Ego Depletion-Induced Aberrant Driving in the Post-Work Commute

Tanya Elise Mitropoulos

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Charles Calderwood, Chair
Rachel Diana
Jorge Ivan Hernandez

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ABSTRACT

Spillover research has shown that workday stress hampers commuting safety, while ego depletion research has demonstrated that prior self-regulation leads to performance decrements in subsequent tasks. This study sought to unite these two lines of research by proposing that ego depletion-induced alterations in attention and motivation are the mechanisms by which workday experiences spill over to the commute and impair driving safety. To examine the daily influences of these within-person processes on driving behavior in the post-work commute, this study adopted a daily survey design, wherein participants took an online survey immediately before and after each post-work commute across one work week. In these daily surveys, fifty-six participants (N = 56; n = 250 day-level observations) reported their workday self-regulatory demands; pre-commute levels of attention, motivation, and affective states; and driving behavior during the commute home. Using multilevel path analysis to isolate within-person effects, the current study found no evidence to suggest that workday self-regulatory demands lowered pre-commute attention and motivation, nor did it detect associations of attention and motivation with post-work aberrant driving. Results indicated that an ego depleted state might impair attention and motivation but not driving safety in the commute. Instead, the results pointed to the person-level factor of trait self-control as potentially having a greater impact on post-work aberrant driving than daily experiences.

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GENERAL AUDIENCE ABSTRACT

Research has shown that employees tend to drive more unsafely when commuting home after a stressful workday. However, most of this research has examined what about the *person* makes them drive more unsafely than someone else, but it is also important to understand what about the *workday* makes someone drive more unsafely one day than another day. I predicted that a workday containing more self-control demands would make an employee drive more unsafely when commuting home from work because facing more self-control demands would lower the employee's attention and motivation for driving safely. To test this idea, I gave participants two online surveys per day for five consecutive days, Monday through Friday – one at the end of their workday (asking about their workday demands and current levels of attention and motivation), and one at the end of their commute home (asking about their driving behavior during that post-work commute). The data from my final sample of 56 participants (N = 56; n = 250 study days) showed no evidence to support my hypotheses: the amount of workday self-control demands was not found to associate with attention and motivation before driving home, and attention and motivation before driving home were not found to relate to driving safety during that commute home. On the other hand, I did find that a person's general ability to maintain self-control was associated with their driving safety during the commute home (regardless of workday self-control demands). These results suggest that a person's character might be more important in determining their day-to-day driving safety during the commute home than the self-control demands they face during the workday.

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1 Introduction

Driving is a ubiquitous and necessary task for most people in the United States, with 85% of Americans using a car as their main method of getting to and from work (Brookings, 2017). Sadly, in spite of its near ubiquity, driving with sub-optimal performance can have grave consequences. In 2015 alone, car accidents injured 2.4 million people in the United States and killed 35,485, making it the 13th leading cause of death (National Highway Traffic Safety Administration, 2017). In another recent yearly estimate, 24% of fatal car accidents occurred during commute times, with a majority of these accidents occurring during the post-work commute (National Highway Traffic Safety Administration, as cited in Big Think, 2018).

Empirical research has indicated that workday demands co-vary with post-work unsafe driving behaviors. For example, increased cognitive demands during the workday, abusive supervision, and the spillover of negative affect from the workday have all been linked to more *aberrant driving behaviors* during the post-work commute (Elfering et al., 2012; 2013; Turgeman-Lupoa & Biron, 2017; Calderwood & Ackerman, 2019), which reflect driving maneuvers that facilitate accidents. However, what remains uncertain are the mechanisms underlying the relationships of work-related factors to aberrant driving during the post-work commute (Calderwood & Ackerman, 2019). I seek to explain workday-to-commuting relationships via a heretofore unexplored mechanism – ego depletion stemming from self-regulatory demands during the workday.

Self-regulatory demands refer to any situation that requires the use of self-control (DeWall et al., 2005), such as persistence in an unpleasant task or hiding one's true emotions (Hagger et al., 2010). Employees commonly engage in self-regulation at work in response to various workplace demands and stressors (Diestel & Schmidt, 2009; Schmidt & Neubach, 2007).

For example, service workers regularly perform impression management, a form of emotion self-regulation (Grandey, 2000; Schmidt et al., 2007). Furthermore, even problem-solving has been shown to require self-regulation (Hagger et al., 2010).

As a result of prior self-regulation engagement, employees become vulnerable to an impaired state known as *ego depletion*, which is characterized by self-control impairment and performance decrements when completing a subsequent task (Baumeister, Schmeichel, & Vohs, 2006). Tasks relevant to safe driving, such as cognitive processing, impulse control, and decision-making (Lawton & Parker, 1998), have been shown to be vulnerable to ego depletion-induced performance degradations (Hagger et al., 2010). Therefore, it is reasonable to expect that workers commuting home following a demanding workday may show performance decrements during their drive home. However, the commute home has not yet been studied in an ego depletion framework.

By carrying over self-control decrements from one task to another, the phenomenon of ego depletion is similar to that of *spillover*, in which the strain bred in one domain carries over to another domain (Bakker, Westman, & Emerick, 2009). Spillover has been demonstrated to occur between the work domain and the home domain (see Edwards & Rothbard, 2000, for a review), with the commute lying as the transition between these two domains. Such transitions from one domain into another are theorized to be crucial to the quality of experiences in each domain, but these inter-domain transitions are rarely directly evaluated (Winkel & Clayton, 2010). This proposed investigation of the commute is an opportunity to directly evaluate the transition between work and home via the theoretical framings of ego depletion and spillover, thereby adding to the limited body of work on commuting-related spillover (see Calderwood & Mitropoulos, 2020, for a review).

The proposed study aims to make three primary contributions. First, at a theoretical level, I seek to unite spillover theory with ego depletion theory in a novel application of the commuting environment. Second, I intend to explicate the process through which ego depletion explains decrements in driving performance during the post-work commute. Finally, I will utilize a within-person, within-day approach to link variability in driving performance during the post-work commute to variability in workday self-regulatory demands and corresponding ego depletion states. Job demands have been shown to vary from day to day (e.g., Simbula, 2010), and evidence exists of day-to-day variability in driving performance during the post-work commute (e.g., Calderwood & Ackerman, 2019), yet the within-person co-variation of workday events and commuting performance has largely been neglected in favor of investigations of enduring, between-person tendencies (Calderwood & Mitropoulos, 2020). By explaining within-day variability in driving performance via the previously unexplored within-person mechanism of ego depletion stemming from workday self-regulatory demands, the proposed study offers the potential for development of targeted, short-term interventions to improve daily driving performance in the commute home from work.

2 Literature Review and Hypotheses

2.1 Spillover

Spillover is a well-established phenomenon between the work and home domains, where experiences in the two domains interact and affect one another (Edwards & Rothbard, 2000). The contemporary study of spillover focuses on how experiences in one domain (i.e., work) influence experiences in another domain (i.e., home) on a within-person level via explorations of the co-variation of daily work and home experiences (Bakker et al., 2009). However, despite the post-work commute being more temporally proximate to the end of the workday than most other post-work experiences, there have been only a few investigations of work-to-commute spillover (i.e., the spillover of workday experiences to the commuting environment), which have primarily emphasized the prediction of safety during the post-work commute (see Calderwood & Mitropoulos, 2020, for a review).

However, the limited empirical evidence focusing on work-to-commute spillover does suggest that workday experiences can indeed spillover and influence commuting safety outcomes. In particular, an increase in workday stressor exposure has been shown to diminish the quality of driving during the post-work commute (Elfering et al., 2012; 2013; Turgeman-Lupoa & Biron, 2017; Rowden et al., 2011). Therefore, just as a more stressful workday predicts decrements in the quality of home life (Staines, 1980; Lambert, 1990), a more stressful workday similarly predicts decrements in safe driving during the post-work commute, pointing to the existence of a within-day, within-person work-to-commute spillover phenomenon. However, mechanisms to explain the influence of workday experiences on commuting performance remain poorly understood (Calderwood & Ackerman, 2019). There is reason to suspect that ego depletion stemming from self-regulatory demands at work is a particularly likely mechanism to underlie this daily work-to-commute spillover, a possibility that I expand on in greater detail in the next section.

2.2 Self-Regulation and Ego Depletion

Self-regulation is the act of expending effort to control one's thoughts, emotions, and/or behaviors to come closer to a desired goal state (Baumeister et al., 2006). As such, self-regulation has been argued to underlie much of cognitive and social processing and plays a role in a wide array of effortful behaviors, from decision-making to task persistence (Hagger et al., 2010). The workplace is a common area where people engage in self-regulation (Grandey, 2000; Schmidt et al., 2007), and there are consequences to doing so. For example, call center workers who engage in self-regulation while handling demanding callers have been shown to display greater deficits in subsequent impulse control and task persistence than workers who deal with pleasant callers (Zyphur et al., 2007). This phenomenon of prior exertion of self-regulation leading to performance deficits in future behavior is referred to as *ego depletion* (Baumeister et al., 2006).

The process model of ego depletion explains post-self-regulation performance decrements as consequences of shifts in both attentional and motivational orientations resulting from self-regulatory exertion (Inzlicht & Schmeichel, 2012). More specifically, when in an ego depleted state, attention and motivation are argued to reorient towards gratifying desires and impulses in lieu of fulfilling task goals. Similar to control theories of motivation (Lord & Levy, 1994), the act of overriding impulses is theorized to occur upon detecting a discrepancy between the current state and the desired, goal state. According to the process model, in an ego-depleted state, attention shifts away from cues signaling deficiencies in the current state and towards those leading to instant gratification, thus making the discrepancy between current and desired states less likely to be noticed. At the same time, in the context of ego depletion, motivation shifts away from quelling impulses that hinder goal achievement and instead moves towards gratifying them. As a consequence, one becomes less motivated to work to achieve the desired state and more motivated to give in to impulses. These two mechanisms – *attentional* and *motivational* – are argued to interact and compound to result in the observed performance decrements following self-regulatory demand exposure.

Results from empirical studies of ego depletion suggest that the effects of self-regulatory exertion carry over across domains (see Hagger et al., 2010, for a meta-analytic review), which demonstrates that ego depletion is synthesizable with spillover theorizing. While driving deficits stemming from workday self-regulatory demands have not been directly tested in an ego depletion framework, there is evidence that the workday does induce ego depletion in employees (Wallace et al., 2009) and that ego depletion states hinder complex psychomotor tasks similar to driving (Wallace et al., 2009; Zyphur et al., 2007). In particular, performance in a high-fidelity naval simulator that required navigation and decision-making skills similar to those used in driving was shown to be reduced following self-regulatory exertion (Zyphur et al., 2007), as was performance on a computer-based driving task (Fischer et al., 2012). Thus, the effects of ego depletion appear transferable to driving-like tasks, and accordingly the mechanisms of the process model of ego depletion may be likely to contribute to these relationships. Synthesizing the arguments of the process model of ego depletion with these lines of empirical evidence and spillover theorizing, I anticipate that encountering more self-regulatory demands during the workday will co-vary with lower pre-commute attention and lower pre-commute motivation to drive safely during the post-work commute.

