and the coefficient alpha for the 4-item state self-control while engaging in social media measure was .939. These coefficient alpha's provide initial support for the reliability of many of the variables to be used in the primary study. In terms of correlations, I found a strong and positive correlation between the primary and backup measures of state self-control. Specifically, current levels of state self-control strongly correlated with state self-control while engaging in social media ($r = .731$, $p < .01$; see "Measures in the morning survey" and "Measures in the evening survey" for more information about these measures). As expected, I also found a positive correlation of habit strength regarding social media with time spent on social media ($r = .337$, $p < .05$). The correlation also appeared to provide some early evidence for the validity of variables included in the primary study.

Having established that enough participants were successfully able to take the baseline survey, I wanted to ensure that I retained a sufficient number of these participants going into the morning and evening surveys. Thus, the third pilot study served to identify how many participants from the baseline survey also took the morning and/or evening survey. A number of steps were taken to ensure that individuals who completed the baseline survey would continue on to complete the morning and evening surveys. First, to complete the baseline survey, the participants needed to click yes on an item that asked if they were available and willing to complete the subsequent morning and evening survey. Participants received one dollar for completing the baseline survey. Second, participants received an additional forty cents for each morning survey and each evening survey. Third, although it was not feasible to give notifications to Mechanical Turkers for completing the subsequent morning and evening surveys, explicit instructions were provided about how to find the morning and evening surveys and what times these surveys would be available. However, only 3 out of the 30 participants in the baseline went on to complete both the morning and evening surveys. This indicated roughly 90% attrition and the need to develop a new way of retaining participants across all types of surveys. One potential option was to use Mechanical Turk Prime. Mechanical Turk Prime has a number of advantageous in doing longitudinal research above and beyond the regular Mechanical Turk platform. For example, it offers a function that allows researchers to notify participants each time a new study is available for them to complete. Thus, I adopted *Mechanical Turk Prime* in the fourth pilot study.

The primary purpose of the fourth and final pilot was to assess whether, using *Amazon Mechanical Turk Prime*, enough participants were retained from the baseline survey to the morning and evening surveys. I began by making the criteria more stringent to find even more participants that frequently used social media. For example, I included only participants that used social media at least three times per week. Also, I eliminated any individuals who strongly disagreed that their social media use interfered with their work goals. We made the incentives for the baseline, morning, and evening surveys the same (all 30 cents) to try to encourage individuals in the baseline survey to also take the subsequent morning and evening surveys. Overall, 30 of 502 individuals passed the filters and went on to take the baseline survey. Results indicated that 21 of these 30 individuals participated in the morning survey. In addition, 19 of the 30 individuals participated in the evening survey. Overall, 19 of the 30 baseline participants completed both the morning, and evening survey, representing an attrition level of roughly 37%. This attrition level was acceptable so I went on to evaluate one of the remaining main effects that had not yet been evaluated. Specifically, I expected a negative correlation between the measure of intention strength in the morning with the actual time spent on social media in the evening. Three items assessed intention strength for reducing time on social media for non-work related purposes while on the job (Norman & Cooper, 2011). One example item is "Today, I intend to reduce the time I spend on social media for non-work related purposes while on the job". The total time on non-work related social media served as the primary way of assessing social media use. The measure of social media was an adapted version of the social media dimension of Lim's (2002) cyberloafing scale. Appendix G provides information about the measure as well as steps taken to help ensure accuracy of the self-reports. In line with expectations, I found a moderate, negative correlation (r = -.283); yet, the p value was non-significant ($p = .227$). However, the non-significant finding may be due to the small sample size of the pilot study (i.e., 19 participants in both morning and evening survey). Overall, the correlations appear to provide some preliminary evidence for convergent validity of the study variables.

Primary Study

Mechanical Turk

Using experience-sampling methodology, one baseline, ten morning surveys, and ten evening surveys were administered to Mechanical Turkers in the United States. Amazon Mechanical Turk is a platform in which individuals are hired to do tasks for fairly small amounts of money. Mechanical Turk has been successfully used in past research (Mason & Suri, 2012), has been used to replicate past findings (e.g., Boynton & Richman, 2014) and is appropriate for several reasons. First, similar to sampling all employees from a single organization, the filters enabled me to identify individuals who work in an organization outside Mechanical Turk and that engage in non-work related social media use at least daily. The psychological mechanisms underlying social media use when sampling employees in a single organization versus sampling employees across a range of organizations are similar in some respects. For example, non-work related social media is an issue across a wide range of organizations (Rajah & Lim, 2011). As such, the notion that some employees hope to reduce their non-work related social media use despite habits to the contrary would likely be present in employees across many organizations. Second, measures given to Mechanical Turkers have been shown to have high test-retest reliabilities and high internal consistencies (e.g., Buhrmester, Kwang, & Gosling, 2011).

Past researchers have successfully used Mechanical Turk with an experience sampling methodology design. For example, Boynton and Richman (2014) investigated alcohol consumption by testing a multi-level model with a daily diary study. Recruiting participants on Amazon's Mechanical Turk, they were able to replicate several findings commonly found in daily studies of alcohol use. The results demonstrate that online recruitment using Mechanical Turk can be a fruitful method of collecting daily diary alcohol research. They also found acceptable levels of attrition despite the 5 min daily surveys. Of the 518 participants that were sent surveys, 130 were removed because of completing less than 4 surveys, and an additional 19 participants were removed because they did not complete consecutive surveys. Thus, the attrition rate was 28.76%. Using twice daily surveys, other researchers have also successfully recruited participants using Mechanical Turk (e.g., Hatch, 2015).

Sample Size

In computing an a priori power analysis, I used an anticipated effect size of $r = .2$ to represent the size of interactive effects. This effect size is consistent with the size of effects involving habits and intentions in the literature (e.g., Neal, Wood, & Drolet, 2013). Using this effect size and three predictors, G Power indicated a minimum sample of 56 was necessary to detect effects at the between-person level of analysis. I increased this number to 100, with the expectation of roughly 45% attrition. This is a conservative or safer estimate given that other ESM study designs with Mechanical Turk have found lower levels (e.g., 29% attrition; Boynton & Richman, 2014). A sample size of 100 is within the range of experience sampling studies published in top-tier journals. On the slightly higher end, for example, Rebar et al. (2014) collected data from 128 participants. They investigated the effect of habits and intentions on exercise behavior using a daily diary study over the course of two weeks. On the lower end, Lanaj, Johnson, and Barnes (2014) collected data from 82 participants to capture the effects of sleep quantity, sleep quality, and state-depletion on work engagement. They administered surveys twice a day—one in the morning and one in the evening—to participants over a week-long period. I collected usable data from 208 participants, which exceeds the number of participants in the studies mentioned above. All study participants were collected in a single wave spanning a two-week period.

Sample Characteristics

The inclusion criteria for allowing individuals into the study was consistent with the fourth pilot study. Mechanical Turk was programmed to only let in individuals who achieved a 95% or higher approval rating, and completed at least 1,000 tasks. Qualtrics was then used to further screen participants based on additional criteria. First, Mechanical Turkers needed to speak English as their primary language and have a full-time job outside of Mechanical Turk in which they worked five days a week and at least 30 hours per week. Second, they needed to have access to at least one of the four forms of social media while at their job. Third, participants had to indicate they used social media for non-work related purposes at least three days a week while at work. Fourth, they needed to perceive their non-work related social media use while on the job as having no effect, or a marginally bad, bad, or very bad effect on work goals, which excluded participants who believed social media use has a positive effect. Fifth, I eliminated any individuals who strongly disagreed that their social media use interfered with their work goals and participants who admitted they were not available to complete the daily surveys. 342 out of 1,369 participants passed the Qualtrics filters and were allowed to complete the baseline survey. I eliminated 134 of the 342 participants who completed the baseline survey because they did not go on to complete any of the daily surveys. In addition, there were instances when a participant took the morning survey but failed to take the evening survey and vice versa. The absence of the morning or evening survey eliminates either the independent variable or the dependent variable, making it difficult to evaluate the theoretical model. As such, I removed these cases. As a result, the final sample size dropped to 208. In comparison to those individuals who took the baseline survey (342), the response rates for the daily surveys were the following: Day 1 (59.06%), Day 2 (54.39%), Day 3 (56.43%), Day 4 (53.80%), Day 5 (52.05%), Day 6 (52.34%), Day 7 (51.17%), Day 8 (50.58%), Day 9 (50.58%), Day 10 (49.12%). Of those individuals in the final sample, 134 participants (64.42%) completed all 10/10 morning and evening surveys, 158 participants (75.96%) completed *at least* 9/10 morning and evening surveys, and 184 participants (88.46%) completed *at least* 6/10 morning and evening surveys.