Hypothesis 1: *Greater workday self-regulatory demands co-vary with lower pre-commute attention.*

Hypothesis 2: *Greater workday self-regulatory demands co-vary with lower pre-commute motivation to drive safely.*

2.3 Ego Depletion and Driving Performance

Driving is a complex task, requiring simultaneous planning, motor movements, and navigation (Choi et al., 2017). Both attentional and motivational processes play vital roles in facilitating the driving task (Lundqvist, 2001), making ego depletion-induced decrements in attention and motivation particularly likely to facilitate an increase in aberrant driving behaviors during the post-work commute. Aberrant driving behaviors are defined as actions that contribute to accidents. They fall into two categories, errors and violations (Reason et al., 1990; Blockley & Hartley, 1995; Zhang et al., 2015). Errors are unintentional failures in safe driving and are rooted in attentional breakdowns, while violations are deliberate breaches of acceptable behavior that extend from motivational failings (Reason et al., 1990). As these definitions make clear, the mechanisms underlying aberrant driving behaviors align closely with the attentional and motivational decrements theorized to result from an ego-depleted post-work state (Inzlicht & Schmeichel, 2012). Thus, I expect ego depletion to shift participants' attention and motivation away from safe driving behaviors during the post-work commute. More specifically, I expect that ego depletion-induced shifts in attention and motivation will increase the frequency of aberrant driving behaviors during the post-work commute, predictions that I expand upon in the following two sections.

2.3.1 Pre-Commute Attention and Aberrant Driving. Safe driving requires effective use of attention for processing the demands of the driving environment and coordinating the various tasks complicit in the driving process, such as steering, navigating, and attending to the road (Trick et al., 2007; Choi et al., 2017; Lundqvist, 2001). If ego depletion-induced attentional decrements remove a commuter's focus away from the already numerous demands in the driving situation and instead toward unrelated, gratifying stimuli (as would be theorized within the process model of ego depletion; Inzlicht & Schmeichel, 2012), then a commuter should become more likely to neglect driving demands that are present during the commute and commit errors that could put the commuter, passengers, and others nearby in harm's way (Avolio et al., 1985; Elander et al., 1993).

Initial empirical support for the adverse impact of ego depletion stemming from workday demands on the commute via attentional alterations comes from a study on railway controllers (Elfering et al., 2012). Controllers experiencing more workday mental demands, which have been shown to induce ego depletion (Hagger et al., 2010), drove more dangerously during the commute home, with cognitive failures (which included attentional failures) fully mediating this relationship. Synthesizing this empirical evidence with theorizing regarding ego depletion and driving attention yields the basis for two complementary predictions. First, I predict that pre-commute attention decrements will co-vary with increased aberrant driving during the post-work commute. Second, I predict that workday self-regulatory demands will enhance aberrant driving during the post-work commute via reductions in pre-commute attention.

Hypothesis 3: *Pre-commute attention decrements co-vary with increased aberrant driving behavior during the post-work commute.*

Hypothesis 4: *Workday self-regulatory demands enhance aberrant driving during the post-work commute via reductions in pre-commute attention.*

2.3.2 Pre-Commute Motivation and Aberrant Driving. Based on Campbell et al.'s (1993) theory on determinants of performance, one's motivation to perform safe behaviors should correlate with the execution of safe behaviors. In accordance with this theorizing, Neal, Griffin, and Hart (2000) demonstrated that more motivation to behave safely does indeed translate into executing behavior that is safer. Similarly, I expect that if ego-depleted commuters have decreased motivation to drive safely, then they in turn will execute more aberrant driving behaviors during the post-work commute.

Empirical evidence to support this theorizing can be derived from applying Campbell's determinants of performance, which explicate that motivation is a major contribution to enacted behavior, to the driving environment. For example, drivers more permissive of aberrant behaviors have been found to execute riskier driving maneuvers and commit more driving violations (Parker et al., 1995; Ulleberg & Rundmo, 2003). Looking specifically at the commuting environment, results from Turgeman-Lupoa and Biron (2017) suggest empirical support for a relationship among post-work ego depletion, reduced motivation for safe commuting, and aberrant driving during the commute. In their study, employees suffering worse abusive supervision and work-family conflict, both of which tend to exacerbate ego depletion (Mackey et al., 2017; 2018; Dahm, 2017; Liu et al., 2014), were more permissive of aberrant driving behaviors in the commute. This reduction in motivation for safe driving translated into more self-reported driving violations during the commute. In accordance with these lines of theoretical and empirical evidence, I predict that pre-commute motivation decrements will co-vary with increased aberrant driving during the post-work commute and that workday self-regulatory demands will undermine aberrant driving behaviors during the post-work commute via reductions in pre-commute motivation for safe driving.

Hypothesis 5: *Pre-commute motivation decrements co-vary with increased aberrant driving behaviors during the post-work commute*.

Hypothesis 6: *Workday self-regulatory demands enhance aberrant driving behaviors during the post-work commute via reductions in pre-commute motivation for safe driving.*

2.4 Study Overview

The current study explores the impact of workday self-regulatory demands on the post-work commute via pre-commute attentional and motivational mechanisms extending from the ego depleted state. As shown in Figure 1, I hypothesize that greater workday self-regulatory demands will associate directly with decreases in attention and motivation, which will in turn relate to increased aberrant driving during the post-work commute. I also expect greater workday self-regulatory demands to associate indirectly with increased aberrant driving through reductions in attention and motivation. I adopted a within-person approach for this investigation, in line with recent approaches to modeling intra-individual influences on unsafe commuting (e.g., Calderwood & Ackerman, 2019; Elfering et al., 2012; Turgeman-Lupoa & Biron, 2017), and consistent with the daily- and state-level nature of my theorizing.

Participants partook in the study for five consecutive days across a single workweek. At the end of each workday and prior to commuting home from work, participants provided information via self-report questionnaires related to self-regulatory demands faced throughout that workday and their current levels of attention and motivation. Immediately following the post-work commute, participants filled out the Driving Behavior Questionnaire (DBQ) (Reason et al., 1990), a widely validated instrument that records the frequency of unsafe driving behaviors, to provide information on the safety of their commute home.

3 Method

3.1 Sample and Procedure

Participants were employees who drove to work daily across the United States. Individuals were eligible to participate if they: a) were over 18 years in age, b) worked Monday through Friday, c) drove her/himself from work each day, d) did not have job-related driving demands (e.g., bus driver); (e) worked only 1 job per day, and f) had a commute from work with an average trip time of at least 15 minutes. See Table 1 for the reasoning behind each inclusion criterion.

To determine a target sample size, a Monte Carlo power analysis was computed with 10,000 repetitions, the specification of 5 Level 1 observations per participant, a moderate effect size relationship underpinning each hypothesized pathway (r = .30), and a Type I error rate of α = .05 (Muthén & Muthén, 2002; Cohen, 1992). Under these parameters, a minimum Level 2 sample size of 34 was required to reach an estimated statistical power of .80 for detecting a multilevel indirect effect. However, to avoid the problem of biased standard errors that accompanies using an insufficiently large Level 2 sample size with an asymptotic estimation method (e.g., maximum likelihood estimation methods commonly employed in multilevel analyses), I targeted a Level 2 sample size of 50 (see Maas & Hox, 2005). At this higher sample size, the statistical power to detect a multilevel indirect effect was estimated at .96, while the estimated statistical power to detect the hypothesized direct effects was greater than .98. Given that my power exceeds .95, I will lend substantive interpretation to any observed non-statistically significant findings, consistent with the recommendations of Nickerson (2000).

To reach this target sample size of 50, I recruited participants via Prolific. Prolific is an online crowdsourcing platform that is widely used in the social sciences to connect individuals interested in participating in research studies with researchers providing these opportunities. Using an online platform provided easier access to a large participant pool, which I considered necessary due to COVID-19-induced reductions in eligible participants (i.e., a key eligibility requirement was commuting from a physical workplace, and stay-at-home orders present in most states in the U.S. at the time data were collected restricted commuting employees to essential workers; Secon, 2020). I selected Prolific in favor of other platforms offering similar services due to its focus on behavioral research, recognition from research universities, efforts to reduce fraudulent responding, and multi-thousand-member participant pool (Prolific, 2020).

I first screened Prolific members for eligibility by applying select filters built into the Prolific platform. The filters made participation available only to Prolific members who were over 18 years old, fluent in English, and lived and worked in the United States. Interested members then took a short *eligibility survey*, hosted on Qualtrics. Qualtrics is a survey management system widely used in social sciences research that meshes smoothly with Prolific due to an existing integration. For these reasons, all online surveys administered in this study were hosted on Qualtrics. The eligibility survey consisted of questions pertaining to the inclusion criteria, as well as study information and an informed consent page. Only participants who answered the survey questions consistent with each inclusion criterion were invited to join the study. Two-hundred twenty Prolific members took the eligibility survey. Of those 220, 94 participants consented and met all of the inclusion criteria as indicated by their responses and were invited to join the study.

Participants who joined the study were required to then complete an online *opt-in survey*. This approximately 20-minute survey contained demographic questions, select statistical control measures (described subsequently), and attention check items. The attention check items were used for quality control purposes to determine if any participants were not taking the survey seriously, as past research has used such items to identify careless responders (Bennett et al., 2016). Participants were informed that the survey included these attention check items and that these items would ask them to choose a specific response (e.g., "Please select Strongly Agree for this question"); if they failed to mark the requested item correctly, then they would be excluded from the remainder of the study. The 94 Prolific members who were eligible to join the study were emailed the opt-in survey through the Prolific platform. Of these 94 members, 82 completed the opt-in survey.

These 82 participants were then invited to participate in a five-day daily survey period. The daily survey period began on a Monday after the participant completed the opt-in survey at the completion of their workday and lasted until they finished commuting from work on Friday of the same week (i.e., for five consecutive working days). On the Sunday prior to the daily survey period, each participant received a reminder email with instructions to complete 1) the *end-of-workday survey* at the immediate conclusion of their workday and prior to their commute the next day, and 2) the *post-commute survey* immediately following their commute the next day, along with a link to each survey that they could use across the daily survey period. During the daily survey period, each participant had the option of receiving daily reminder emails at a time of their choosing during the workday, which again contained these survey links. The end-of-workday survey contained measures of workday self-regulatory demands, current attention level, current motivation level, and current mood (the latter included for statistical control purposes), while the post-commute survey contained a self-report driving measure and general inquiries about perceptions of properties of the drive.

As is standard with studies administered via Prolific, compensation was based on an hourly rate set for each survey. The eligibility survey used an hourly rate of $6.50, which was lower than the rates used for the other surveys because it included just 8 questions meant to screen participants before entering the study. With an estimated time of 4 minutes, those who completed the eligibility survey received $0.44. An hourly rate of $8.00 was used for the opt-in and daily surveys. A higher rate was chosen because these surveys require greater concentration and to encourage participants to complete all 11 surveys. Based on an estimated completion time of 20 minutes, participants who filled out the opt-in survey were compensated $2.67. For those participants who participated in the daily survey period, they received $1.34 for each daily survey submitted, based on an estimated 10 minutes per survey. Participants who completed all parts of the study (eligibility survey, opt-in survey, and 10 daily surveys) also received a $2.00 bonus payment, totaling up to $18.51 for study participation.

Of the 82 participants who were invited to the daily survey period, 56 were retained for data analysis. The 26 participants who were excluded were screened out for the following reasons: (1) failing more than 2 attention checks (n = 1); (2) responding from outside of the United States, as indicated by Qualtrics metadata and thus violating an inclusion criterion (n = 3); (3) suspicions of fraudulent responding, arising from duplicate responses with duplicate time stamps (n = 2); (4) completing fewer than 3 complete survey days to ensure sufficient intraindividual variability to model (Gabriel et al., 2019; n = 5); or (5) suspicions of not complying with survey response instructions on more than 2 survey days (n = 15). Suspicions of failure to comply with survey response instructions arose when the duration of time between taking the end-of-workday survey and post-commute survey: a) exceeded 2 hours past the participant's typical commute duration as reported in the opt-in survey, excluding cases when participants reported making a stop (e.g., grocery shopping); b) was shorter than 0 minutes (i.e., the post-commute survey was completed before the end-of-workday survey); or c) was shorter than 15 minutes, thus contradicting the participant's prior report of commute length in the eligibility survey.