The final sample of 208 participants were majority white (84.1%), male (51.9%), with an average age of 38.53 (SD = 38.08). Participants typically were in their current work position for a mean of 5.18 years (SD = 4.74). They typically were in their current organization for a mean of 6.21 years (SD = 5.24). Most participants had at least a bachelor's degree (76.9%). I ran a one-way ANOVA to look for any differences in the demographic or focal variables when comparing those who *only* completed the baseline survey to those included in the final sample. The ANOVA indicated there were no significant differences in gender, education level, position experience, organization experience, race, state self-control, habits or time individuals spend on social media at work. These results provide support against the notion of differential attrition in this study.

Filtering Participants

Filters, incentives, and flags for careless responding were used to enhance data quality. In addition to the filters described in the pilot, Mechanical Turkers had to be 18 or older and live in the U.S. and speak English as their first language. Regarding incentives, participants received 1 dollar for completing the baseline survey, as well as 40 cents for completing each morning survey and 40 cents for completing each evening survey. Participants also received an extra bonus of a dollar for completing 75% of the surveys and then an additional dollar for completing at least all but one of the surveys. Thus, each participant could earn a maximum of 11 dollars in this study. Careless responding was flagged using three quality checks in the baseline survey as well as 1 quality in the morning and 1 quality check in the evening survey (e.g., “Mark strongly agree for this question”). 51 out of 1781 cases (2.9%) were eliminated due to individuals who missed the quality checks in either the baseline, morning, or evening surveys. The 2.9% reflects a relatively low rate of missing quality checks and provides some indication of the high-quality nature of the data.

Broad Procedure

Participants first completed a single baseline survey. Then, they completed a morning and evening survey every day for ten consecutive weekdays from Monday to Friday. For example, Monday they completed both the morning and evening surveys. On Tuesday, they again completed the morning and evening surveys. The last survey distributed was the evening survey on Friday. For the baseline survey, level 2 variables were collected (i.e., habit strength regarding social media, and almost all control variables). For the morning and evening surveys, level 1 variables were collected. Intention strength for reducing social media and state self-control was measured in the morning; social media behaviors were measured in the evening.

Participants had a window from Friday morning to Sunday night in order to complete the baseline survey. The morning survey opened at 6am and participants had 8 hours to complete the survey. The evening survey opened at 4pm and participants had 8 hours to complete this survey. There was no overlap in time between the morning survey and the evening survey. To ensure that participants did not provide the same data multiple times, I eliminated any repeat participants.

Measures in Baseline Survey

Demographics. Participants were asked about their gender, highest level of education, work experience, age, and race (see Appendix B).

Dysfunctional behavior. An assumption of the theoretical model was that some employees viewed their non-work related social media use on the job as dysfunctional (at least to some extent). To test this assumption, the measure of dysfunctional behaviors in Neal, Wood, and Drolet (2013) was used (see Appendix A). This assessment captured the extent to which participants believed non-work related social media use on the job was helpful or harmful to their work goals (answering responses: 1 = very bad, 2 = bad, 3 = marginally bad, 4 = no effect, 5 = marginally good, 5 = good, 6 = very good). 10.42% of participants chose “very bad”, 11.46% chose “bad”, 41.15% chose “marginally bad”, and 36.98% chose “no effect”. Overall, 63% of participants stated that their social media use was marginally bad, bad, or very bad for their work goals. These findings show that a majority of individuals view their non-work related social media use as dysfunctional.

Habit strength. Habit strength regarding social media was assessed in the baseline survey in part because it has shown to be fairly stable over time. Habit strength should not vary much over a short period of time (e.g., a week) because the automatic system is only responsible for encoding typical aspects of the environment over the long-term via the slow-learning memory system. In other words, habits involve making connections using typical aspects of the environment and are therefore slow to change. As another reason, individuals generally have less awareness and control over strong habits, making it difficult for participants to change these automatic behaviors over short time periods. Supporting this notion, Verplaken and Melkevic (2008) found that the self-report habit index had a test-retest reliability of $r = .87$ across two time points a month apart. To test the stability of habits, habits were assessed during both the baseline survey and during the morning survey on days 5 & 10. Habits during the baseline survey exhibited a significant effect on habits assessed in the morning survey ($b = .673$, $p < .001$). After following the HLM procedures outlined in the section entitled "Analysis", I tested for fluctuations in habits by regressing the morning measure of habits onto the "Day" variable. Results indicated no significant change in habits from Day 5 to Day 10 ($b = .069$, $p = ns$), supporting the stability of the habits construct.

Although both major methods of assessing habit strength were incorporated into the baseline survey, one measure served as the primary method and another was secondary (see Appendix C). As the primary method, participants rated the three dimensions of habits—mental efficiency, awareness, and controllability—associated with social media use (Polites & Karahanna, in press). As discussed in the section on measurement of habits, Polites and Karahanna (in press) provide correlations that support the validity of this measure; they also ran confirmatory factor analyses and exploratory factor analyses that support the three dimensional structure of the measure. An example item of low awareness is “Oftentimes when on my computer or phone, I choose to browse social media without even being aware of making that choice”. An example item of efficiency is “While on my computer or cell phone at work, I do not need to devote a lot of mental efforts to deciding if I want to use social media or not”. An example item of controllability is “While on my computer or cell phone at work, I would find it difficult to overrule my impulse to use social media”. Scores on each of these dimensions of habits were aggregated in order to form the higher-level construct of habit strength. The coefficient alpha for the 11-item habits measure was .910. The coefficient alphas for the individual dimensions were controllability = .928, awareness = .932, and mental efficiency = .683. Thus, the controllability and awareness dimensions demonstrated high internal consistency, and the mental efficiency dimension approached the threshold for internal consistency.

As a secondary method of measuring habits, participants provided self-reported ratings of behavioral frequency combined with stability of the physical and temporal context in which the behavior is enacted (Wood & Neal, 2009). The frequency of behavior and stability of physical and temporal context are important because together they capture the notion that strong habits are performed repeatedly in similar physical and temporal environments. Behaviors corresponding to strong habits would be enacted frequently in the same physical locations and around the same time. The following was used to assess similarity of physical context: “In the past two weeks, was the location where you engaged in social media use for non-work related purposes while on the job (1 - rarely or never in the same place, 2 - sometimes in the same place, 3 - usually or always in the same place)?” The following was used to assess similarity of temporal context: “In the past two weeks, was the time of day during which you normally used social media for non-work related purposes while on the job (1 - rarely or never at the same time of day, 2 - sometimes as the same time of day, 3 - usually or always at the same time of day)?”. To assess convergent validity of the habits measure, I analyzed the relationships among the secondary habits measure, the primary habits measure. and time on social media. After following the HLM procedure outlined in the “Analysis” section, a model was run that includes the primary and secondary measure of habits as well as time on social media. Findings indicated that the secondary measure of habits failed to show a significant relationship with either the primary measure of habits ($b = -.001$, $p = ns$) or time on social media ($b = -.008$, $p = ns$). In contrast, the primary measure of habits did have the expected and significant association with time on social media ($b = 1.651$, $p = < .001$). Thus, the patterns of results do not provide support for the validity of the secondary measure of habits. The lack of validity of the secondary measure of habits aligns with theory. According to dual modes theory (Smith & DoCoster, 2000), three dimensions of automaticity characterize the automatic system. Thus, the primary measure should be used because it captures the three dimensions of automaticity. The secondary measure taps into frequency of behavior in similar environments, which does not directly assess the automatic nature of habits.

Control variables and exploratory measures. It is important to assess contextual factors that may account for why individuals engaged in social media use on a particular day. To capture contextual influences, I assessed busyness levels (using a 2-item measure) and limited access to social media (using a 1-item measure) each day in the evening survey (See Appendix G). Participants indicated their responses to these measures through a 7-option Likert scale. The coefficient alpha for the 2-item busyness variable was .816. How much time participants spent on the computers at work each day as well as their cellphones were measured because these factors influence the time spent on social media (See Appendix G). I acquired baseline levels of how often they used social media the day they took the baseline survey. The different forms of social media—twitter, instagram, facebook, and snapchat—were assessed. How often participants engaged in social media on their phone and on the computer were assessed (see Appendix G). The Big Five were assessed because these personality dimensions have shown to influence social media use (e.g., extraversion has been shown to positively influence Facebook use; Ross et al, 2009). The measure by Gosling et al. (2003) was used to assess the Big Five (see Appendix D). I also assessed trait self-control (as shown in Appendix E). This measure indicated a coefficient alpha of .887.

Study 1 Measures in Morning Surveys

State self-control. State self-control was included in the daily morning survey in part because it is believed to vary over time. According to dual modes theory, state self-control should vary substantially over time along with fluctuations in attentional resources. This is the case because certain factors (e.g., sleep) may influence one's attentional resource levels on any particular day. Supporting this notion, Ghumman and Barnes (2013) studied variance in sleep from day to day over the course of a week. According to their findings, 81% of variability in sleep quantity and 77% of variability in bed time resides at the within-person level. Because these factors directly influence state self-control, one would expect that state self-control also varies over time. Consistent with pilot 2, I used a shortened measure of ego depletion by Twenge et al. (2004) that captures state self-control, which was used in the morning surveys (e.g., "Today, I feel drained"; "Today, my mind feels unfocused right now"; "Today, it would take a lot of effort for me to concentrate on something"; "Today, my mental energy is running low"). See Appendix E. The coefficient alpha for this measure was .950.

Intention strength. Intention strength was included in the daily morning survey in part because it is believed to vary over time. From a theoretical standpoint, intentions strength should vary over time because it resides in the controlled system in which the fast-learning system is in part responsible for the formation and recollection of explicit intentions. From an empirical standpoint, Rebar et al. (2014) measured daily intentions for engaging in physical activity over the course of a week-long period. They found that more than half of the variability in intention strength and physical activity resided at the within-person level of analysis. Three items assessed intention strength for reducing time on social media for non-work related purposes while on the job (Norman & Cooper, 2011). I adapted these items to be specific to social media. One example item is "Today, I intend to reduce the time I spend on social media for non-work related purposes while on the job". A three-item measure is a common approach for assessing intention strength (Norman & Cooper, 2011). Validity evidence has been shown for this specific measure. In line with expectations, for example, Norman and Cooper (2011) found that intention strength positively relates to social norms, perceived behavioral control, frequency of past behavior, and habits. Meta-analyses of self-report measures of intention strength also provide validity evidence. For example, Armitage and Conner (2001) showed that intentions are a stronger predictor of behavior than desires. The coefficient alpha for this measure was .972. Please see Appendix E for all items.

Study 1 Measures in Evening Surveys

Time spent on non-work related social media use while on the job. Social media use was measured by assessing how much time participants spend across all four social media platforms (i.e., Facebook, Instagram, Twitter, Snapchat) for non-work related issues while on the job. These four media platforms were chosen because Facebook and Twitter are the first and third most popular according to their eBizMBA rank (http://www.ebizmba.com/articles/social-networking-websites). Interest in the other platforms, Instagram and Snapchat, is skyrocketing. Both the time individuals spend on social media and the number of separate occasions they visit these sites were measured. The total time on non-work related social media served as the primary method in part because total time on social media likely has practical importance. For example, organizations hope to limit time on social media in order to maximize employee productivity. They may be less concerned with frequency of trips to social media if it does not lead to large amounts of time on social media. The measure of social media was an adapted version of the social media dimension of Lim's (2002) cyberloafing scale. Given the measure of time spent on social media is subjective, various techniques were used to help ensure accuracy. First, participants were asked to recall various points in the day they may have opened social media and to recall different memories associated with social media use. For more detail about these various prompts, see Appendix G. Second, participants were asked how confident they were in their assessment of how much time they spent on social media. This measure helped provide some indication of the confidence participants hold in their reporting about the time they spend on social media. The participants indicated a mean confidence level of 84.09%, indicating relatively high levels of confidence in self-ratings of time spent using social media. See Appendix G for this measure.

Secondary self-control measures. Although the primary method for assessing self-control was administered in the morning survey, two secondary measures of self-control were assessed in the evening survey which derived the same four items from Twenge et al. (2004). Major reasons for incorporating the two secondary measures were to show validity evidence for the primary measure and to examine the stability of state self-control measures throughout the day. Given participants reported their primary state-control levels in the morning, these levels may have changed slightly by the time they engage in social media use. To supplement the primary measure of state self-control, participants completed a retrospective report in the evening of the typical levels of state self-control they experienced earlier that day when engaging in social media use. To test its stability throughout the day, participants also divulged their current levels of state self-control in the evening so that it could be correlated with the morning measure. The secondary measures provided opportunity to examine validity evidence for the primary measure. Before examining the relationships of the primary with the secondary measures of self-control, I followed the HLM guidelines in the "Analysis" section and group mean centered the three variables. As expected, the primary method in the morning survey correlated with both the self-report of evening state self-control ($b = .327$, $p > .001$), and the retrospective survey ($b = .254$, $p < .001$). This provides preliminary support for the validity of the primary method for assessing state self-control. It also suggests there is at least a minimal level of stability in state self-control resources throughout the day. As such, the primary method of state self-control was used to examine the hypothesized relationships.

Confirmatory Factor Analysis: Distinctiveness of Constructs

Habit dimensionality. I tested three alternative models to assess the factor structure of the habits construct (See Table 2). The three models I considered included: (1) A single factor model consisting of controllability, awareness, and mental efficiency; (2) A two-factor model that combines controllability and awareness into a single factor while including mental efficiency as the second factor; (3) A three-factor model that separates all dimensions of habits into their respective constructs. Results showed that the three-factor model fit the data better than the two-factor model, which in turn fit the data better than the single-factor model. These results align with initial validation studies by Polites and Karahanna (in press). In two separate studies, they ran confirmatory factor analyses and showed that the three-dimension factor structure of habits fit the data better than the single-factor structure. The results in this dissertation also revealed moderate to strong correlations among the dimensions of automaticity. Moderate size of relationships emerged between controllability and mental efficiency ($r = .332$, $p < .01$) and between awareness and mental efficiency ($r = .466$, $p < .01$). A strong relationship emerged between controllability and awareness ($r = .663$, $p < .01$). Taken together, the confirmatory analysis and examination of relationships provide support for the distinctiveness of the individual dimensions of habits. Thus, in testing each hypothesis, I include the results for the higher-order construct of habits as well as the findings for the individual dimensions of habits.

Table 2: *Comparison of Alternative Factor Structure for Habits Measure*

Model	χ_2/df	$\Delta\chi 2/\Delta$df (Model comparison)	RMSEA	CFI	SRMR
(1) One factor: Controllability, Awareness, Mental efficiency	301.912/44*	----	.059	.733	.105
(2) Two Factors: Factor 1 (Controllability, Awareness), Factor 2 (Mental efficiency)	256.559/43*	45.353/1* (Model 1)	.054	.779	.083
(3) Three factors: Factor 1 (Controllability), Factor 2 (Awareness), Factor 3 (Mental efficiency)	1020.655/55*	764.096/12* (Model 2)	.000	1.00	.035

Note. N = 208 (level-2: Between-person). RMSEA = root-mean-square error of approximation; CFI = comparative fit index; SRMR = standardized root-mean-square residual; * $p < .01$.

Distinctiveness of morning measures. In the daily surveys, I tested two alternative models to assess the distinctiveness of the constructs (See Table 3). In the first model, state self-control and intention strength were grouped into a single factor. In the second model, state self-control and intention strength were each separate factors, resulting in two factors total. Overall, the two-factor model fit the data significantly better than the single-factor model, providing support for the distinctiveness of the constructs. The results align with theoretical perspectives that conceptualize intentions and state self-control as unique constructs (Smith & DeCoster, 2000).

Table 3: *Comparison of Alternative Factor Structure for Morning Measures*

Models	χ_2/df	$\Delta\chi2/\Delta df$ (Model comparison)	RMSEA	CFI	SRMR
(1) One factor: State self-control, Intention Strength	1744.774/21*	------	.211	.393	.249
(2) Two Factors: Factor 1 (State self-control), Factor 2 (Intention Strength)	167.881/20*	1576.893/1*	.063	.948	.064

Note. n = 1742 (level-1: Within-person). RMSEA = root-mean-square error of approximation; CFI = comparative fit index; SRMR = standardized root-mean-square residual; * $p < .01$.

Analysis. Analyses were conducted using the Mplus 7 statistical software (Muthén & Muthén, 2012) using full information maximum likelihood (FIML) as the estimation method. Hierarchical Linear Modeling (HLM) (Hofmann, Griffin, & Gavin, 2000) was used to test the hypothesized relationships. HLM was appropriate because of the nesting within the data and to avoid violating the non-independence assumption. HLM is also necessary to examine the hypotheses because they span multiple levels of analysis. Some predictors resided at the within-person level (i.e., explicit intentions, state self-control) whereas the other (i.e., habits) resided at the between-person level. For a given level 1 predictor, there were ten time points that were nested within each individual and these scores were non-independent. HLM takes into account this nested structure and allows for modeling the effects of level 1 predictors and level 2 predictors on the level 1 outcome. Utilizing the HLM approach involved three primary steps. First, I ran the intercepts only model to identify the portion of variance at each level of analysis. Significant portions of the variance at level 1—as judged by interclass correlation coefficients—determine support for using a multi-level approach. Second, grand mean centered variables were used when assessing between-person effects; group mean centered variables were used when examining within-person effects. I group mean centered all level 1 predictor variables (Hoffman & Gavin, 1998). Group mean centering primarily serves to strip away between-person variance in the within-person constructs. Doing so provides greater certainty that the effects of predictors on outcomes are originating from a within-person level and not a between-person level of analysis. Next, I tested the means-as outcomes model in order to assess the effects of level 2 predictors on the level 1 outcome. Finally, the random-coefficient regression model was used to look at the effects of level 1 predictors (e.g., intention strength) on the level 1 outcome (i.e., time spent on social media).