After screening individuals on these grounds, there was a remaining sample size of 56 participants (N = 56), who completed 250 survey days (n = 250, 89.3% study day response rate; 90.0% response rate for end-of-workday surveys, 89.6% response rate for post-commute surveys), which exceeded the a priori power calculation threshold of a minimum sample of 50 participants. I performed a non-compliance bias analysis by computing independent samples *t*-tests on demographics and opt-in survey scales across participants who were retained for subsequent data analysis (N = 56) versus those who were screened out during data screening (N = 26). Statistically significant differences across these groups are displayed in Table 2. The two groups differed on multiple demographics, namely: age, race, marital status, primary caregiver status, job and organizational tenure, and years of driving experience. The two groups also varied in their responses to the following opt-in survey scales: trait self-control, amount of home demands, and work-home boundary management. My decision to person-mean center variables at Level 1, as described subsequently in the "Analytic Approach" section, statistically controls for the potential confounding influence of between-person characteristics when estimating within-person relationships, which will account for this non-compliance bias when evaluating testing the hypothesized model.

Participants were majority White (85.7%), with the remaining participants being Asian (7.1%), Black or African American (1.8%), or more than one race (5.4%). They were majority male (57.1%), with an average age of 36 years old (SD = 12.3). As reported in the opt-in survey, on average they had been driving regularly for 17.5 years (*SD* = 12.4) and had a post-work commute time of 27.0 minutes (*SD* = 11.7). Data were collected from June to July of 2020, which coincided with stay-at-home orders for non-essential workers in many U.S. states in response to the COVID-19 pandemic (Secon, 2020). Consequently, nearly a third of participants worked in healthcare (28.5%) and nearly a fifth in retail or food service (17.8%); the remainder were spread across a variety of industries (e.g., office and administrative support; transportation and material moving; and computer and mathematical).

3.2 Measures

3.2.1 Self-Regulatory Workday Demands. Participants completed the Self-Control Demands scale (Neubach & Schmidt, 2007) in the end-of-workday survey to quantify daily self-regulatory demand exposure. This self-report measure focuses specifically on the extent of self-control required in the workplace and is broken up into 3 subscales, each focusing on a different element of self-control: impulse control (IC), resisting distractions (RD), and overcoming inner resistance (OIR). The subscales contain 6 items, 4 items, and 5 items that respectively correspond to these subscales, which are measured on a 5-point, Likert-type scale ranging from "Not at all" to "A great deal" (Schmidt, Neubach, & Heuer, 2007). Each subscale measures a distinct and moderately correlated factor (Neubach & Schmidt, 2007; Schmidt & Neubach, 2009; 2010; across the five-day daily survey period, average $\alpha_{IC} = .912$, $\alpha_{RD} = .911$, $\alpha_{OIR} = .950$). In the current study, the scales inter-correlated at a range from $r = .647 - .686$.

The scale can distinguish differing levels of self-control demands across different professions, as well as predict strain-related outcomes such as burnout, turnover, and depressive symptoms (see Schmidt & Diestel, 2015, for a review). Because this study's goal is to examine the impact of self-regulatory workday demands overall and not a particular kind of workday demand, the composite score was used in all analyses (average α = .951). Furthermore, as the sample is not restricted to any particular type of industry or occupation, utilizing the composite score allows the measure to encompass the full spectrum of workday self-control demands faced by an employee (Neubach & Schmidt, 2007). Analyzing the cumulative effects of workday self-control demands in this way is consistent with prior research (e.g., Diestel & Schmidt, 2010).

A potential limitation of the Self-Control Demands scale for the proposed study was its stability across time (i.e., the extent of intra-individual variation when using this scale repeatedly over time has not been directly tested prior to this study; Schmidt & Diestel, 2015). The scale by design assesses stable characteristics of the job, with items worded for example as "My job requires me never to lose my temper." However, consistent with the approach of other researchers to adapt measures of enduring characteristics to the daily level (e.g., Van Hooff & Van Hooft, 2016), the scale items were modified by prepending them with "Today," for example changing the aforementioned item from the original scale to "Today, my job required me to control my temper." As subsequently described in the "Descriptive Analyses and Assumption Checking" section, I did observe day-to-day variability in participant responses to this self-regulatory work demands scale.

3.2.2 Attention. To assess pre-commute attention level, participants filled out the PANAS-X attentiveness subscale (Watson & Clark, 1994) in the end-of-workday survey. This self-report scale has been found to correlate with distractibility (Payne & Schnapp, 2014), which can impact how well drivers scan the environment for hazards (Kass, Beede, & Vodanovich, 2009). Participants were asked the extent to which they identify with each of the subscale's 4 items ("concentrating," "attentive," "determined," and "alert") at the current moment. Each item was rated on a 5-point, Likert-type scale ranging from "very slightly or not at all" to "extremely" (average α = .91). The self-report nature of this scale might be a limitation in predicting driving behavior because self-report measures of attention have been found to poorly reflect behavioral performance (Williams et al., 2017).

3.2.3 Motivation. To assess pre-commute motivation level and orientation, participants completed a variation of the Self-Control Motivation and Capacity scale (SCMCS; Papova, 2016) in the end-of-workday survey. Because ego depletion is expected to shift motivation towards capitulating to desires, a measure of self-control motivation specifically should reflect the particular impact of ego depletion. Participants completed the three 5-item subscales that relate to capacity of motivation, internal motivation, and external motivation. Each scale was modified to assess current rather than general levels of motivation as in the original scale. An example modification is changing the item "When I have the motivation, I'm able to resist temptation" to "Currently, I'm able to resist temptation." Each item was reported on a 5-point, Likert-type scale, ranging from "Very easily" to "With much difficulty" (average α = .941 for the capacity of motivation subscale, average α = .933 for the internal motivation subscale, and average α = .972 for the external motivation subscale). The subscale pertaining to capacity of motivation was used in the tests of hypotheses due to its correspondence with one's current amount of motivation to resist desires.

The SCMCS's reliability and validity have been tested in 2 studies, with samples of 400 university students each (Papova, 2016). SCMCS capacity scores correlated with motivation-relevant outcome variables like alcohol use, exercise amount, GPA, and food addiction. Additionally, SCMCS capacity scores were moderately correlated with scores on a related construct, the Brief Self-Control Capacity Scale (BSCS), indicating both convergent and discriminate validity. Finally, the SCMCS was correlated with injunctive norms in relation to driving and personal views on drinking and driving, even above and beyond the BSCS.

3.2.4 Aberrant Driving. The Driving Behavior Questionnaire (DBQ; Reason et al., 1990), modified for a North American audience (Cordazzo et al., 2014), was administered to participants in the post-commute survey to evaluate their own subjective driving performance retrospectively following the post-work commute. The DBQ is a widely used self-report measure of aberrant driving, having been used in at least 174 studies (de Winter & Dodou, 2010). It contains a 3-factor underlying structure of errors, lapses, and violations (Parker et al., 1995). Violations are intentional breaches of accepted conduct and reflect failures of safety motivation. Errors, in contrast, are not intentional and reflect deficiencies of attention. They are failures in achieving the intended action, and lapses comprise a subcategory that specifically refers to failures extending from straying from an effective plan. Together, the three subscales reflect the level of aberrant driving behavior.

Participants received the North American version of the shortened DBQ (Parker et al., 1995), chosen to reduce participant burden. They were administered 19 of the 20 scale items, dropping one item that asked about drinking while driving to minimize potential legal risks for participants. Tests of hypotheses focused on the aggregate aberrant driving behavior, while follow-up exploratory analyses were computed for errors (which also included the lapses subcategory) and violations separately (see “Analytic Approach” section). An example item is “Failed to check your rear-view mirror before pulling out, changing lanes, etc.” Each item was rated on a 6-point, Likert-type scale ranging from “never” to “nearly all the time” (average α = .668).

3.2.5 Manipulation Check, Statistical Control, and Exploratory Variables.

Ego depletion self-report. As a manipulation check that self-regulatory demands co-vary with an ego depleted state, participants completed the Scale of Momentary Self-Control Capacity (SMS-5; Lindner et al., 2019) in the end-of-workday survey to measure end-of-workday ego depletion. The SMS-5 is a self-report instrument developed to reflect the extent to which one's self-control capacity has been depleted at a state level. It contains 5 items measured using a 7-point, Likert-type scale ranging from "Completely incorrect" to "Exactly right," and it was validated across 4 studies and 3 different samples – education apprentices (N = 2,395), tenth-graders (N = 129), and university students (N = 95; N= 140). An example item is "I feel drained" (average α = .85).

Affect. Because angry and excited moods have been shown to correlate with risky driving (Arnett, Offer, & Fine, 1997), participants reported their current mood in the end-of-workday survey using the positive and negative affect subscales of the PANAS-X (Watson & Clark, 1994). Participants were asked the extent to which they identified with each item at the current moment, for example "excited" from the positive affect subscale and "afraid" from the negative affect subscale. Each item was rated on a 5-point, Likert-type scale ranging from "very slightly or not at all" to "extremely" (average α = .93 for positive affect; average α = .89 for negative affect).

Recovery. To account for the potential opportunity to recover from workday demands in a small way between leaving the workplace and driving home (Zijlstra & Sonnentag, 2006), participants were asked how long it took them to reach their car from their workplace in the post-commute survey.

Trait Self-Control. Because aberrant driving has traditionally been studied at the between-person level (Calderwood & Mitropoulos, 2020), participants also completed a trait-level measure related to self-regulation. Recognizing that self-regulatory demands refer to situations requiring self-control (DeWall et al., 2005), trait self-control can be conceptualized as an individual's capacity to engage in self-regulation (de Ridder et al., 2012). Consequently, this measure allows for the possibility of exploring person-level differences in ego depletion as a predictor of aberrant driving, since those with less trait self-control are theorized to experience more ego depletion on average (Baumeister, 2002).

In the opt-in survey, participants filled out the Brief Self-Control Scale (Tangney, Baumeister, & Boone, 2004), which is one of the most widely used self-report measures of self-control ability (Lindner, Nagy, & Retelsdorf, 2015). The scale contains 13 items, measured on a 6-point, Likert-type scale ranging from "strongly disagree" to "strongly agree". An example item is "I refuse things that are bad for me" ($\alpha = .84$).

3.3 Analytic Approach

I tested my hypotheses using multilevel path analysis with full information maximum likelihood robust estimation in Mplus Version 8.4 (Muthén & Muthén, 2017). Figure 1 displays the hypothesized model that was specified. I estimated a fixed-effects model, as I expected the hypothesized effects to generalize across the population of participants as opposed to being limited to subpopulations of participants (i.e., no specification of random slopes incorporated into the model). An advantage of using a fixed effects model was that it controlled for unmeasured sources of variance attributable to individuals and time when using person-mean centering (Bliese et al., 2020). Pre-commute attention and motivation were allowed to correlate in the model based on theorizing that the two constructs co-vary in an ego depletion scenario (Inzlicht & Schmeichel, 2012) and to consequently avoid biased standard error estimates that can result from ignoring inter-correlations (Hansen, 2007). Predictors, mediators, and Level 1 statistical control variables were person-mean centered to exclude between-person variation when estimating within-person relationships (Curran & Bauer, 2012).

End-of-workday positive and negative affect were entered as statistical control variables in predicting aberrant driving behavior. I allowed these two variables to correlate in the model due to prior research indicating low-to-moderate inter-correlations between positive and negative affect (Watson & Clark, 1994). Time between leaving the workplace and arriving at the car was also entered as a statistical control variable in predicting pre-commute attention and motivation levels. This variable was included in the model because this amount of time spent not working allowed for the possibility of recovery (Zijlstra & Sonnentag, 2006), with a longer duration between the workplace and car potentially allowing for more recovery. Finally, to account for time-based, cyclical variation, I controlled for the day of the week by including the weekday, sine of the weekday, and cosine of the weekday in the model, as recommended by Beal and Weiss (2003). This methodology applies a similar treatment to if a quadratic trend existed in the data: the variables are regressed onto a sine and cosine transformation of time to account for cyclical trends, similar to regressing onto a quadratic transformation of a variable that has a quadratic trend. In so doing, I can examine cyclical time components as opposed to simply eliminating them (West & Hepworth, 1991).