An accurate test of dual modes theory requires that the proposed hypotheses are tested simultaneously. Dual modes theory suggests that constructs in the controlled system (e.g., intention strength, state self-control) and constructs in the automatic system (e.g., habit strength) hold independent effects on outcomes such as behavior (Smith & DeCoster, 2000). It is therefore important to model intention strength and state self-control alongside habits in verifying the independent nature of the controlled and automatic systems. Thus, all five hypotheses were modelled simultaneously using two models: (1) The first containing the higher-order construct of habits; (2) the second containing the individual dimensions of habits.

Table 4 depicts the portion of variance that resides at each level of analysis. Findings indicate that percentages of variance at the within-person level range from 40.7% to 73.7%. Thus, considerable variance resides at both levels of analysis. These results provide support for using HLM to test the hypothesized relationships. Thus, we now turn to the between-person and within-person correlation matrices and multi-level tests of the model.

Table 4: *Hierarchical Linear Modeling Estimates of Null Model*

Variables	Level 1 Variance	Level 2 Variance	% of Level 1 Variance
State self-control	.811	.949	46.1
Intention Strength	1.150	1.682	40.7
Time on Social Media	22.338	20.385	53.6
LimitAcc	2.718	1.350	67.2
Busyness	2.489	.912	73.7

Note. n = 1742 (level-1: Within-person); Level-2 n = 208. Note: LimitAcc = limited access to social media; Busyness = The busyness of the particular work day. Both of these variables are control variables included in the evening surveys.

RESULTS

RESULTS

The means, standard deviations, and correlations among focal variables are shown in Table 5 (between-person correlations) and Table 6 (within-person correlations). Correlations are provided at both a within-person level and between-person level for the following constructs—state self-control, intention strength, time on social media, limited access to social media, and busyness—because they have been shown to vary at both levels of analysis. Overall, the demographic variables (i.e., gender, education, position experience, organization experience, age, race) are minimally related with the focal variables (i.e., Habits, state self-control, and intention strength). Of the significant relationships, gender showed a positive relationship with intention strength, suggesting that males have stronger intentions to reduce social media than females. Education showed a positive relationship indicating that more educated people tend to spend more time on social media. Finally, age negatively related with time on social media such that younger people spend more time on social media than older individuals.

Table 5: *Means, Standard Deviations, and Between-Person Correlations Among Variables*

	Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.	Habits	3.414	.792	1	.879**	.905**	.616**	.172**	.641**	.135	.280**	-.046	-.098	.004	.095	-.114	-.062	-.051	-.013
2.	Low controllability	3.230	1.064		1	.663**	.332**	.203**	.564**	.152*	.282**	-.017	-.085	.045	.099	-.048	-.016	-.016	-.006
3.	Low awareness	3.300	1.027			1	.466**	.163*	.603**	.114	.250**	-.033	-.102	-.040	.042	-.150*	-.087	-.163*	-.029
4.	Mental Efficiency	3.810	.680				1	-.016	.306**	.028	.101	-.096	-.033	.001	.114	-.085	-.055	.144*	.016
5.	Trait self-control	3.636	1.050					1	.283**	.045	.113	-.084	-.151*	.089	-.013	-.170*	-.143*	-.147*	.046
6.	State self-control	2.954	1.029						1	.166*	.241**	.000	-.078	.030	.033	-.104	-.089	-.137	.006
7.	Intention strength	4.221	1.425							1	-.300**	.385**	.246**	.279**	-.120	.060	.080	.092	.095
8.	SNS Time	5.653	4.915								1	-.277**	-.383**	-.124	.208**	-.038	.018	-.191**	-.125
9.	LimitAcc	3.680	1.280									1	.631**	.088	-.258**	.155*	.094	-.01	.026
10.	Busyness	4.380	1.153										1	.148*	-.228**	.168*	.104	.173*	.121
11.	Gender	.519	.500											1	-.170*	.015	-.014	.184*	.143*
12.	Education	4.100	1.074												1	-.142*	-.063	.081	-.037
13.	PosExp	5.18	4.74													1	.790*	.414*	.017
14.	OrgExp	6.21	5.24														1	.410*	.097
15.	Age	38.53	38.08															1	.174*
16.	Race	.841	.381																1

Note. Level-2 n = 208. Between-person correlations are represented above the diagonal. The level 1 variables were aggregated across time before correlating with the level 2 variables. Low control = Low controllability; SNSTime = Time on social media; LimitAcc = limited access to social media; Busyness = The busyness of the particular work day. Both LimitAcc and Busyness are covariates included in the evening surveys. PosExp = Experience in position (years); OrgExp = Experience in organization (years); Gender was coded as 1 = Male, 0 = Female. Race was coded as 1 = White, 0 = non-white. *p < .05. **p < .01.

Table 6: *Means, Standard Deviations, and Within-Person Correlations Among Variables*

Variables	Mean	SD	1	2	3	4	5
1. LimitAcc	3.635	1.305	1				
2. Busyness	4.419	2.067	.690**	1			
3. State self-control	2.453	2.369	-.028	-.017	1		
4. Intention Strength	4.278	1.1910	.147**	.201**	-.069	1	
5. Time on Social Media	5.610	2.102	-.416**	-.400**	.086*	-.216**	1

Notes: Level-1 n = 1742; LimitAcc = limited access to social media; Busyness = The busyness of the particular work day. Both of these variables are covariates included in the evening surveys. *p < .05. **p < .01

Main Effects[2]

Appendix H contains the MPLUS output for the multi-level modeling results for all tests of the proposed hypotheses. Table 7 summarizes results of the hypothesis testing. Hypotheses 1 and 2 covered the main effects of intention strength for reducing time on social media and habits regarding social media in influencing time on social media. Hypothesis 1 stated that intention strength for reducing time on social media would negatively predict the slope of time on social media at a within-person level. As shown in Table 7, intention strength for reducing social media was negatively associated with time on social media ($b = -.590$, $p < .01$), providing full support for Hypothesis 1. Hypothesis 2 suggested that habit strength regarding social media would positively predict time on social media at a between-person level. The results indicate support for this hypothesis since habit strength was positively related with time on social media ($b = 1.504$, $p < .01$). In examining the individual dimensions of habits, low controllability exhibited a positive and significant relationship with time on social media ($b = .797$, $p < .05$) as consistent with expectations. Contrary to predictions, low awareness showed a positive but marginally significant relationship with time on social media ($b = .632$, $p =$ ns), and high mental efficiency did not significantly relate with this outcome ($b = -.286$, ns). Taken together, while Hypothesis 2

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[2]The method sections detailed a number of control variables including trait self control, limited access to social media on a given day, busyness levels on a given day, big five personality traits, and perceived confidence in self-reports of social media. The first variable—trait self control—was included in modelling the hypothesized relationships because it has high theoretical relevance to attentional resource levels, which is a central component of dual modes theory (Smith & DeCoster, 2000). The second two variables—limited access, and busyness—exerted significant impacts on the outcome of time on social media and thus they were controlled for in testing the proposed hypotheses. The third group of variables—big five personality and confidence in reports of social media—do *not* have theoretical relevance to dual modes theory. Nevertheless, I included them in testing the hypotheses. Rheir inclusion did not affect the significance of any of the relationships. Thus, because they do not play a clear role in testing the hypothesized relationships, they were excluded from the final model and were not reported in the results section.

received support when examining the aggregate construct of habits, the individual dimensions appear to provide mixed support for this expectation.

Table 7: *Multi-level Modeling Results for Tests of the Hypothesized Relationships*

Hypothesis	Independent variable	Dependent Variable	Level of analysis	*b*	SE	Support for hypothesis?
1	Intention Strength	Social media time	1	-.590**	.141	Yes
2	Habit Strength	Social media time	2	1.504**	.372	Yes
2	Low controllability	Social media time	2	.797*	.361	Yes
2	Low awareness	Social media time	2	.632	.364	Marginal
2	High Mental Efficiency	Social media time	2	-.286	.477	No
3	Habits * Intention Strength	Social media time	Cross-level interaction	-.245	.167	No
3	Low controllability * Intention Strength	Social media time	Cross-level interaction	-.353*	.159	No
3	Low awareness * Intention Strength	Social media time	Cross-level interaction	.029	.188	No
3	Mental Efficiency * Intention Strength	Social media time	Cross-level interaction	.352	.249	No
4	State self-control * Intention Strength	Social media time	1	-.117	.105	No
5	Habits * State self-control	Social media time	1	-.010	.158	No
5	Low controllability * State self-control	Social media time	1	-.127	.176	No
5	Low awareness * State self-control	Social media time	1	.287	.214	No
5	Mental Efficiency * State self-control	Social media time	1	-.259	.270	No

Note. Level-1 n = 1742; Level-2 n = 208. *p < .05. **p < .01

Interactive Effects

Hypotheses 3-5 covered all two-way interactions among the constructs of intention strength, habit strength, and state self-control. Hypothesis 3 stated that Habit strength regarding social media would weaken the negative within-person effects of fluctuations in intentions (to reduce social media use) on fluctuations in time spent on social media. Before testing this cross-level moderation effect, habit strength was grand mean centered. As shown in Table 5, the findings did not support Hypothesis 3 since habit strength failed to significantly interact with intention strength in affecting time on social media ($b = -.245$, ns). The individual dimensions of habit strength also did not indicate support for Hypothesis 3. Although low controllability showed a significant interaction with intention strength in impacting time on social media, the sign of the effect ran contrary to predictions ($b = -.353$, $p < .05$). The negative sign indicates that low controllability strengthens the negative effect of intention strength on social media time rather than weakening it. Low awareness and high mental efficiency also do not provide support for Hypothesis 3. Specifically, intention strength showed a non-significant interaction with both low awareness ($b = .029$, ns) and mental efficiency ($b = .352$, ns).

Hypothesis 4 proposed a within-person interaction such that state self-control would moderate the effect of intention strength on social media time. The findings run contrary to this prediction since state self-control did not significantly interact with intention strength in affecting social media time ($b = -.117$, ns). Thus, Hypothesis 4 was not supported. Finally, Hypothesis 5 proposed a cross-level moderation of habit strength regarding social media with state self-control on social media time. Habit strength was grand mean centered before running analyses. According to the findings, habit strength exhibited a non-significant interaction with state self-control in affecting time on social media ($b = -.010$, ns). The individual dimensions of habits showed similar results. Intention strength failed to significantly interact with low controllability ($b = -.127$, ns), low awareness ($b = .287$, ns), or mental efficiency ($b = -.259$, ns) in influencing time on social media. Thus, Hypothesis 5 was not supported.

DISCUSSION

DISCUSSION

This dissertation aimed to understand why individuals experience difficulties in changing their behavior. In approaching this question, research to date has emphasized self-regulation perspectives and explored goal-driven constructs such as goal commitment. The view taken in this dissertation complements previous work by exploring more automatic and subconscious factors such as habits. To this end, I developed and tested a model based on dual modes theory that recognizes both self-regulation factors (i.e., intentions) and automatic constructs (i.e., habits) in influencing behavioral change in the social media context. In particular, tests of hypotheses in the proposed model were developed to extend empirical work on self-regulation (e.g., Ilies & Judge, 2005; Northcraft, Schmidt, & Ashford, 2011) and cyberloafing (Wagner et al., 2012) by surfacing hidden factors (e.g., habits and dimensions of automaticity) that can hamper behavioral change (e.g., reduce SNS use). This work also has practical importance given the recent explosion in social media and resulting financial impacts on organizations.

Summary of Findings and Implications

Hypothesis 1 stated that intention strength for reducing time on social media would negatively predict time on social media at a within-person level. Findings offered support for this expectation since intention strength for reducing time on social media motivated individuals to devote less time on social media at a within-person level. These findings highlight the role of strong explicit intentions in enhancing motivation and propelling individuals to execute the intended action, consistent with a dual modes perspective (Armitage & Connor, 2001). Although past work in applied psychology has focused on linking intentions with desirable behaviors such as exercising (Rebard et al., 2014), this dissertation emphasized difficulties in avoiding undesirable behaviors—or actions that are viewed by the individual to be incongruent with work goals. Thus, the findings shed light on intention strength as a useful cognitive self-regulation construct by which employees reduce dysfunctional behaviors, as a strategy for maximizing their work productivity. More importantly, intention-behavior linkages to date have primarily been studied at the between-person level (Rebar, Elavsky, Maher, Doerksen, & Conroy, 2014), and scholars have devoted less attention to within-person relationships, especially in empirical investigations of social media. As such, the within-person linkage of intentions with behavior fills an important gap by casting the controlled system as core to the dynamic regulation of work behaviors.

Hypothesis 2 stated that habit strength regarding social media would positively predict time on social media at a between-person level. The findings fully support the expected relationship such that habits positively predicted time on social media. In addition, the effects of habits on social media time remained significant even while incorporating self-regulation constructs such as intention strength and trait self-control. This pattern of findings is consistent with dual modes theory in which the automatic system is a unique and central force that impacts behavior. These results cast the automatic system as core to understanding why some individuals exhibit high rates of dysfunctional work behaviors. Taken together, this dissertation helps to surface a hidden factor, habits within the automatic system, that meaningfully impacts dysfunctional work behaviors.

Regarding the individual dimensions of habits, low controllability but not low awareness or high mental efficiency significantly impacted time on social media. According to dual modes theory, all three dimensions—controllability, awareness, and mental efficiency—are core features of the automatic system. Yet, dual modes theory does not directly speak to which dimension(s) is more closely linked with behaviors. The findings cast low controllability as perhaps the most important dimension in understanding why some individuals exhibit high rates of undesirable behaviors. This conclusion makes sense from a theoretical standpoint because those individuals who perceive low controllability may indeed have trouble in controlling their social media use, thereby leading to high rates of use. Other dimensions such as mental efficiency may play a smaller role in predicting social media use. For example, mental efficiency suggests that few attentional resources are necessary for individuals to make the decision to perform social media behaviors. However, the consumption of few attentional resources may not hamper individuals from reducing their time on social media. Thus, it makes sense that mental efficiency may be less useful than other dimensions in predicting those individuals who spend the most time on social media. Accordingly, this study helps to extend dual process theory by uncovering the dimensions of habits that underlie high rates of undesirable behaviors.

Hypotheses 3-5 hold relevance to active conversations in the literature about the degree of independence versus dependence between dual processes in affecting behavior. While some researchers have viewed the two systems as mutually dependent in influencing behavior, other scholars believe the systems operate independently in affecting actions (Fiske & Taylor, 2013). I refer to independence as meaning there are limited or no interactive effects across the two systems in influencing outcomes such as behavior. I refer to dependence as suggesting that the effects of one system on outcomes such as behavior are highly contingent on the other system. In this way, the two systems of dual modes theory likely lie on a spectrum somewhere from highly independence to highly dependent in terms of their effects on cognition and behavior (Fiske & Taylor, 2013). These conversations have important implications because dependence would mean that individuals could potentially control the effects of one system (e.g., strong habits) by influencing the other (e.g., strong intentions). In contrast, independence would make it more difficult to control the automatic system through the controlled system and vice versa. In line with the former viewpoint, Hypotheses 3-5 were grounded in the idea of interaction among the core variables in the automatic and controlled systems in influencing behavior. Hypothesis 3 stated that habits strength regarding social media would weaken the negative relationship of slope of intention strength with time on social media. Hypothesis 4 suggested that high state self-control would strengthen the within-person effects of intention strength with time on social media. Hypothesis 5 covered a cross-level moderation such that, at a within-person level, slope of state self-control would weaken the positive effects of habit strength regarding social media on social media time. Each hypothesis was evaluated with respect to the higher-order construct of habits, and the three sub-dimensions of habits. The results concerning the overall construct of habits did not support any of the expected two-way interactions in Hypotheses 3-5. Results concerning the sub-dimensions revealed that only one out of nine tests spanning Hypotheses 3-5 were significant. Specifically, low controllability moderated the within-person effects of intentions on social media time. Yet, the finding ran contrary to predictions since individuals low on controllability were more likely to act on their intentions to curb social media over time than individuals high on controllability. Overall, tests of Hypotheses 3-5 run counter to my initial viewpoint that the two systems are dependent on each other in affecting behavior.

Taken together, tests of hypotheses 1-5 revealed significant main effects of intention and habit strength but hardly any significant interactions in influencing time on social media. One explanation for this broad pattern of findings is that the constructs in the controlled and automatic systems operate independently in their impacts on behavior. Some central tenets of dual modes theory are consistent with this conclusion (Smith & DeCoster, 2000). For example, the automatic and controlled systems encode different kinds of information (Smith & DeCoster, 2000). Under the automatic system, humans encode typical information into memory across many experiences, over the long run. Under the controlled system, individuals encode new and unexpected information, sometimes gained from a single experience. The two separate encoding processes allow each system to function independently without being dependent on the other system to impact behavior. Indeed, Wood and Neal (2007) suggest that habits can influence behavior without the need for conscious goals in the controlled system to mediate this process. For example, employees may find themselves automatically checking Facebook without having an explicit intention for doing so. Conversely, even those who possess strong social media habits may sometimes experience increases in intention strength and resulting effects on social media time.