To evaluate the hypothesized direct relationships (Hypotheses 1-3 and 5; see Figure 1), I assessed the two-tailed statistical significance of each pathway's multilevel regression coefficient. To evaluate the indirect effects proposed in Hypotheses 4 and 6, I used the Monte Carlo method developed by Preacher and Selig (2012). This method for testing indirect effects can be used in multilevel data structures, accounts for covariance among estimates, and performs well from a statistical power perspective in comparison to other methods (Preacher & Selig, 2012). I inferred statistical significance of the indirect effects from the 95% confidence interval (i.e., a 95% confidence interval that does not contain zero), consistent with the two-tailed tests of statistical significance used to detect direct effects in the current study.

Additionally, I computed separate models in which aberrant driving was subdivided out into the two criterion variables of errors and violations. The goal of these alternative models was to evaluate whether attentional and motivational pathways differentially contributed to these forms of aberrant driving. Driving errors are theorized to emerge from attentional deficits and driving violations from motivational deficits (Parker et al., 1995), so it is possible that reductions in pre-commute attention would be more strongly contributive to errors than violations and that reductions in pre-commute motivation would be more strongly contributive to violations than errors. However, because this possibility has not been empirically evaluated in past research, this comparison was made for exploratory purposes only.

To evaluate this exploratory comparison statistically, I computed four models, displayed in Figure 2. Models 1 and 2 were an unconstrained and constrained model, respectively, with driving errors as the criterion. Because lapses are a subset of errors due to their attentional nature, the errors criterion comprised both the errors and lapses subscales of the Driving Behavior Questionnaire. Models 3 and 4 were an unconstrained and constrained model, respectively, with driving violations as the criterion. The two unconstrained models were the same as the hypothesized model with the exception that aberrant driving was subdivided into errors or violations. The constrained models were the same as the corresponding unconstrained model save that the pathways linking pre-commute attention and motivation to the errors or violations criterion were constrained to be equal.

The corresponding unconstrained and constrained models were then compared to each other (e.g., the unconstrained model with errors as the criterion was compared to the constrained model also with errors as the criterion). A likelihood ratio test (Wilks, 1938), with degrees of freedom set to the difference in degrees of freedom between the two models, was used to determine if a differential contribution of attention versus motivation to errors/violations existed. If the model in which the pathways were *not* equal displayed a statistically superior fit (i.e., smaller -2 *loglikelihood*) compared to the corresponding model in which the pathways were constrained to be equal, then I inferred that attention and motivation were not equally contributive to errors/violations. I determined *which* was more contributive, attention or motivation, based on which path estimate was higher. Through this process, I could evaluate whether attention was a stronger predictor of driving errors and whether motivation was a stronger predictor of driving violations.

4 Results

4.1 Descriptive Analysis and Assumption Checking

Reliability estimates, means, standard deviations, intraclass correlations, skewness and kurtosis values for all study variables are displayed in Table 3. Stability coefficients across the 5-day survey period are given in Table 4. Ranging from .403 - .874, the stability coefficients indicate a moderate-to-high level of inter-correlation in study variables from day to day (Cohen, 1992), suggesting there is state-level variability over time but also some sources of stability. Inter-correlations at both daily and person levels are shown in Table 5. Justification for the use of multilevel modeling was supported by the prevalence of within-person variance in the hypothesized and control variables, where more than a fifth of variance for each variable arose from within-person sources (24.6% - 42.1%) as indicated by ICC values, which ranged from .579 - .754.

Turning to skewness and kurtosis, results indicate that aberrant driving was skewed and kurtotic, suggesting a lack of normality in this criterion variable. A histogram of aberrant driving displayed in Figure 3 shows that the lack of normality stemmed from an abundance of 1.0 scores in the data, corresponding to reports of no aberrant driving events in a day's commute. The use of loglinear modeling wherein I would treat aberrant driving as a count variable rather than a continuous variable was considered. In this scenario, an aberrant driving event (represented by a given item of the Driving Behavior Questionnaire) would be added to the daily count if marked as *having* occurred at all during that day's commute, in contrast to measuring the *level* at which each aberrant driving event occurred (as in the continuous treatment originally proposed). However, the continuous treatment was chosen in favor of the count conceptualization due to the non-independence of aberrant driving events, which violates an important assumption of loglinear modeling (Cameron & Trivedi, 1998). To account for the lack of normality and independence in the aberrant driving data, maximum likelihood robust estimation was used when estimating the multilevel path models. Maximum likelihood robust estimation provides standard errors that are robust to both non-normal and non-independent data (Heck & Thomas, 2015).

Finally, the ego depletion theory justifying the relationships in the proposed model rested on the contention that workday self-regulatory demands would co-vary with an ego depleted state at the conclusion of the workday. To examine whether this association held, I evaluated the statistical significance of the correlation coefficient between workday self-regulatory demands and end-of-workday ego depletion at the daily level. I looked at the daily-level correlation because my model examines within-person associations and excludes between-person variation. I person-mean centered these two variables to isolate within-person variation and found that they shared a moderately-sized correlation coefficient of .385 (Cohen, 1992), statistically significant at a Type I error rate of $\alpha = .05$.

4.2 Hypothesized Model

Full model results are shown in Table 6, and the model diagram with coefficient estimates is depicted in Figure 4. Hypotheses 1 and 2 stated that greater workday self-regulatory demands would co-vary with lower pre-commute attention and motivation, respectively. However, I did not find support for co-variation between workday self-regulatory demands and pre-commute attention and motivation ($\gamma = -.066$, $SE = .043$, $z = -1.543$, *ns* and $\gamma = -.108$, $SE = .128$, $z = -.844$, *ns*, respectively). Hypotheses 3 and 4 respectively proposed that pre-commute attention and motivation would co-vary with post-work aberrant driving, but I did not find evidence to support these associations ($\gamma = .006$, $SE = .029$, $z = .225$, *ns* and $\gamma = .021$, $SE = .018$, $z = 1.184$, *ns*, respectively). Furthermore, no direct relationship was observed between workday self-regulatory demands and post-work aberrant driving (γ = .021, *SE* = .016, *z* = 1.248, *ns*). Consequently, the expected direct associations between workday self-regulatory demands, pre-commute attention, pre-commute motivation, and post-work aberrant driving were not found.

Hypotheses 4 and 6 stated that workday self-regulatory demands would indirectly influence aberrant driving via reductions in pre-commute attention and motivation for safe driving. Indirect effect coefficients and corresponding confidence intervals used to evaluate Hypotheses 4 and 6 are shown in Table 7. As with the hypothesized direct effects, I did not find support for the presence of indirect effects of workday self-regulatory demands on post-work aberrant driving through pre-commute attention and motivation (95% C.I. = -.005032, .004678 and 95% C.I. = -.01279, .00411, respectively). Therefore, Hypotheses 4 and 6 were not supported.

4.3 Exploratory Analysis

For exploratory purposes, I evaluated whether pre-commute attention relates more strongly to driving errors, and whether pre-commute motivation relates more strongly to driving violations. Looking first at driving errors as the criterion, Model 2 (i.e., the unconstrained model; see Figure 2) fit the data better than Model 1 (i.e., the constrained model in which the paths from pre-commute attention and motivation to driving errors were held equal; Δ —2 X loglikelihood = 27.160, *df* = 1, $p < .001$). The difference between these two models indicates that attention and motivation contributed differentially to driving errors. Looking at driving violations as the criterion, Model 4 (i.e., the unconstrained model) displayed a statistically significant improvement over Model 3 (i.e., the constrained model; Δ —2 X loglikelihood = 15.636, *df* = 1, $p < .001$). Therefore, these results suggest that attention and motivation also contributed differentially to driving violations.

The specific nature of these relationships were evaluated by comparing the path estimates of the attentional versus motivational path in each unconstrained model. In predicting driving errors, pre-commute attention contributed more than motivation (γ = .053, *SE* = .020, *z* = 2.712, *p* < .01 and γ = -.008, *SE* = .030, *z* = -.256, *ns*, respectively), as expected. With respect to driving violations, neither pre-commute attention nor motivation related to driving violations (γ = .026, *SE* = .045, *z* = .578, *ns* and γ = .003, *SE* = .022, *z* = .132, *ns*, respectively), and so substantive interpretations regarding their relative contribution will not be made.

4.4 Supplemental Analyses

4.4.1 Affect as a Mediator. Due to the moderate within-person correlations of positive and negative affect with workday self-regulatory demands, I tested the possibility of pre-commute affect, rather than attention and motivation, explaining a relationship between workday self-regulatory demands and aberrant driving in the post-work commute. Because I was interested in examining positive and negative affect as mediators in place of attention and motivation, I removed attention and motivation from this model. The model with coefficient estimates is displayed in Figure 5, and the full model results are given in Table 8. The results indicated a direct relationship between workday self-regulatory demands and negative affect but not positive affect (γ = .166, *SE* = .041, *z* = 4.017, *p* < .0001 and γ = -.140, *SE* = .089, *z* = -1.574, *ns*, respectively). However, on the back half of the model, no association was found between negative or positive affect and aberrant driving (γ = .047, *SE* = .043, *z* = 1.074, *ns* and γ = -.009, *SE* = .017, *z* = -.551, *ns*, respectively). I also did not find support for an indirect relationship between workday self-regulatory demands and post-work aberrant driving through negative and positive affect (95% C.I. = -0.006065, 0.02453 and 95% C.I. = -0.003448, 0.00897, respectively), and so affect was not supported as mediating an association between workday self-regulatory demands and post-work aberrant driving.

4.4.2 Ego Depletion as a Predictor. My hypothesizing that employees would experience alterations in attention and motivation from workday self-regulatory demands emerged from the process model of ego depletion (Inzlicht & Schmeichel, 2012). Because I directly measured end-of-workday ego depletion, I evaluated whether an ego depleted state at the conclusion of the workday predicted pre-commute attention and motivation, along with downstream post-work aberrant driving. Table 9 shows ego depletion's correlation with the focal study variables and indicates that end-of-workday ego depletion was associated with attention and motivation at the within-person level, and with attention, motivation, and aberrant driving at the between-person level.

Consequently, I re-ran the hypothesized model with ego depletion in place of workday self-regulatory demands as a predictor. The resulting model with coefficient estimates is shown in Figure 6, and the full model results are presented in Table 10. Unlike in the original hypothesized model, ego depletion did relate to pre-commute attention and motivation (γ = -.122, *SE* = .057, z = -2.137, p < .05 and γ = -.368, *SE* = .117, z = -3.135, p < .01, respectively). As found in the original model, though, attention and motivation did not associate with aberrant driving (γ = .008, *SE* = .030, z = .250, *ns* and γ = .024, *SE* = .017, z = 1.390, *ns*, respectively). Similarly, ego depletion did not relate to aberrant driving indirectly through attention and motivation (95% C.I. = -0.01279, 0.00411 and 95% C.I. = -0.0304, 0.008412, respectively), nor did it relate to aberrant driving directly (γ = .019, *SE* = .010, z = 1.950, *ns*). Therefore, ego depletion did appear to relate to alterations in both pre-commute attention and motivation, as my theorizing anticipated; however, with the lack of association found from attention and motivation to aberrant driving, these ego depletion-related attentional and motivational alterations were not supported as the explanation behind trends in aberrant driving during the post-work commute.

4.4.3 Trait Self-Control as a Predictor. The hypothesized model was not supported at the within-person level, but as shown by the ICC values in Table 3, the focal variables displayed more between- than within-person variance. Consequently, I tested a model that substituted the day-level workday self-regulatory demands for a trait-level measure of self-control, as illustrated in Figure 7. Table 9 shows trait self-control's inter-correlations with the focal variables. Trait self-control was correlated with pre-commute attention, motivation, and aberrant driving.