The current work represents one of the first studies to examine the three dimensions of automaticity in applied fields such as organizational psychology or organizational behavior. Thus, the study breaks new ground in our understanding of habits and dimensions of automaticity and their positive effects on work behaviors such as social media. Although the primary contribution of this dissertation is to work subdomains, the dissertation findings may shed light on existing research, conversations, and debates in the social psychology literature. For example, existing studies in social psychology have offered mixed findings for the degree of independence (vs. dependence) between constructs in the automatic and controlled systems. For instance, some studies have revealed interactive effects between habits and intentions in predicting behavior such that individuals with weak habits exhibit a stronger relationship of intentions with behavior than those with strong habits (e.g., Aarts, Verplanken, & Knippenberg, 1998; Ji & Wood, 2007; Neal, Wood, Wu, & Kurlander, 2011). These findings are more aligned with viewing the two systems as dependent on each other in influencing action. In contrast, other studies have revealed main effects but no significant interactions of intentions and habits on behavior (e.g., Baranowski, et al., 2014; Fleig, Pomp, & Schwarzer, 2013; Peters, 2009), which supports an independent view of the two systems. Also, consistent with the independent viewpoint, some researchers have shown differences across the nomological networks of automatic versus controlled constructs. For example, Peters (2009) found that expected outcomes more strongly predicted habits than intentions to adopt mobile phone technology. As another example, Neal et al. (2012) found that contextual cues associated with past performance such as locations strongly predicted habitual behaviors but not intentions. Finally, some studies have shown a weak or null relationships between intentions and habits. For example, studying habitual dietary behavior, Gardner, Sheals, Wardle, and McGowan (2014) found that, even when subject matter experts rated five goals on a continuous scale from optimal to suboptimal for forming habits, none of these ratings significantly predicted habit formation. Neal, Wood, Labrecque, and Lally (2012) concluded based on two empirical studies that habits "are relatively unaffected by goals" (p. 492).

The dissertation is nicely positioned to offer a novel perspective and approach to this important conversation because it helps to address limitations of the above mentioned studies. First, findings in the existing literature predominantly reside at the between-person level of analysis and not the within-person level. Overlooking within-person relationships does not fully capture dual processes because, according to dual modes theory, constructs within the controlled system can readily change over time as individuals receive and encode new pieces of information (Smith & DeCoster, 2000). Exclusively between-person examinations also fail to capture the roughly fifty percent of variance in intention strength that resides at a within-person level, as shown in this dissertation. Second, the existing literature often draws from frequency of past behavior to partly or fully measure habit strength. Past behavior does not fully capture the automatic nature of habits and may be contaminated with other constructs, which could lead to spurious findings of moderation. For example, past frequency of behavior may inadvertently tap into high levels of enjoyment rather than strong habits. In turn, high enjoyment may make a focal behavior more tempting, thereby accounting for why some individuals experience greater intention-behavior gaps than others. In this way, the method of assessing habit strength in the literature (e.g., past frequency of behavior) opens the door to alternative explanations (e.g., enjoyment) that explain the interaction between habit strength and intentions on future behavior. A more direct measurement of the automatic nature of habits is needed to gain a more precise test of dual modes theory. To help address this issue, the dissertation included each of the three dimensions of automaticity in order to capture habit strength. The pattern of findings in this study—including the main effects of habits and intentions but hardly any interactions, and the non-significant correlation between habits and intentions—offer initial support for viewing the two systems as more independent in influencing behavior.

The conclusion that the controlled and automatic systems operate independently in influencing behavior, if verified by future research, has potential to inform the challenges of changing dysfunctional behaviors. For example, the dissertation findings imply that intention strength is an important cognitive construct that has *beneficial* effects for the self-regulation of social media behaviors. In contrast, habit strength regarding social media is an important automatic construct with *undesirable* effects, in that it predicts individuals who spent greater time on social media. The notion of independent systems suggests that habits may have deleterious effects regardless of self-regulation concepts such as intentions and attentional resources. Thus, interventions built around self-regulation constructs may not be fully effective for habitual users because they do not weaken the effects of habits on behaviors. From a dual modes standpoint, this conclusion makes sense given that habits have low awareness and low controllability (Smith & DeCoster, 2000). The low controllability and low awareness means that individuals may have trouble changing the dysfunctional behavior despite their best intentions or high state self-control. In this way, the potential independence of the two systems, if verified by future research, sheds light on the puzzling and persistent challenges associated with behavioral change.

Although the findings in general support a more independent view of the two dual process systems, there may be one area of potential interaction across the systems: Low controllability showed a significant interaction with intention strength in impacting time on social media. Yet, the sign of the effect ran contrary to predictions in that low controllability strengthened the negative effect of intentions on social media time rather than weakening it. The findings suggest that individuals with lower perceived control over their social media habits experience smaller intention-behavior gaps. This effect is surprising given that according to dual modes theory, individuals should experience larger gaps between intention and behavior for actions they have difficulty controlling.

Practical Implications

The findings point to several practical implications in helping employees curb their dysfunctional work beahviors. Organizations have seen a recent explosion in non-work related social media use, which has resulted in estimates of hundreds of billions of dollars in financial losses nationwide (Vitak, Crouse, & Lacrose, 2011; Wagner, Barnes, Lim, Ferris, 2012). Thus, managers across many organizations have sought to reduce dysfunctional behaviors such as social media use, yet interventions often underperform their expectations. These facts highlight the importance and challenges of reducing dysfunctional behaviors in organizations. As the current study highlighted, the time employees spend on social media is highly variable and fluctuates day-to-day. Organizations may therefore want to identify and intervene on days when employees display particularly high levels of dysfunctional work behaviors. The results imply that daily intentional strength can be used as a proxy to identify days when employees are likely to engage in particularly high rates of dysfunctional work behaviors such as non-work related social media use. The significant variability of intention strength over time as shown in this dissertation indicates the malleability of this construct. Hence, organizations may want to manipulate intention strength by designing evidence-based interventions in an effort to reduce dysfunctional behaviors. For example, organizations could present employees with data on how their social media use affects their productivity each day, motivating individuals to develop intentions for curbing social media time.

The study also showed that certain employees spend greater time on social media than others. As the findings highlighted, those individuals with stronger social media habits spent greater time on social media. These effects of habits remained significant even while incorporating self-regulation constructs such as intention strength and trait self-control. These set of findings may be useful from a selection standpoint. For example, organizations could develop hiring tools that select candidates who hold weaker habits for a wide range of dysfunctional behaviors such as social media use in their most recent job. This method might aid organizations in avoiding the selection of candidates who exhibit particularly high rates of dysfunctional behaviors, thereby helping to ameliorate the resulting profit losses. Organizations could also administer habit strength assessments to existing employees in order to identify which employees engage in highest rates of dysfunctional work behaviors. A habit strength assessment may be necessary because sometimes organizations are unable or unwilling to directly monitor dysfunctional work behavior ssuch as social media use because of privacy concerns (Prasad, Lim, and Chen, 2010).

Limitations

There are three main limitations with the existing research. A first limitation concerns the measurement of the dependent variable. This study captured self-ratings of time on social media as consistent with the broader cyberloafing literature (Lim, 2002). A number of steps were taken to increase the accuracy of the self-reports. First, participants were given substantial space to report various times they visited social media and their specific activities each time (e.g., create post, browse news feed). Second, participants reported on their perceived confidence in accurately estimating their time on social media. The findings indicated a fairly high mean average of 84.09%. Yet, participants may have provided some inaccurate ratings without being fully aware of doing so, which is a limitation of the study. Future researchers may want to combine self-reports with more objective methods such as having participants use applications to track their time on social media.

A second limitation concerns the measurement of one of the independent variables. Intention strength was intended to reflect a self-regulation feature that captured conscious and deliberative processes, yet the measure of intentions could have picked up on automatic processes. For example, emerging research has shown that employees have subconscious goals that can independently influence work performance even while controlling for conscious goals (for a review of subconscious goals, see Latham, Stajkovic, & Locke, 2010). Applied to this dissertation, the intention measure in this dissertation could have picked up on subconscious goals as opposed to more reflective and deliberative calculations of one's current desires and abilities to curb social media. To control for these automatic processes, I examined whether the effects of intentions were still significant while controlling for habit dimensions. Findings indicated that the effects of intentions remain significant even while modeling the habit dimensions. Yet, controlling for habit dimensions may not fully solve the problem because they reflect automatic *behavioral* processes and do not necessarily account for automatic *cognitions* such as subconscious goals. Thus, researchers may want to measure subconscious goals alongside explicit intentions in order to generate a more precise test of dual processes.

A final limitation concerns the measurement of state self-control. I employed a self-report measure that assessed individual's current state of self-control resources. This morning measure served as the assessment of employee's level of state self-control later that day while engaging in social media. However, state self-control could vary throughout the day (Lanaj, Johnson, & Barnes, 2014); thus, levels in the morning could diverge from levels while engaging in social media use. Given this limitation, I included a secondary measure in the evening—which asked participants to retrospectively estimate their average levels of state self-control while engaging in social media. In evaluating fluctuations in self-control resources, I analyzed the effects of the primary measure in the morning with the secondary measure in the evening. This finding of a positive correlation between the two measures indicated at least some degree of stability in state self-control resources throughout the day. Yet, the inability to measure state self-control resources in-the-moment could have contributed to some of the null results found in the dissertation, such as interactions of state self-control with habit strength and intentions. Future research could achieve better precision by asking participants to indicate their levels of state self-control each time they visit social media.

Direction for Future Research

This study examined individuals who perceived social media use as at least somewhat undesirable and disruptive of work goals. However, some employees may find social media use to be a refreshing break from work and opportunity to recharge by interacting with friends and family. For example, a “like”, positive comment, friend request, or making connections with online users can activate the brain’s reward system and create positive emotions (Meshi, Tamir, & Heekeren, 2015). According to Broaden-and-Build (Fredrickson, 2004), positive emotions broadens cognition and builds personal resources that often outlast the original feeling of positive affect. Generating social connections may be particularly potent in fostering positive emotions, and thereby generating increases in personal resources and well-being. Thus, social media breaks may help some employees to broaden their attention and build cognitive energies, enhancing performance once they return to work. Social media breaks may be especially beneficial for employees who are able to limit these breaks and efficiently divert attention back to work once they feel refreshed. Unfortunately, research to date has primarily investigated social media as a form of cyberloafing, which ignores the potentially beneficial effects of this behavior. Taken together, there is a need to study the beneficial effects of social media on attentional capacities and job performance through the dynamic process mechanism of positive emotions.

This study focused on a particular dysfunctional behavior, non-work related social media use, as a way of shedding light on broader questions of behavioral change. Future research should examine whether the current approach applies to dysfunctional behaviors beyond social media. Indeed, a dual modes account may have broader significance since individuals can develop habits towards a wide range of dysfunctional behaviors. For example, studies have shown that about 45% of the actions participants listed in daily diaries are repeated behaviors that occur in the same location about every day (e.g., Wood, Quinn, & Kashy, 2002). Moreover, a great deal of behavior in organizations is repeated in response to similar cues over time (George, 2009; Weiss & Ilgen, 1985). Unhealthy eating practices and smoking are two candidate dysfunctional behaviors worthy of future study. It is important to understand how employees can reduce unhealthy eating and smoking in particular because they have contributed to high insurance costs and absenteeism (Armitage, 2007; Schmier, Jones, & Halpern, 2006). Yet, evidence-based interventions and wellness programs often do not sufficiently curb rates of undesirable behaviors, even for employees with strong desires to change (Moher, Hey, and Lancaster, 2005). A dual modes account may provide some insight into this puzzling phenomenon. The automatic system, for example, may have significance here because employees tend to form strong habits to unhealthy eating and smoking in particular. The controlled system may also an important role since employees often have explicit intentions for eliminating or at least mitigating unhealthy eating and smoking. Unfortunately, research on work behaviors have devoted very limited attention to dual modes theory and habits. Taken together, a wider application of dual modes theory may help explain the puzzling and persistent challenges of reducing a variety of dysfunctional work behaviors.

Although this dissertation did not examine inertia and addiction, future research may want to study these phenomena because they inform the difficulties of behavioral change. To date, organizational scholars have largely taken a self-regulation perspective, which is insufficient for fully understanding inertia and addiction. Future examinations of these phenomena could draw from dual process theory because of its relevant to unpacking the processes that underlie inertia and addiction. Inertia, for example, involves attachment to existing behavioral patterns despite better alternatives and incentives to change (Polites & Karahanna, 2012). The behaviors leading to inertia are often habituated, but this is not always the case. For example, comfort levels with the current behavioral regimen may lead to inertia. The process of forming dysfunctional habits may therefore shed light on *one reason* why employees develop inertia (Polites & Karahanna, 2012). For example, habits could be used to understand one instance of inertia in which employees continue to use outdated technology platforms despite the opportunity to use more updated technology. Researchers could also study the environmental cues and habit strength that drive individuals to use old technology, or design and evaluate interventions that help employees cultivate strong habits towards using new technology. Future research could also draw from habits in understanding symptoms of addiction such as relapse (Marlatt & Donovan, 2005). For example, individuals who hold strong drinking habits may have greater changes of relapse when cues in the environment (e.g., observing other people drinking) trigger those habitual behaviors (e.g., drinking). Thus, future researchers could identify the specific cues that are most likely to trigger relapse, and study ways to weaken habits, thereby decreasing the likelihood of relapse.

Changes in habits over time and habit interventions fell outside the scope of this dissertation work, yet they are vital for addressing automatic influences on social media. Indeed, the dissertation showed the importance of habits in affecting time on social media above and beyond self-regulation constructs such as intention strength, trait self-control, and state self-control. Dual process perspectives support the notion that individuals can change their habits over time, opening up avenues for future intervention work. According to dual modes theory (Smith & DeCoster, 2000), individuals form strong habits by continually repeating behaviors in response to similar cues in the performance environment. However, this process can also work in the opposite direction as people try to eliminate dysfunctional habits. People can slowly dissociate these strong interconnections by refraining from performing the focal behavior while in the presence of the environmental cue. Social psychology research has shown that individuals can experience habit disruption by monitoring these external cues and habits. For example, Quinn, Pascoe, Wood, and Neal (2010) showed that vigilant monitoring (e.g., carefully monitoring for slipups and "thinking don't do it") inhibited performance of unwanted habits. As another example, Adriaanse, de Ridder, and Wit (2009) instructed participants to identify six cues associated with unhealthy snacking and identify the cue they believed were most responsible for unhealthy snacking. Afterwards, participants wrote down and visualized themselves eating a healthy snack whenever they observed the external cue they previously identified as being responsible for unhealthy snacking. Results indicated participants who used this technique displayed lower unhealthy snacking and higher healthy snacking than participants in the control condition.

Polites and Karahanna (2013) create theory around three kinds of interventions for triggering automatic mechanisms in order to facilitate behavior change. First, interference involves introducing an obstacle to performing a habitual behavior. For example, employees could use applications that block or limit use of social media websites on their computer and phone. Second, distraction involves distracting an individual while they are performing the habit sequence in order to persuade them to pursue the goal associated with the new behavior. Monitoring is one way organizations can carry out the technique of distraction (Polites & Karahanna, 2013). For example, managers could overtly monitor employee behaviors. This might help employees become more aware of their own behavior and remind them of the goal to pursue the new behavior (Polites & Karahanna, 2013). Finally, organizations can engage in reprogramming responses—or identifying situational triggers associated with the old behavior and reprogramming the behavioral responses to those triggers. Critically, any training designed to reprogram responses must be in-context so that it includes the cues that trigger the old behavior. Interventions under this third category could involve identifying cues that lead to social media use and then reprogramming a more productive behavioral response to those cues.

Conclusion

The current study developed and examined an alternative explanation and model based on dual process theory for shedding light on the difficulties of curbing social media behaviors at work. The results highlighted the value of the controlled system given the dynamic interrelationship of intention strength with social media over time. The findings also demonstrate the importance of the automatic system since individuals with stronger social media habits spent more time on social media. These results reveal a hidden factor—habits—that can illuminate why some individuals exhibit particularly high rates of social media use. Further, the findings provide initial support for viewing the controlled and automatic systems as relatively independent in affecting social media behaviors at work. Overall, the results provide support for a dual modes explanation of behavioral change in the social media context.

APPENDICES

APPENDIX A: Perceived Dysfunctional Behaviors

Participants rated on a 7-point scale the importance of social media use while on the job in helping them obtain their work goals and also hindering them in obtaining their work goals.

APPENDIX B: Demographics

What is your gender?
What is your highest level of education?
Work experience: ____years, _____months
How long have you been in your current work position? ____years, _____months
How long have you worked for your organization? ____years, _____months
What is your age? ____
My race is (mark one or more)
White
Black, African American
American Indian or Alaska Native
Asian Indian
Chinese
Filipino
Other Asia

APPENDIX C: Habits

Please answer the following question in regards to using social media for non-work related purposes while on the job.

Primary habits measure

Oftentimes when on my computer or cell phone at work, I choose to browse social media without even being aware of making the choice [Awareness 1].

Oftentimes when on my computer or cell phone at work, I unconsciously start using social media [Awareness 2].

Choosing to use social media at work while on my computer or cell phone is something I do without being aware [Awareness 3].

While on the computer or cell phone at work, choosing to use social media is something I do unconsciously [Awareness 4].

While on my computer or cell phone at work, I do not need to devote a lot of mental efforts to deciding if I want to use social media or not [Mental Efficiency 1].

While on my computer or cell phone, selecting the behavior of using social media at work does not involve much thinking [Mental Efficiency 2].

Choosing to use social media while on my computer or cell phone at work requires little mental attention [Mental Efficiency 3].