The full model results for this variation of the proposed model are given in Table 11. Trait self-control related to pre-commute motivation (γ = .661, SE = .117, z = 5.663, p < .0001) but not to attention (γ = -.041, SE = .074, z = -.557, *ns*). As in the original, day-level model, pre-commute attention and motivation did not associate with post-work aberrant driving (γ = .004, SE = .029, z = .123, *ns* and γ = .021, SE = .016, z = 1.312, *ns*, respectively). The indirect relationships of trait self-control with post-work aberrant driving through attention and through motivation were also not supported (95% C.I. = -0.008636, 0.01068 and 95% C.I. = -0.002635, 0.02349, respectively). On the other hand, unlike the day-level predictors workday self-regulatory demands and end-of-workday ego depletion, trait self-control did have a direct relationship with post-work aberrant driving (γ = -.072, SE = .034, z = -2.100, p < .05). These results suggest that between-person differences might be more important than day-to-day changes in predicting aberrant driving during the post-work commute.

5 Discussion

The hypothesized relationships were not supported by the data collected for this study. Greater workday self-regulatory demands were not found to relate to pre-commute attention and motivation, an association that was anticipated to stem from end-of-workday ego depletion (Schmidt et al., 2007; Inzlicht & Schmeichel, 2012). Pre-commute attention and motivation were also not found to co-vary with aberrant driving during the post-work commute, a connection that was expected based on empirical research showing decrements in attention and motivation to hamper safe driving performance (e.g., Elfering et al., 2012; Ulleberg & Rundmo, 2003). Furthermore, no indirect relationship was found between workday self-regulatory demands and post-work aberrant driving through alterations in attention and motivation, which were theorized to be mechanisms underlying the association between prior self-regulatory exertion and future performance impairment (Inzlicht & Schmeichel, 2012).

5.1 Theoretical Implications

Despite the lack of evidence to support the proposed model, this study's findings make important contributions to the understanding of the workday's impact on the commute home. This study adds to the developing literature on commuting spillover, defined as the interrelationships between the workday and the commute (Calderwood & Mitropoulos, 2020). In particular, a dearth of research exists that assesses spillover from the workplace to the commute at the within-person level, as this study examines. In their review, Calderwood and Mitropoulos (2020) identified only four studies that evaluated within-person effects of the workday on post-work driving performance, with three of the four studies narrowly focusing on the effects of sleepiness. In contrast, the current study looks at the impact of a demanding workday more broadly, where the measure of workday demands was designed to encompass the full range of self-regulatory demands that employees of any occupation might experience throughout the workday.

By focusing on self-regulatory demands, the current study united spillover with self-regulation theory. This synthesis was appropriate because both theoretical frameworks describe how one's prior experiences influence their future performance. The lack of evidence found to support the hypothesized relationships suggests that daily self-regulatory exertion does not spill over from the workday to influence commuting safety in a meaningful way. Interestingly, results from the current study also indicate that negative affect does not spill over from the workday to impact commuting safety, which contradicts findings in Calderwood and Ackerman's (2019) recent study on daily work-to-commute spillover. An important methodological distinction between their study and the current one that could account for this discrepancy is Calderwood and Ackerman (2019) used an objective measure of unsafe driving, which I explore in the "Limitations and Future Research" section below.

Additionally, within the self-regulation literature, few studies evaluate the impact of ego depletion on performance of a complex task (Zyphur et al., 2007). Instead, most studies have measured performance on simple tasks like handgrip, math, and anagram tests (Hagger et al., 2010; Carter et al., 2015). This study presents the opportunity to examine ego depletion with respect to a situation requiring simultaneous engagement of multiple processes like planning, motor movements, and navigation (Choi et al., 2017). Evidence was not found to support a link between workday self-regulatory demands and the complex task of aberrant driving, nor was one found between end-of-workday ego depletion and aberrant driving. The lack of an identified association could indicate that ego depletion does not extend to complex task performance.

Alternatively, the lack of relationships could offer further support to the growing controversy that the ego depletion effect is small or does not exist at all.

Meta-analytic studies performed by Carter et al. (2015) and Hagger et al. (2016) found that accounting for publication bias and small-study effects reduced the effect size of ego depletion on subsequent performance to small-to-nonexistent, not medium-to-large as had previously been estimated (Hagger et al., 2010). The current study had adequate power to detect a moderate ego depletion effect but failed to do so, and so this study's findings are in line with updated assertions that the effects of prior self-regulatory exertion on future performance have been inflated (Hagger et al., 2016). When coupled with the high statistical power of the design, researchers can begin chipping away at which relationships are *not* supported and shift efforts towards other, more promising avenues for research, which I explore further in the "Limitations and Future Research" section below.

This study aimed to go beyond simply identifying the relationship between workday self-regulatory demands and post-work aberrant driving by *explaining* the link via the intermediary mechanisms of attention and motivation. These hypothesized associations rested on the process model of ego depletion, which proposes that engagement of self-regulation leads to alterations in attention and motivation away from performance goals (Inzlicht & Schmeichel, 2012). This study used workday self-regulatory demands as the means by which one engages self-regulation, since many workday tasks require self-regulation to solve problems, persist in uninteresting tasks, and control one's emotions (Hagger et al., 2010; Schmidt et al., 2007; Grandey, 2000), as just a few examples. While results showed workday demands to moderately correlate with end-of-workday ego depletion, workday demands did not appear to associate with pre-commute attention and motivation. On the other hand, a direct measure of end-of-workday ego depletion did relate to both pre-commute attention and motivation. The diverging impact of these two predictors suggests the states that ego depletion induces are more relevant to attentional and motivational orientations than the demands that engender ego depletion.

Unexpectedly, pre-commute attention and motivation were not supported as co-varying with aberrant driving during the post-work commute. As there was sufficient power to detect a moderate but not small effect size, one possibility for this lack of association is that the effect was small and thus was missed due to Type II error. Additionally, the influence of attention and motivation on aberrant driving might have been small due to this study's focus on the commute, a drive that is mostly automatized (Trick et al., 2004). When performance of a task is automatized, the task is performed outside of conscious awareness as if "on auto-pilot." Once an automatized process is initiated, it is carried out quickly and effortlessly, with little influence from attention or motivation. The commute is typically a driver's most practiced drive, thus enhancing participants' ability to carry out the drive "on auto-pilot." As a result, decrements in attention and motivation likely had a reduced impact on driving safety (i.e., task performance) in the current study's commuting context.

Another phenomenon in the current study context that might have reduced the influence of attention and motivation on aberrant driving was the co-occurrence of COVID-19 stay-at-home orders with the data collection time frame (Secon, 2020). Attention is needed in safe driving to recognize any hazards and handle unexpected situations, and motivation is required to maintain safety behaviors like scanning the driving environment for hazards. However, hazards and unexpected situations were likely less common during the current study period due to COVID-19 stay-at-home orders keeping most people at home and off the roads (Sutherland, McKenney, & Elkbuli, 2020; Barnes et al., 2020). Consequently, participants likely faced fewer obstacles and surprises in their commutes than normal, which would reduce the importance of attention and motivation for driving safely. Plus, anxiety generally heightens attention to threats (Eysenck et al., 2007), and adults' anxiety levels being higher during the pandemic (Twenge & Joiner, 2020; Gallagher et al., 2020) may have manifested in more attentive driving regardless of workday experiences.

In my exploratory analysis, I examined whether attention and motivation differentially contributed to errors and violations. These associations are implicit in the definition of errors as failures rooted in attentional breakdowns and in the definition of violations as deliberate breaches of acceptable behavior extending from motivational failings (Reason et al., 1990), but they had not been empirically tested. My results indicate that attention was more strongly linked to driving errors than was motivation, lending empirical support to the implicitly assumed association. On the other hand, no associations were found between pre-commute attention and motivation with post-work driving violations, which calls the current understanding of violations as motivational failings into question. However, workday self-control demands were found to predict driving violations. This finding suggests the possibility of self-control depletion as a better measurement of unwillingness to comply with socially acceptable behaviors and thus likelihood of committing violations than measuring motivation itself.

5.2 Limitations and Future Research

To capture aberrant driving during the post-work commute, this study used a self-report questionnaire. This method enabled contactless data collection, a necessity during COVID-19 stay-at-home orders, as well as recruitment from a nationwide sample, another important benefit when only essential workers were commuting to a physical workplace. However, the validity of self-report measures of driving behavior has been called into question. Lajunen and Summala

(2003) found driving behavior self-reports to be subject to social desirability bias. Participants might also unwittingly fail to report aberrant driving behaviors because they failed to notice them. Lapses, in particular, are defined as memory failures (e.g. failed to notice pedestrians; Reason et al., 1990; Parker et al., 1995). Similarly, less memory of the drive accompanies increased automaticity (Tice et al., 2004), making the commute particularly susceptible to deficiencies in recall. Furthermore, as results showed increased ego depletion to co-vary with reduced motivation, ego-depleted drivers might have been insufficiently motivated to report the full extent of their aberrant driving behaviors.

Each of these possible scenarios implies under-reporting of aberrant driving behaviors and thus reduces the likelihood that an association with increased aberrant driving is found. The highly skewed and kurtotic nature of the aberrant driving data indicates that these scenarios might have been at play in the current study, as reports of zero aberrant driving behaviors were over-submitted relative to what would be expected from a normally distributed sample (see Figure 3). To address these potential issues, I encourage researchers to utilize objective and naturalistic driving measures moving forward. Compared to self-reports, objective measures have the potential to more fully capture the frequency of aberrant driving maneuvers, as well as more accurately capture the severity of unsafe maneuvers, with potential for nuanced investigations into unsafe driving. The use of naturalistic measures allows further examination of the commute specifically, as opposed to driving performance more generally. Driving performance captured on driving simulators and even on unfamiliar roads may not extend to commuting performance, a notion that I also encourage researchers to investigate.

Concerns about the generalizability of findings from the current study arise from the timing of data collection. Because data were collected during the COVID-19 pandemic, findings might not generalize to a non-pandemic context. The driving environment differed from pre-pandemic times in that fewer cars were present on the roads due to stay-at-home orders (Sutherland, McKenney, & Elkbuli, 2020; Barnes et al., 2020). This lighter traffic extended to common commuting hours, as only essential workers were commuting to the physical workplace in most states (Secon, 2020). Fewer collisions occurred as a result of fewer cars being on the road (Sutherland, McKenney, & Elkbuli, 2020; Barnes et al., 2020), but interestingly some states reported a higher incidence of fatal or severe crash rates, likely due to more egregious speeding (e.g., Qureshi et al., 2020; Gao et al., 2020). With the roads being safer in some ways and more dangerous in other ways relative to non-pandemic times, this study's findings regarding the commuting environment may not extend to the typical post-work commute.

The specific sample included in this study also raises generalizability concerns. In addition to likely having higher anxiety and attention to threats relative to before the pandemic (Twenge & Joiner, 2020; Gallagher et al., 2020; Eysenck et al., 2007), this sample was primarily composed of essential workers. Nearly half (46.3%) of the participants worked in healthcare, retail, and food service rather than representing a broader snapshot of American employees. The results of the non-compliance bias analysis also raise concerns about the generalizability of the sample, in that participants who were excluded due to non-compliance with study instructions differed from those who were retained for data analysis in multiple demographic and survey scales (see Table 2). While person-mean centering variables at Level 1 prevented these discrepancies from statistically biasing the hypothesized model, these differences lend further support to the notion that this study's sample does not represent the wider population of commuting workers. Therefore, I recommend that research replicate the current study outside of the pandemic and with a sample that is more representative of American commuters.

Finally, an important objective of this study was to examine within-person and daily influences on driving behavior, which are under-studied relative to between-person effects (Calderwood & Mitropoulos, 2020). While meaningful within-person variation does appear to exist in post-work aberrant driving ($1 - ICC = .421$), stability coefficients across the daily survey period indicate that aberrant driving behavior was moderately-to-highly consistent throughout the workweek (inter-correlations ranged from .505 – .867). These findings suggest that trait-level factors might be more important than daily factors in determining aberrant driving behavior.

In particular, trait self-control predicted aberrant driving during the post-work commute. Therefore, those who have chronic difficulties self-regulating may be more dangerous drivers following the workday. To protect both themselves and others on the road, this subset of commuters should consider taking public transportation or using rideshare services rather than driving themselves home from work. Future research should examine whether those low in trait self-control also display a high incidence of aberrant driving behaviors during the commute *to* work and whether stressful driving conditions like high traffic exacerbate unsafe driving tendencies. A measure of trait self-control could also be useful as a selection tool for jobs with driving demands. Exploring other characteristics and subgroups of employees could be an important step in finding what about the workday impacts whether an employee will drive more unsafely on the commute home.

6 Conclusion

This study applied ego depletion theory to the novel context of the post-work commute. Uniting ego depletion with spillover theory, workday self-regulatory demands and corresponding alterations in attention and motivation were tested as an explanation for daily impairment in driving safety previously observed in the spillover literature. Despite the hypothesized relationships not being detected, this study's findings offer theoretical contributions and guidance for future research. This study adds to a growing body of literature exploring within-person variability in commuting spillover, a phenomenon dominated by studies of between-person differences. The lack of within-person effects detected points to the need for objective measures of driving behavior, especially in the commuting context which might be particularly vulnerable to self-report memory failures. The lack of an observed ego depletion effect on driving safety also adds to the burgeoning controversy surrounding ego depletion theory, which might have over-stated the impact of self-regulatory exertion on subsequent performance. On the other hand, chronic difficulties in self-regulation as captured via trait self-control did appear to influence aberrant driving in the post-work commute, suggesting the importance of trait-level factors in determining commuting safety.

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Tables

Table 1

Participant inclusion criteria for the current study and reasoning behind each criterion

Inclusion Criterion	Reason
1. Is over 18 years in age	To ensure participant is of age to consent
2. Works Monday through Friday	For the potential to acquire 5 daily observations across a single work week comprised of all workdays
3. Drives her/himself from work each day	To measure post-work driving performance, the participant must drive her/himself from work
4. Does not have job-related driving demands (e.g., bus driver)	To avoid confounds from work-related driving fatigue
5. Works only 1 job per day	To ensure the participant does not have an additional "commute" between jobs
6. Has a commute from work with an average trip time of at least 15 minutes	In accordance with previous standards in post-work commuting research (e.g., Calderwood & Ackerman, 2019)

Table 2

Demographics and Opt-In Scales with Non-Compliance Discrepancies

	Group 1 Mean	Group 2 Mean	Mean Difference	*t*-statistic
Demographics				
Sex	1.43	1.56	-.131	-2.460*
Age	36.05	31.48	4.574	4.131**
Race	1.63	2.20	-.575	-2.999**
Primary caregiver status	1.68	1.44	.239	4.534**
Job industry	13.75	11.48	2.270	3.671**
Organizational tenure	6.10	4.76	1.338	2.969*
Years with driver's license	18.05	12.32	5.734	5.110**
Years driving regularly	17.52	11.60	5.918	5.262**
Opt-in survey scales				
Segmentation preferences	5.30	4.75	.549	6.799**
Rumination response scale	1.90	2.04	-.145	-2.207*

Note. Group 1 comprises the participants who were retained for analysis, while Group 2 is composed of those who were excluded due to non-compliance. $N_{\text{Group 1}}$ = 56 participants; $N_{\text{Group 2}}$ = 26 excluded participants. Sex: 1 = male, 2 = female. Race: 1 = White, 2 = Black or African American, 3 = American Indian or Alaskan Native, 4 = Asian, 5 = Native Hawaiian or Other Pacific Islander, 6 = More than One Race. Primary caregiver status: 1 = yes, 2 = no. Job industry: 1 = Architecture and Engineering; 2 = Arts, Design, Entertainment, Sports, and Media; 3 = Building and Grounds Cleaning and Maintenance; 4 = Business and Financial Operations; 5 = Community and Social Service; 6 = Computer and Mathematical; 7 = Construction and Extraction; 8 = Education, Training, and Library; 9 = Farming, Fishing, and Forestry; 10 = Food Preparation and Serving Related; 11 = Healthcare Practitioners and Technical; 12 = Healthcare Support; 13 = Installation, Maintenance, and Repair; 14 = Legal; 15 = Life, Physical, and Social Science; 16 = Management; 17 = Military Specific; 18 = Office and Administrative Support; 19 = Personal Care and Service; 20 = Production; 21 = Protective Service; 22 = Sales and Related; 23 = Transportation and Material Moving. Segmentation preferences: A higher score indicates preference for greater segmentation between work and home; from 1 = "strongly disagree" to 6 = "strongly agree." Rumination response scale: A higher score indicates a greater tendency to ruminate; from 1 = "almost never" to 4 = "almost always."
* $p < .05$. ** $p < .01$.

Table 3

Internal Consistency Estimates and Descriptive Statistics of Study Variables

	α	*M*	*SD*	(1 – *ICC*)	Skewness	Kurtosis
Focal Variables						
Workday self-regulatory demands	.951	2.670	1.002	.310	.396	-.543
Pre-commute attention	.910	3.255	.942	.314	-.254	-.761
Pre-commute motivation	.941	3.594	1.072	.331	-.467	-.645
Post-work aberrant driving	.668	1.160	.192	.421	2.179	7.138
Control Variables						
Positive affect	.932	2.685	.897	.256	.202	-.693
Negative affect	.891	1.270	.439	.414	3.605	16.929
Minutes between workplace and car	---	3.220	2.417	.246	1.358	1.580

Note. *N* = 56 participants, with *n* = 250 day-level observations. The internal consistency estimates reflect the average internal consistencies across the five-day daily survey period. The intraclass correlation (ICC) indicates the proportion of between-person variance, and the reported (1 – *ICC*) values represent the proportion of within-person variance.

Table 4

Stability Coefficients of Study Variables Across 5-Day Daily Survey Period

Days:	1,2	2,3	3,4	4,5	1,3	2,4	3,5	1,4	2,5	1,5
Focal Variables										
Workday self-regulatory demands	.844**	.712**	.710**	.467**	.773**	.644**	.628**	.656**	.724**	.693**
Pre-commute attention	.749**	.670**	.656**	.713**	.714**	.681**	.662**	.687**	.714**	.661**
Pre-commute motivation	.851**	.745**	.647**	.652**	.778**	.635**	.626**	.730**	.588**	.538**
Post-work aberrant driving	.707**	.785**	.867**	.861**	.505**	.827**	.782**	.608**	.755**	.645**
Control Variables										
Positive affect	.834**	.759**	.740**	.691**	.849**	.763**	.644**	.743**	.736**	.680**
Negative affect	.834**	.709**	.437**	.403**	.782**	.549**	.762**	.487**	.845**	.813**
Minutes between workplace and car	.874**	.851**	.845**	.603**	.771**	.754**	.795**	.720**	.789**	.686**

Note. N = 56 participants, with n = 250 day-level observations.
* $p < .05$. ** $p < .01$.

Table 5

Inter-Correlations of Study Variables

	1	2	3	4	5	6	7	8	9	10
Focal Variables										
1. Workday self-regulatory demands	--	.133	-.371**	-.028	-.011	.272*	-.001	--	--	--
2. Pre-commute attention	-.239**	--	.493**	-.331*	.915**	-.179	-.145	--	--	--
3. Pre-commute motivation	-.187**	.334**	--	-.301*	.497**	-.325*	.002	--	--	--
4. Post-work aberrant driving	.133*	-.071	-.021	--	-.324*	.299*	.330*	--	--	--
Control Variables										
5. Positive affect	-.208**	.820**	.380**	-.104	--	-.220	-.203	--	--	--
6. Negative affect	.416**	-.349**	-.219**	.164**	-.387**	--	.050	--	--	--
7. Minutes between workplace and car	-.073	.093	.089	-.025	.127*	-.183**	--	--	--	--
8. Day of week	-.051	.036	.216	-.315**	.092	-.103	.138*	--	--	--
9. Sine(day of week)	.070	-.041	-.134*	.251**	-.017	.162*	-.090	--	--	--
10. Cosine(day of week)	.003	.033	.120	-.028	.088	-.035	.072	--	--	--

Note. N = 56 participants, with n = 250 day-level observations. Day-level correlations are below the diagonal, while person-level correlations are above the diagonal.
* $p < .05$. ** $p < .01$.

Table 6

Hypothesized Model Results

	Pre-Commute Attention			Pre-Commute Motivation			Post-Work Aberrant Driving		
	Est.	*SE*	*z*	Est.	*SE*	*z*	Est.	*SE*	*z*
Intercept	.139*	.070	1.987	-.218	.130	-1.676	1.275**	.050	25.521
Statistical Controls									
Positive Affect	.933**	.062	15.122	.421**	.134	3.138	-.025	.030	-.821
Negative Affect	-.010	.115	-.085	-.002	.208	-.010	.048	.042	1.147
Minutes between workplace and car	-.011	.021	-.520	.040	.046	.870	---	---	---
Day of Week	-.046*	.023	-2.006	.073	.044	1.671	-.038**	.012	-3.287
Sine (Day of Week)	-.076*	.039	-1.974	.016	.068	.241	-.017	.011	-1.634
Cosine (Day of Week)	.023	.039	.582	-.004	.057	-.075	.034*	.015	2.221
Focal Variables									
Workday Self-Regulatory Demands	-.066	.043	-1.543	-.108	.128	-.844	.021	.016	1.248
Pre-Commute Attention	---	---	---	---	---	---	.006	.029	.225
Pre-Commute Motivation	---	---	---	---	---	---	.021	.018	1.184

Note. N = 56 participants, with n = 250 daily survey observations. Predictor and mediator variables are person-mean centered, with the exception of those variables relating to the day of the week. Paths were estimated as fixed effects without random slope terms. Positive affect and negative affect were allowed to correlate ($r = -.386$, $p < .05$), and attention and motivation were allowed to correlate ($r = .045$, *ns*). The model's R^2_1 for post-work aberrant driving is .10.
* $p < .05$. ** $p < .01$.

Table 7

Indirect Effect Coefficients for Hypothesized Model

Indirect Effect	Estimate	*SE*	95% CI
Workday Self-Regulatory Demands → Pre-Commute Attention → Post-Work Aberrant Driving	.000	.002	[-.005032, .004678]
Workday Self-Regulatory Demands → Pre-Commute Motivation → Post-Work Aberrant Driving	-.002	.003	[-.01279, .00411]

Note. Confidence intervals were generated from a Monte Carlo simulation with 20,000 bootstrapped samples (see Preacher & Selig, 2012).

Table 8

Full Model Results for Negative and Positive Affect as Mediating Mechanisms

	Pre-Commute Negative Affect			Pre-Commute Positive Affect			Post-Work Aberrant Driving		
	Est.	*SE*	*z*	Est.	*SE*	*z*	Est.	*SE*	*z*
Intercept	-.053	.063	-.844	-.104	.115	-.907	1.271**	.049	25.919
Statistical Controls									
Minutes between workplace and car	-.080*	.035	-2.286	.096**	.037	2.624	---	---	---
Day of Week	.018	.021	.849	.035	.038	.917	-.037**	.011	-3.246
Sine (Day of Week)	.049	.032	1.514	.065	.068	.947	-.018	.011	-1.650
Cosine (Day of Week)	-.022	.024	-.953	.007	.043	.169	.034*	.015	2.204
Focal Variables									
Workday Self-Regulatory Demands	.166**	.041	4.017	-.140	.089	-1.574	.018	.017	1.070
Pre-Commute Negative Affect	---	---	---	---	---	---	.047	.043	1.074
Pre-Commute Positive Affect	---	---	---	---	---	---	-.009	.017	-.551

Note. N = 56 participants, with n = 250 daily survey observations. Predictor and mediator variables are person-mean centered, with the exception of those variables relating to the day of the week. Paths were estimated as fixed effects without random slope terms. Positive affect and negative affect were allowed to correlate (r = -.276, p < .01).
* p < .05. ** p < .01.