While on my computer or cell phone at work, oftentimes I find it difficult to overrule my impulse to use social media [Controllability 1].

While on my computer or cell phone at work, oftentimes I find it difficult to overcome my tendency to use social media [Controllability 2].

While on the computer or cell phone at work, oftentimes I find it difficult to control my tendency to use social media [Controllability 3].

While on the computer or cell phone at work, oftentimes I find it hard for me to restrain my urge to use social media [Controllability 4].

Secondary habits measure

In the past two weeks, how many times on average did you use social media [for non-work related purposes while on the job] (1 – A few times per week or less, 3 - just about every day, 4- About once every couple hours, 5 – More than once every couple hours)?

In the past two weeks, was the location where you engage in social media use [for non-work related purposes while on the job] (1 - rarely or never in the same place, 2 - sometimes in the same place, 3 - usually or always in the same place)?

In the past two weeks, was the time of day during which you normally used social media [for non-work related purposes while on the job] (1 - rarely or never at the same time of day, 2 - sometimes as the same time of day, 3 - usually or always at the same time of day)?

APPENDIX D: Personality Measures (Gosling, Rentfrow, & Swann, 2003)

I see myself as:
Extraverted, enthusiastic.
Critical, quarrelsome.
Dependable, self-disciplined.
Anxious, easily upset.
Open to new experiences, complex.
Reserved, quiet.
Sympathetic, warm.
Disorganized, careless.
Calm, emotionally stable.
Conventional, uncreative.

APPENDIX E: Ego-Depletion

Morning survey:
Today,

I feel drained.
My mind feels unfocused right now.
It would take a lot of effort for me to concentrate on something.
My mental energy is running low
Response options: likert scale with 5 options.

Retrospective report in evening survey:
When I decided to use social media at work today,

I felt drained.
My mind seemed unfocused.
It seemed like it would take a lot of effort for me to concentrate on something.
My mental energy was running low
Response options: Likert scale with 5 options.

Current state of state self-control in the evening:
Right now,

I feel drained.
My mind feels unfocused right now.
it would take a lot of effort for me to concentrate on something.
My mental energy is running low
Response options: likert scale with 5 options.

Trait self-control:

I am good at resisting temptation.
I have a hard time breaking bad habits.
I am lazy.
I say inappropriate things.
I do certain things that are bad for me, if they are fun.
I refuse things that are bad for me.
I wish I had more self-discipline.
People would say that I have iron self-discipline.
Pleasure and fun sometimes keep me from getting word done.
I have trouble concentrating.
I am able to work effectively toward long-term goals.
Sometimes I can’t stop myself from doing something, even if I know it is wrong.
I often act without thinking through all the alternatives.

APPENDIX F: Explicit Intentions for Reducing Time on Social Media

Today,

1. I intend to reduce the time I spend on social media [for non-work related purposes while on the].
2. I will reduce the time I spend on social media [for non-work related purposes while on the job].
3. I am likely to reduce the time I spend on social media [for non-work related purposes while on the job].

Response options: +2 = yes, definitely; -2 = no, definitely

APPENDIX G: Social Media Use and Other Variables

1. Today was an exceptionally busy day at work (busyness).
2. There was a lot of free time today at work (busyness, reverse scored).
3. I had very limited access to social media today at work (limited access).
4. How many times per week do you typically use Facebook for required aspects of your job: (Once per week, two or three times per week, once a day, multiple times per day)
5. How many separate occasions per day at work do you typically engage in [non-work related social media use]? _______
6. How much time do you typically spend engaging in [non-work related social media at work]? (0, 10 min, 20 min)
7. In the next question, you will be asked how much time you spend on social media today. In order to make this calculation, recall various points in the day they may have opened Facebook, Twitter, Snapchat, and Instagram "please exclude authorized lunch time and work breaks i.e., times when you are not scheduled to be working". For example, did you use Facebook at work in the morning, before lunch, after lunch, later in the afternoon, in the evening? When you used social media [at work], which platform did you use (i.e., Facebook, Instagram, Twitter, Snapchat)? What did you do? Did you create new posts? did you browse your news feed? What information did you learn? Did you communicate with any other Facebook uses? Consider times that you used social media both on your phone and computer.

   ____
   ____
   ____
8. About how many separate occasions have you opened up Instagram today [at work (excluding lunch breaks) for non-work related use]?___1,2,3,4,5 (…)
9. About how much time have you spent on Instagram [today at work (excluding lunch breaks) for non-work related use]?_____0, 10min, 20min (…)
10. About how many separate occasions have you opened up Twitter today [at work (excluding lunch breaks) for non-work related use]?___1,2,3,4,5 (…)
11. About how much time have you spent on Twitter today [at work (excluding lunch breaks) for non-work related use]?_____0, 10min, 20min (…)
12. About how many separate occasions have you opened up Snapchat today [at work (excluding lunch breaks) for non-work related use]?___1,2,3,4,5 (…)
13. About how much time have you spent on Snapchat today [at work (excluding lunch breaks) for non-work related use while on the job]?_____0, 10min, 20min (…)
14. About how many separate occasions have you opened up Facebook today [at work (excluding lunch breaks) for non-work related use]?___1,2,3,4,5 (…)
15. About how much time have you spent on Facebook today [at work (excluding lunch breaks) for non-work related use while on the job]?_____0, 10min, 20min (…)
16. About how many separate occasions in total today [at work have you opened up social media [for non-work related use] have you opened up social media] (including Instagram, Twitter, Snapchat, and Facebook? ___1,2,3,4,5 (…) today for non-work related use?
17. About how much time in total today [at work have you spent on social media today for non-work related use]?_____0, 10min, 20min (…)
    How confident are you in your assessment of how much time you spent on social media? _______ 10%, 20%, 30%.

APPENDIX H: Output in Testing Hypothesized Relationships Using Aggregate Habits Construct

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
TIMESM ON				
LIMITACC	-0.825	0.190	-4.330	0.000
BUSYNESS	-0.559	0.238	-2.349	0.019
INT	-0.117	0.105	-1.115	0.265
Residual Variances				
TIMESM	16.776	3.610	4.647	0.000
Between Level				
SI ON				
HABITBD	-0.010	0.158	-0.064	0.949
SI2 ON				
HABITBD	-0.245	0.167	-1.474	0.141
TIMESM ON				
SELFCONTD	-0.368	0.355	-1.036	0.300
HABITBD	1.504	0.372	4.047	0.000
Intercepts				
TIMESM	5.660	0.354	15.988	0.000
SI	0.310	0.144	2.148	0.032
SI2	-0.590	0.141	-4.190	0.000
Residual Variances				
TIMESM	20.974	4.401	4.766	0.000
SI	0.204	0.381	0.535	0.593
SI2	1.165	0.484	2.406	0.016

Note: LimitAcc = limited access to social media; Busyness = The busyness of the particular work day; INT = Interaction between state self-control and intention strength for reducing time on social media; TIMESM = Time on social media; SI = The effect of state self-control on time on social media; SI2 = The effect of intention strength on time on social media; HabitBD = Habit strength regarding social media use; Selfcontd = Trait self-control.

Output in Testing Hypothesized Relationships Using Individual Dimensions of Habits

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MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Within Level

 TIMESM     ON
    LIMITACC          -0.839      0.192     -4.361      0.000
    BUSYNESS          -0.553      0.238     -2.323      0.020
    INT               -0.105      0.106     -0.988      0.323

 Residual Variances
    TIMESM            16.751      3.608      4.642      0.000

Between Level

 SI         ON
    AWAREBD            0.287      0.214      1.338      0.181
    MEBD              -0.259      0.270     -0.960      0.337
    CONTOLBD          -0.127      0.176     -0.725      0.468

 SI2        ON
    AWAREBD            0.029      0.188      0.156      0.876
    MEBD               0.352      0.249      1.414      0.157
    CONTOLBD          -0.353      0.159     -2.221      0.026

 TIMESM     ON
    SELFCONTD         -0.287      0.352     -0.814      0.415
    AWAREBD            0.632      0.364      1.735      0.083
    MEBD              -0.286      0.477     -0.600      0.549
    CONTOLBD           0.797      0.361      2.208      0.027

 Intercepts
    TIMESM             5.673      0.354     16.025      0.000
    SI                 0.277      0.137      2.027      0.043
    SI2               -0.572      0.134     -4.265      0.000

 Residual Variances
    TIMESM            20.718      4.346      4.767      0.000
    SI                 0.286      0.405      0.707      0.480
    SI2                0.983      0.444      2.213      0.027
```

Note: LimitAcc = limited access to social media that day; Busyness = The busyness of the particular work day; INT = Interaction between state self-control and intention strength for reducing time on social media; TIMESM = Time on social media; SI = The effect of state self-control on time on social media; SI2 = The effect of intention strength on time on social media; AwareBD = Low Awareness; MeBD = high mental efficiency; ControlBD = Low controllability; Selfcontd = Trait self-control.

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