Table 9

Means, Standard Deviations, and Inter-Correlations for Supplemental and Focal Variables

	M	*SD*	1	2	3	4	5	6
Supplemental Variables								
1. End-of-Workday Ego Depletion	2.452	.937	--	-.455**	.344**	-.649**	-.692**	.429**
2. Trait Self-Control	3.702	.712	--	--	-.241	.266*	.668**	-.434**
Focal Variables								
3. Workday Self-Regulatory Demands	2.670	1.002	.385**	--	--	.133	-.371**	-.028
4. Pre-Commute Attention	3.255	.942	-.620**	--	-.239**	--	.493**	-.331*
5. Pre-Commute Motivation	3.594	1.072	-.458**	--	-.187**	.334**	--	-.301*
6. Post-Work Aberrant Driving	1.160	.192	.099	--	.133*	-.071	-.021	--

Note. $N = 56$, with $n = 250$ day-level observations. Day-level correlations are below the diagonal, while person-level correlations are above the diagonal.

* $p < .05$. ** $p < .01$.

Table 10

Full Model Results for Ego Depletion as a Predictor

	Pre-Commute Attention			Pre-Commute Motivation			Post-Work Aberrant Driving		
	Est.	*SE*	*z*	Est.	*SE*	*z*	Est.	*SE*	*z*
Intercept	.122	.069	1.783	-.264*	.128	-2.056	1.278**	.050	25.618
Statistical Controls									
Positive Affect	.843**	.080	10.564	.141	.125	1.130	-.013	.031	-.425
Negative Affect	-.019	.116	-.165	.050	.267	.189	.058	.032	1.788
Minutes between workplace and car	-.013	.020	-.644	.035	.046	.751	--	--	--
Day of Week	-.041	.023	-1.802	.088*	.043	2.049	-.039**	.012	-3.396
Sine (Day of Week)	-.070	.037	-1.905	.035	.066	.535	-.018	.010	-1.752
Cosine (Day of Week)	.018	.038	.485	-.016	.056	-.279	.035*	.015	2.249
Focal Variables									
End-of-Workday Ego Depletion	-.122*	.057	-2.137	-.368**	.117	-3.135	.019	.010	1.950
Pre-Commute Attention	---	---	---	---	---	---	.008	.030	.250
Pre-Commute Motivation	---	---	---	---	---	---	.024	.017	1.390

Note. N = 56 participants, with n = 250 daily survey observations. Predictor and mediator variables are person-mean centered, with the exception of those variables relating to the day of the week. Paths were estimated as fixed effects without random slope terms. Positive affect and negative affect were allowed to correlate (r = -.386, p < .01), and attention and motivation were allowed to correlate (r = -.001, *ns*).

* p < .05. ** p < .01.

Table 11

Full Model Results for Trait Self-Control as a Predictor

	Pre-Commute Attention			Pre-Commute Motivation			Post-Work Aberrant Driving		
	Est.	*SE*	*z*	Est.	*SE*	*z*	Est.	*SE*	*z*
Intercept	6.148*	2.994	2.053	4.293	9.323	.461	-4.679	4.163	-1.124
Statistical Controls									
Positive Affect	1.020**	.066	15.538	.445**	.114	3.911	-.057	.043	-1.323
Negative Affect	-.041	.109	-.378	-.270	.247	-1.094	.113*	.057	1.987
Minutes between workplace and car	.039	.023	1.685	.038	.048	.787	--	--	--
Day of Week	-1.847*	.926	-1.994	-1.368	3.076	-.445	2.009	1.384	1.452
Sine (Day of Week)	-.560	2.023	-.277	-.432	.959	-.450	.607	2.798	.217
Cosine (Day of Week)	1.613	1.030	1.566	1.205	2.803	.430	-1.753	1.432	-1.224
Focal Variables									
Trait Self-Control	-.041	.074	-.557	.661**	.117	5.663	-.072*	.034	-2.100
Pre-Commute Attention	---	---	---	---	---	---	.004	.029	.123
Pre-Commute Motivation	---	---	---	---	---	---	.021	.016	1.312

Note. N = 56 participants, with n = 250 daily survey observations. Predictor and mediator variables are person-mean centered, with the exception of those variables relating to the day of the week.

* p < .05. ** p < .01.

Figures

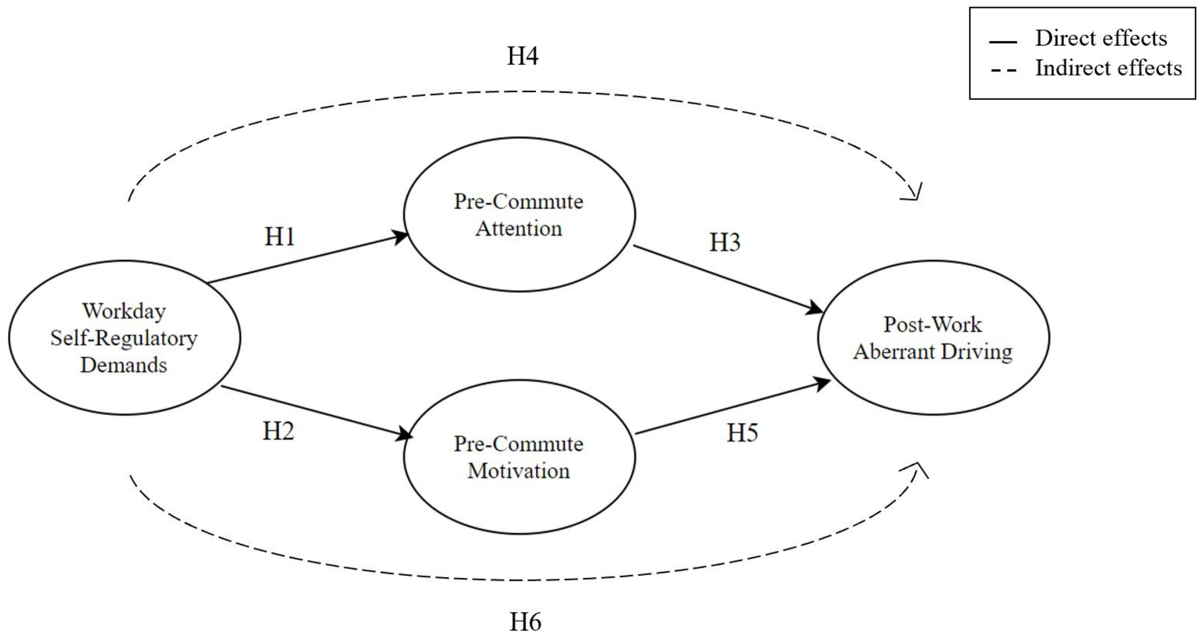

Figure 1. Hypothesized model.

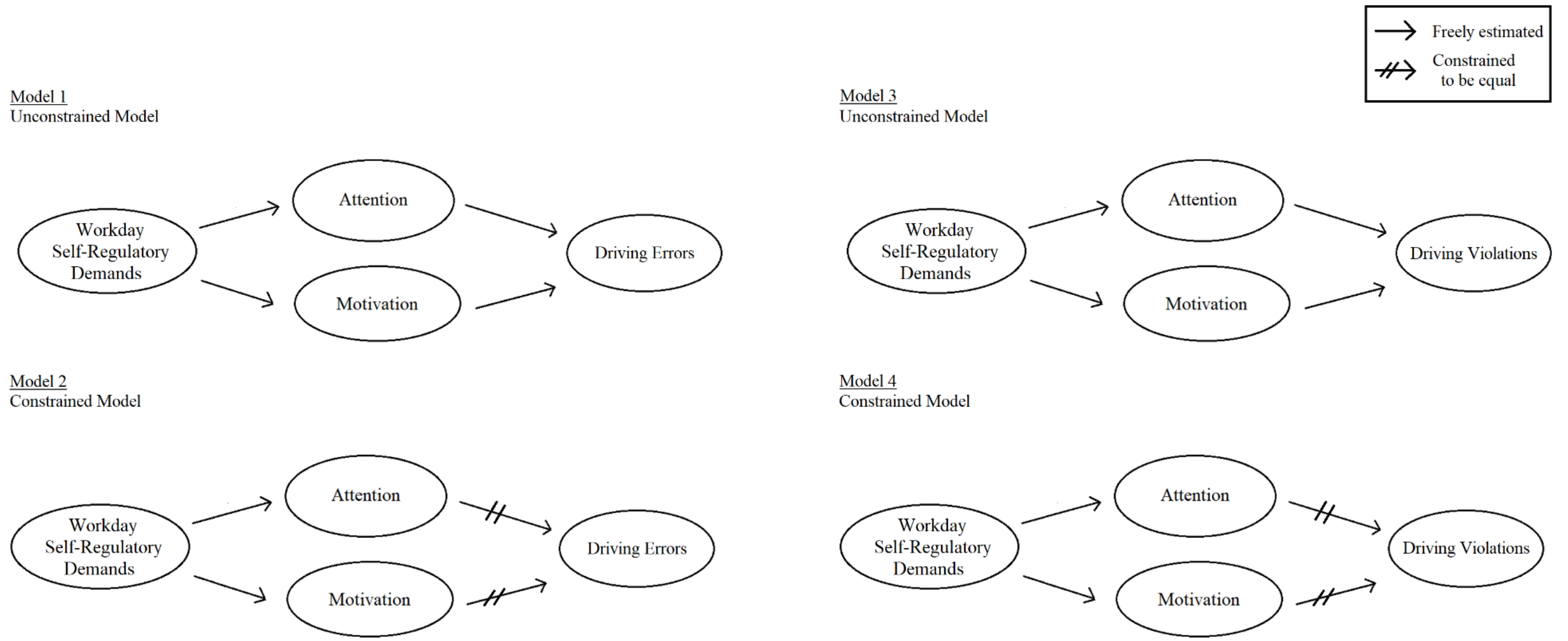

Figure 2. Models computed in exploratory analysis of differential contributions of attention and motivation to driving errors and violations.

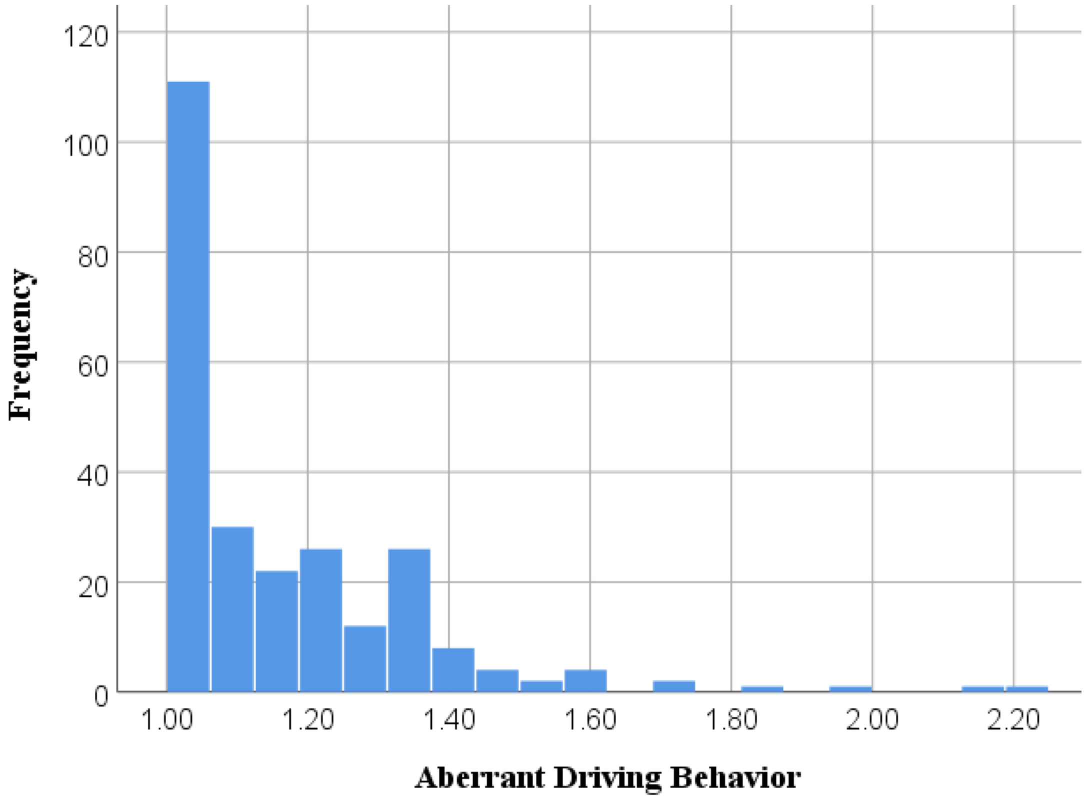

Figure 3. Histogram of post-work aberrant driving behavior as reported in the Driving Behavior Questionnaire. *N* = 56 participants; *n* = 250 observations.

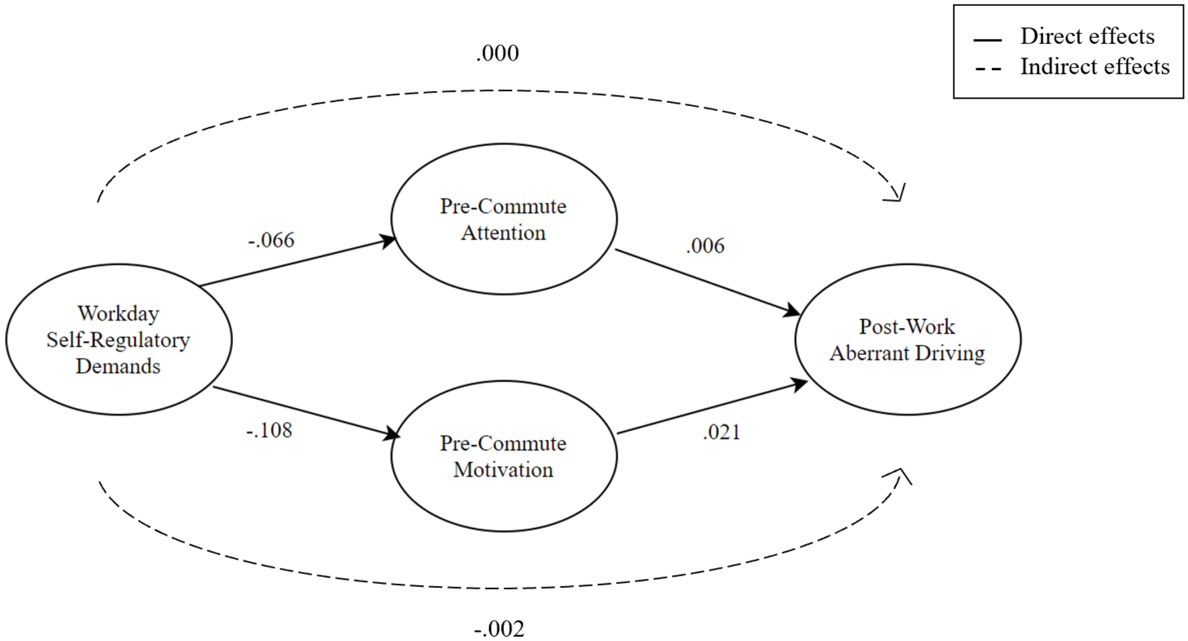

Figure 4. Coefficient estimates among the hypothesized variables.

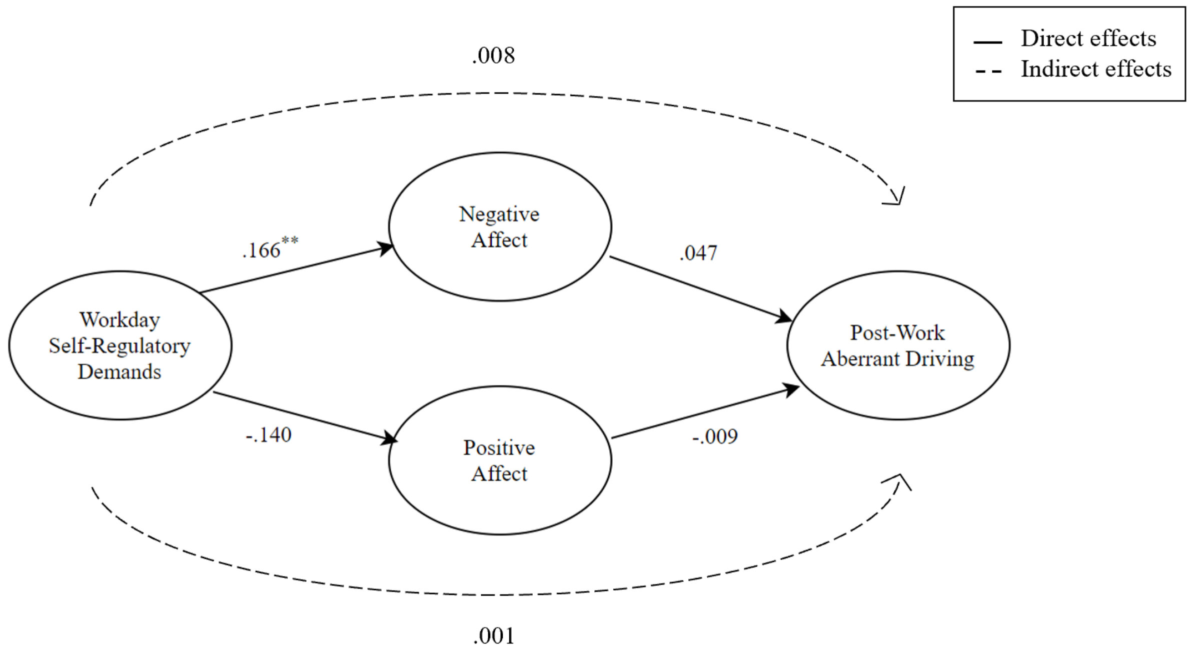

Figure 5. Estimated model with negative and positive affect as mediators.

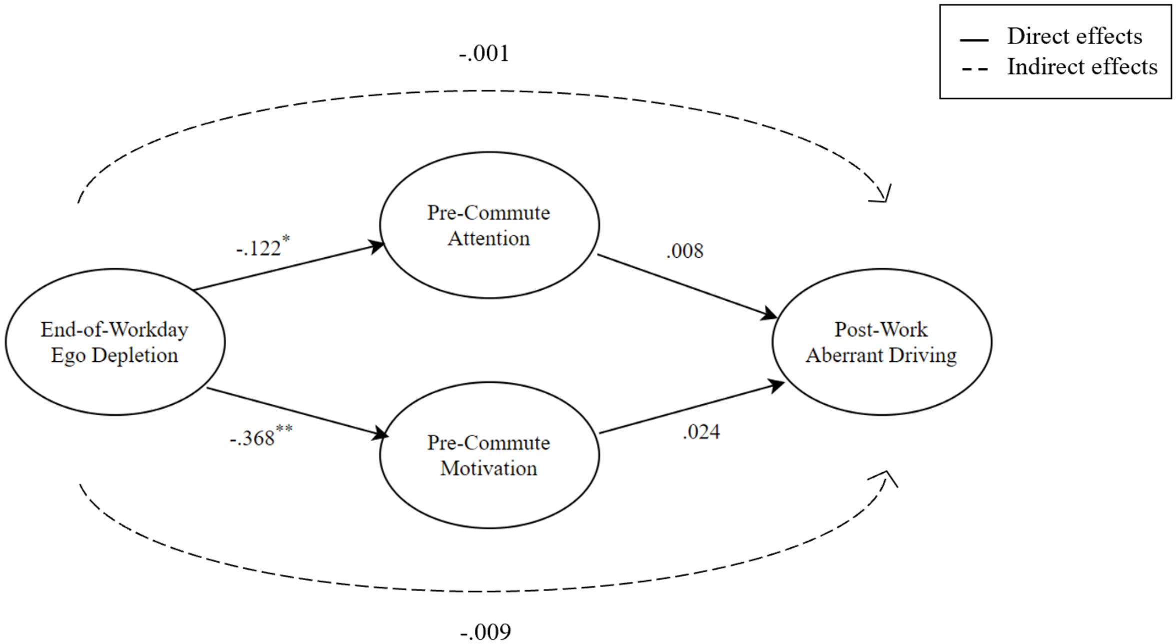

Figure 6. Estimated model with ego depletion as predictor.

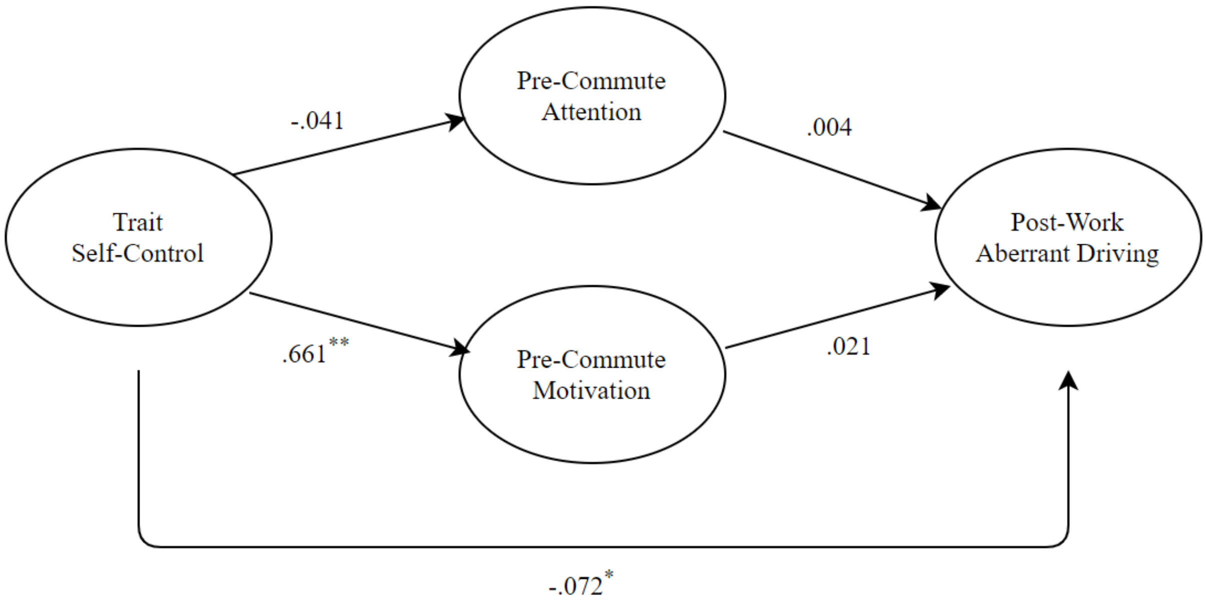

Figure 7. Estimated model with trait self-control as predictor.